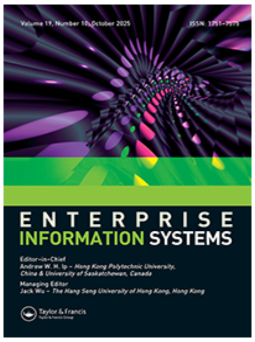

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Creating agri-food supply chain resilience using AI-enabled Information processing: identifying the mediating role of organisational mindfulness and flexibility

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ABSTRACT
Agri-food supply chains (AFSCs) are complex systems that move products from farm to fork. While AI is expected to improve AFSC management, little research has explored the organisational skills needed for success. This study investigates how AI-powered information processing, combined with mindfulness and flexibility, can make AFSCs more resilient. Using a survey of 147 practitioners and structural equation modelling, the findings highlight that organisational mindfulness and flexibility play key roles in building resilient supply chains, boosting long-term performance, and reducing food waste. These insights support both AFSC research and practical applications.

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Artificial intelligence; supply chain resilience; agri-food, organisational mindfulness; information processing

1. Introduction

Agriculture is a global industry responsible for feeding a growing global population with globalised tastes (European Environment Agency 2019; Latino et al. 2023). Agricultural intensification and widespread pressures on the environment and climate have amplified due to domestic material consumption increasing by 65% globally between 2000 and 2019 (Bai and Sarkis 2022; United Nations 2022). Further, it is estimated that organisations involved in the agri-food industry need to increase food production by 70% in 2050, while mitigating issues such as limited farm land, scarcity of natural resources, and climate change (Liu et al. 2021; R. Sharma et al. 2022; Spanaki, Karafili, and Despoudi 2021). In 2020, over 13% of the world's food was lost in the Agri-Food Supply Chain (AFSC) before ever-reaching retail markets (United Nations 2022). In response, the EU has set an ambitious target to reduce the unintentional loss of food mass in AFSCs by half in 2030 (European Commission 2017). As greenhouse gases are generated at every step of the AFSC, food waste in AFSCs account for almost 10% of global greenhouse gases (United Nations 2022). Prioritising food loss reduction is therefore critical for the transition to sustainable agri-food systems (FAO 2022; Trevisan and Formentini 2023).

Recent research has also highlighted the vulnerability of AFSCs to exogenous shocks, and the importance of developing resilient SCs (Müller, Hoberg, and Fransoo 2022; X. Li et al. 2023b; Shen and Sun 2023). Indeed, the severity of the COVID-19 crisis has put supply chain resilience (SCRes) at the centre of academic interest and the need to develop long-term organisational design approaches that can enable rapid and flexible responses to environmental change (Choudhary et al. 2021; Gebhardt et al. 2022; Paul et al. 2021). However, AFSCs are becoming more complex due to the pressure to provide food security, traceability, safety (Balezentis et al. 2023; X. Li et al. 2023), and the perishable nature of agri-food products, a unique characteristic of AFSC (N. K. Tsolakis et al. 2014; Zissis, Aktas, and Bourlakis 2017). This study contributes to this important area of study by evaluating how AI-enabled information processing can be implemented to develop resilient SCs and achieve long-term supply chain performance (SCP).

AFSCs are inherently complex, data-centric systems that are increasingly adopting AI, and analytical technologies (e.g. big data analytics) that place a strong emphasis on data creation and consumption,

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leading to data-informed decisions across the SC (Gonzálvez-Gallego et al. 2015; Maheshwari, Gautam, and Jaggi 2021; Song, Li, and Yu 2021). While technologies such as AI may have a role for generating value for organisations (Dubey et al. 2022), data-centric AFSCs have multiple, diverse stakeholders that create challenges for data collection and storage, information sharing, and data visualisation (Zhong, Tan, and Bhaskaran 2017). Data extraction and dissemination have become a core organisational capability to effectively manage SC, due to time-critical, high-risk, high control and security requirements (Papetti et al. 2012; Toorajipour et al. 2021; Yan et al. 2016). In the context of AFSC, this capability can be a determinant for the sustainability of agrifood as it can enable organisations to better manage the response to unanticipated events (e.g. drought, flooding, war, and isolation of producers from markets) (Jraisat and Sawalha 2013; Trevisan and Formentini 2023).

Previous studies have shown how data analytics capabilities have enhanced SC organisations' information processing, resulting in improved supply chain resilience (SCRes) (Dubey, Gunasekaran, Childe, Roubaud, et al. 2019). The concept of recovering performance after a disruption is referred to as SCRes (El Baz and Ruel 2021). However, AI-enabled information processing has unique characteristics, primarily its predictive and self-learning capabilities (Hendry et al. 2019) (Dubey et al. 2020). AI technologies have benefited greatly from the increasing power of machine computation and availability of data, resulting in AI becoming more capable of addressing prevailing business problems (Issa, Jabbouri, and Palmer 2022), and reducing operational costs (Kumar, Agrawal, and Rahman 2017). Yet, SC research to date is largely concerned about the flow of raw materials and inventory management and has yet to explore the potential of AI-enabled information processing to impact SCRes (Hendry et al. 2019). Furthermore, the implementation of AI technologies alone is not likely to be sufficient to improve organisational performance without considering the necessary organisational capabilities needed to transform the knowledge created (Olan et al. 2022).

Despite contributions of previous studies about SCRes in the context of non-food supply chain, its theoretical development in AFSC organisations is underdeveloped (Datta 2017; Dubey et al. 2020). Given the inherent uncertainties of AFSCs (Kamble, Gunasekaran, and Gawankar 2020) and threat of disruptions (Leat and Revoredo-Giha 2013), decision-making is complex; therefore, an organisation's ability to process information effectively is strategically important for organisations to recover quicker from catastrophic events and thereby reduce food waste (Wong et al. 2020). Similar to recent studies on AI and knowledge sharing capabilities (Olan et al. 2022), this research argues that organisations that increase their AI-enabled information processing capability should improve their ability to deal with the uncertainty of their environment and thereby improve their long-term performance.

Recent research has begun to explore the role of AI technologies in agri-food supply chains (AFSCs), primarily focusing on improving traceability, transparency, and operational efficiency. For instance, Kamble, Gunasekaran, and Gawankar (2020) highlight how AI and big data analytics can enhance sustainable performance by enabling more informed decision-making in agriculture. Similarly, N. Tsolakis et al. (2022) focus on AI's contribution to food traceability and compliance across the supply chain, while Kopka and Grashof (2022) examine its potential to reduce energy consumption and environmental impact. These studies demonstrate AI's utility as a tool for process optimisation and monitoring, but they stop short of investigating the organisational capabilities needed to fully realise AI's potential in turbulent, high-risk environments.

This study extends the existing body of work by examining how AI-enabled information processing contributes to resilience, not through technology adoption alone, but through its integration with organisational mindfulness (OMIN) and organisational flexibility (OFLEX). Rather than viewing AI as a standalone solution, we argue that its ability to generate resilience outcomes is mediated by an organisation's cognitive and structural capacities to interpret, adapt, and respond. In doing so, our research contributes a novel, theoretically grounded perspective to the AI in AFSC discourse by explaining how human-centric and structural enablers interact with AI systems to reduce food waste, improve adaptability, and enhance long-term performance in agri-food contexts.

The correct deployment of information processing technology is under-developed however, with recent research highlighting the importance of implementing mindful management of technology and digital transformation (H. Li et al. 2021). To achieve SCRes, organisations need to maintain situational awareness at all times (Dennehy et al. 2021; Ivanov and Dolgui 2021), yet, the importance of organisations and people in interpreting data and information is frequently not examined (Lee 2021). Organisational mindfulness (OMIN) refers to an organisation's ability to gather and analyse discriminatory details about its internal and external environments (Hendry et al. 2019; Lee 2021).

This paper develops the argument that AFSCs which adopt organisational capabilities related to mindfulness will be better positioned to identify opportunities and discover insights resulting from their data (Hendry et al. 2019), providing organisations with enhanced sensing and alterness, both of which are vital elements to building SCRes. Insights generated from data analysis can identify opportunities for improvements; however, organisations must also possess the capability to actualise these insights (Srinivasan and Swink 2018). An organisation's ability to adapt to changing market conditions by efficiently and effectively deploying resources is referred to as organisational flexibility (OFLEX) (Upton 1994). Cumulatively, this approach will yield useful insights into long term organisational design approaches to achieving supply chain resilience (Gebhardt et al. 2022).

To this end, the aim of this study is *to examine the impact of organisational mindfulness and flexibility on the relationship between AI-enabled information processing to build resilient agri-food supply chains.*

The remainder of this paper is organised as follows: Background to the theories pertinent to this study are presented. Then, the theoretical framework and development of the hypotheses is provided. Next, the research methodology is outlined, followed by data analysis and results. Discussion, implications, and opportunities for future research are then presented. The paper ends with concluding remarks.

2. Theoretical background

2.1. Organisational information processing theory (OIPT)

Conceptualised by Thompson (1967), OIPT was subsequently extended by Galbraith (1974, 1977) and Tushman and Nadler (1978). OIPT is concerned with an organisation's information processing capabilities, structures, and design (Dubey, Gunasekaran, Childe, Fosso Wamba, et al. 2019) and states that an organisation's information processing performance results from the firm's information processing needs and capability (Belhadi, Mani, et al. 2021; Hendry et al. 2019). OIPT depicts organisations as open social systems that aim to mitigate uncertainty in the decision-making process to enable organisations to better execute their strategy (Hendry et al. 2019). In this context, uncertainty is defined as 'the difference between the amount of information required to execute a task and the level of information already available with the organisation' (Galbraith 1973, 5). SC organisations are dependent on both their own internal capabilities and on the capabilities of their stakeholders (L. Li 2012; S. Li and Lin 2006; Zhu et al. 2018). Hence, SC are inherently uncertain, which can negatively impact the link between the organisations information processing capabilities and intended outcomes (I. J. Chen and Paulraj 2004; Zhu et al. 2018). To improve transparency and traceability in the management of SC, it is crucial for organisations to proactively engage and communicate with stakeholders (Belhadi, Mani, et al. 2021).

Historically, organisations largely relied on 'mechanistic' organisational resources which tend to deal with issues referred to as 'exception scenarios' that utilise hierarchy, rules and goals (Belhadi, Mani, et al. 2021; Galbraith 1973). However, the cost and responsiveness of mechanistic models is negatively impacted by the high frequency of expectation scenarios (Peng, Heim, and Mallick 2014). An alternative solution for organisations that seek to improve their information processing capabilities is to enhance their vertical information systems (e.g. systems implemented at different administrative levels of an organisation) (Srinivasan and Swink 2018), which enable efficient and intelligent data processing, enabling organisations to swiftly adjust their plans with little resource involvement to resolve complexities (Peng, Heim, and Mallick 2014).

OIPT is concerned with how organisations develop their capabilities to meet their information processing requirements (Wamba et al. 2020). For example, to maintain performance levels and manage SC disruptions, organisations must process information under increasing uncertainty (Belhadi, Mani, et al. 2021; Srinivasan and Swink 2018). The assumptions of OIPT are supported by other theories such as, dynamic capability theory (DCV) and contingency theory. DCV postulates that lower-order resource capabilities, such as AI and other data-driven systems, develop a foundation for enhancing higher-order capabilities such as SCP (Wamba et al. 2020). However, the shortcoming of DCV is that it fails to provide an explanation for the effect high-scale disruptions have on utilisation and efficiency of lower-order capabilities. While contingency theory holds the perspective that organisations should find a balance between their information processing needs capacity (Tushman and Nadler 1978). This perspective supports the argument that when the scale of disruptions is aligned with an organisation's information processing capacity, SCRes can be positively associated with SCP (Wong et al. 2020). Despite this, there is a gap in contingency theory for explaining how the development organisational capabilities such as OMIN and OFLEX is underpinned by an SC networks' inter-organisational information management capabilities (Belhadi, Mani, et al. 2021).

2.2. Artificial intelligence

In this study, AI is defined as 'the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems' (Hendry et al. 2019, 1438). AI systems possess the capability to learn from the external environment and use these learnings to adapt to changes in that environment (Belhadi, Mani, et al. 2021; Grover, Kar, and Dwivedi 2020; Spring, Faulconbridge, and Sarwar 2022). AI information processing capabilities can be divided into different types of capability (i.e. exploiting, expanding, exploring), which suggest the likelihood of AI systems to complement or replace human decision-making (Baryannis et al. 2019; M. K. Sharma et al. 2010). These three capabilities are described below.

Exploiting refers to AI systems that can help managers process large amounts of information which would not be possible on their own (Haefner et al. 2021). These AI systems play a supporting role helping humans overcome cognitive information processing limits, which regularly restrict managers from considering the extensive amount of information involved in SC decisions. Exploiting techniques of AI include robust optimisation which is used largely for SC problem detection (Haefner et al. 2021), machine learning and big data which allow for processing huge amounts of data (Min et al. 2019; Priore et al. 2019), fuzzy logic (Cavalcante et al. 2019), stochastic programming (Baryannis et al. 2019).

Expanding includes AI systems that are capable of either creating new opportunities and ideas or finding more distant solutions by overcoming local search routines (Haefner et al. 2021). While such systems work adjacent to managers to support the innovation process, level 2 AI technological capabilities are limited (Haefner et al. 2021). AI methods at this level include rough set theory which has been used for supporting SC problem analysis and network-based algorithms used primarily for ideation in the SC innovation process (Bottani et al. 2019; Elhoone et al. 2020; Hosseini and Ivanov 2020), and tree-based clustering which strengthens the interaction between humans and machines (Thomassey 2010).

Exploring refers to AI systems that can develop new methods of identifying problems, providing novel solutions, and evaluating the innovation process in terms of its efficiency and effectiveness (Haefner et al. 2021). AI techniques used at this level include model predictive control (Belhadi et al. 2019), agent-based systems (Muravev et al. 2021), computer vision (Dhamija and Bag 2020; Grover, Kar, and Dwivedi 2022), and robotic process automation (Schniederjans, Curado, and Khalajhedayati 2020). These AI systems can conduct more advanced and complex tasks to support human and partially replace them (Haefner et al. 2021).

2.3. Organisational mindfulness

High reliability organisations (HROs) are organisations which can mitigate turbulent environment conditions with a minimal number of failures. A key characteristic common among HROs is organisational mindfulness (OMIN) (Haefner et al. 2021; Hales and Chakravorty 2016). OMIN is a mix of continually scrutinising existing expectations with the ability to develop new expectations based on unprecedented events (Weick and Sutcliffe 2006). Mindful organisations emphasise the 'big picture' of operations and possess a high degree of reliability by increasing the sensing capabilities of employees, minimising assumptions, rewarding the reporting of failures, and implementation of highly standardised routines (Dennehy et al. 2021). In the context of data-rich SCs, OMIN provides the capability to interpret data and uncover insightful clues for detecting or creating opportunities (Hendry et al. 2019; Lee 2021). Moreover, mindfulness practices develop a sense of urgency to respond to unpredicted events and take the necessary corrective actions (Maitlis and Christianson 2014).

OMIN is utilised in this study to enhance management ability to operate efficiently and effectively during turbulent and complex environments. For example, Dennehy et al. (2021) illustrate how the use of OMIN allowed for the effective adoption of big data technologies in a humanitarian aid SC context. Integrating mindful practices into the data analysis process can improve resiliency during a crisis (Hendry et al. 2019).

Hence, this study explores OMIN in the context of AFSC as a robust foundation for information processing (Reb, Allen, and Vogus 2020) and to provide organisations with the preventative and sensing to mitigate the impact of disruptions.

2.4. Organisational flexibility

Organisational flexibility (OFLEX) refers to an organisations capability to operate in volatile environments (Braunscheidel and Suresh 2009; M. K. Sharma et al. 2010; Dubey et al. 2019). OFLEX is defined as 'the degree to which an organisation has a variety of managerial capabilities and the speed at which they can be activated, to increase the control capacity of the management and improve the controllability of the organisation' (Volberda 1996, 361). Hence, OFLEX can be viewed as both a 'managerial task' (i.e. managements' ability to reconfigure operations during turbulent periods) and 'organisational structure task' (i.e. organisation's ability to react to abrupt environment changes (Dubey, Gunasekaran, Childe, Roubaud, et al. 2019). In the context of SCs, OFLEX refers to the ability of management swiftly adjust operations to meet changing market conditions (Srinivasan and Swink 2018). Prior studies have utilised OFLEX to leverage insights generated from analytical technologies, resulting in strengthened resiliency (Dubey, Gunasekaran, and Childe 2019) and improved SC performance (Srinivasan and Swink 2018). Availing of the abundant data in AFSCs (Kamble, Gunasekaran, and Gawankar 2020), AI-based information processing can provide the insights into market conditions, while OFLEX provides the ability to deploy and adjust resources to actualise these insights, which is a crucial component in developing SCRes (Wong et al. 2020). Hence, OFLEX is employed in this study to provide organisations with the ability to efficiently adapt to highly uncertain environments (Braunscheidel and Suresh 2009; Williams et al. 2013).

2.5. Supply chain resilience

Recent global events have highlighted how critical supply chain resilience (SCRes) is for management teams (Belhadi, Mani, et al. 2021; Remko van 2020). SCRes is predominately focused on the SC's ability to deal with spontaneous disruptions, as well as its ability to take actions that should result in the SC returning to an original or improved state (Belhadi, Mani, et al. 2021; Remko van 2020). There are four distinct phases of SCRes: *readiness* phase (i.e. the organisation's anticipation of a disruption), *response* phase refers to planned efforts to mitigate the impact of disruptions, *recovery* phase (i.e. to repair of loss and/or damage caused by a disruption) and *adaptability* (i.e. the ability to utilise learnings from previous disruptive events and leverage emerging technologies) (Fahimnia and Jabbarzadeh 2016; Leat and Revoredo-Giha 2013; Stone and Rahimifard 2018). Resilient supply chains possess a greater capability to absorb shock from interfering events and are ultimately less susceptible to disruptions (Hohenstein et al. 2015). Moreover, SCRes ensures the continuous smooth flow of products and services during an interruption (Ambulkar, Blackhurst, and Grawe 2015; Hendry et al. 2019).

2.6. Supply chain performance

Supply Chain Performance (SCP) refers to the benefits obtained from the resilience and efficiency of SC operations in a dynamic environment (Chowdhury, Quaddus, and Agarwal 2019; Hendry et al. 2019). SCP involves three main components, namely: output performance (effectiveness), resource performance (efficiency), and flexibility performance (agility) (Khan et al. 2009). Output performance refers to a supply chains ability to create customer value, product quality, and speed of delivery; resource performance is the capability of the SC to deliver more customer value with minimal resource utilisation; and flexibility performance is the capability to maintain preserve customer value in an uncertain environment (Khan et al. 2009). Previous studies have outlined two main measures to evaluate SCP: customers' level of satisfaction, which primarily relates to SC effectiveness and agility, and costs incurred, which relates to the efficiency of the SC (Estampe et al. 2013). Organisations that possess the ability to make quick, effective adjustments can facilitate ongoing high performance (Teece, Pisano, and Shuen 1997). SCRes enable organisations to improve performance levels by effectively responding to change (Christopher and Peck 2004; Yu et al. 2019).

3. Theoretical framework and hypotheses development

Data-driven SCs generate huge amounts of data from their suppliers and customers (Estampe et al. 2013). However, to create value from these data, organisations must extract learnings to help address the uncertainty characteristics of ASFCs. As an information processing tool, AI can provide ASFCs with an enhanced insight into their market conditions and internal operations (Belhadi, Mani, et al. 2021; Ali et al. 2024; Dubey, Gunasekaran, Childe, Fosso Wamba, et al. 2019), which can alleviate uncertainty, enhancing an organisation's ability to anticipate and recover from disruptions (Wong et al. 2020). As a result, AFSCs can reduce food waste created from disruptive events and develop sustained SCP. How organisations transform the insights generated from AI-based information processing into learnings that can strengthen SCRes is described through the mindful practices of OMIN. However, the ability to implement these learnings is explained through the principles of OFLEX. Drawing on the OIPT, this study proposes the research model (see Figure 1) to empirically test the interrelated relationships between AI, OMIN, OFLEX and SCRes to attain enhanced SCP.

3.1. The effect of AI-based information processing on SCRes

Several studies have examined the potential of AI for improving SCRes. For example, Belhadi, Mani, et al. (2021) demonstrated the potential of AI techniques (i.e. agent-based systems, fuzzy logic programming) for promoting SCRes strategies. Moreover, Gupta et al. (2021) and Gupta et al. (2024) argue that AI can aid the development of resilient information systems, enabling organisations to better cope with SC disruptions. Modgil et al. (2022) claim that an SC facilitated by AI can help develop resilience in its network and structure, enabling organisations changing environments and during disruptive events. In this study, we adopt the perspective of OIPT, proposing that implementing AI can enable AFSC organisations to develop or improve their information-processing capabilities (Belhadi, Mani, et al. 2021; Le and Behl 2024; Srinivasan and Swink 2018). Previous studies suggest that AI as an information processing tool can reduce uncertainty, resulting in improved SCRes. Given that AFSCs are data rich (Kamble, Gunasekaran, and Gawankar 2020) and highly uncertain in nature (Wong et al. 2020), this study proposes that AI-based information processing can mitigate the uncertainties surrounding AFSCs by allowing organisations to decrypt, analyse and provide insight from data collected from a variety of data sources (Grover, Kar, and Dwivedi 2020). Thus, we hypothesise:

H1. AI-based information processing has a significant and positive effect on supply chain resilience (SCRes).

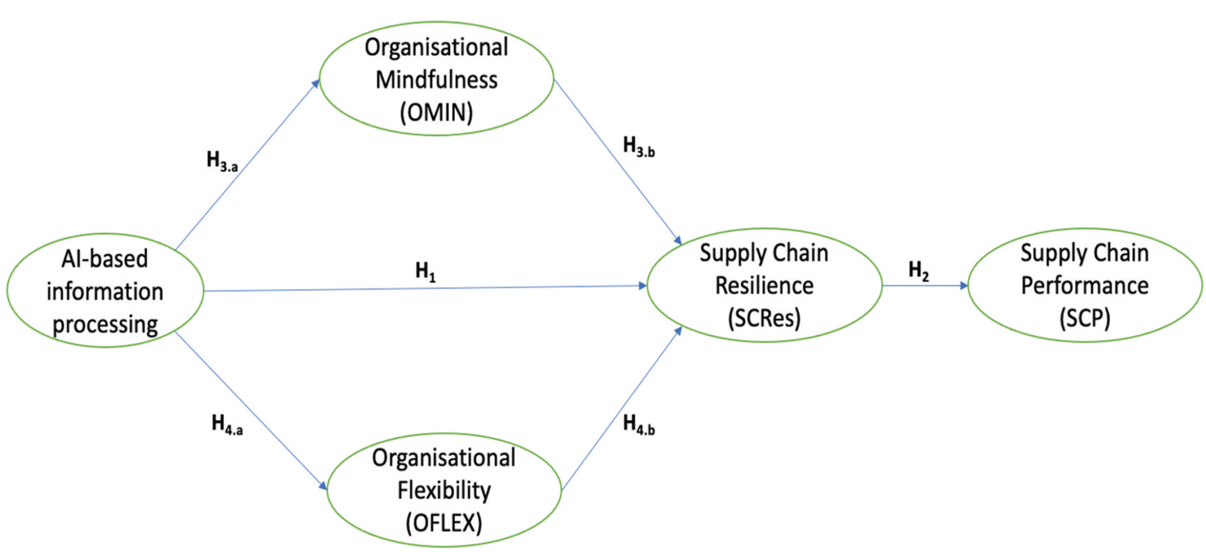

Figure 1. Research model and corresponding hypotheses.

3.2. Supply chain resilience and supply chain performance

Recent studies have shown that SCRes play a critical role in sustaining a certain level of SCP (e.g. Chowdhury, Quaddus, and Agarwal 2019; Wieland et al. 2013; Yu et al. 2019). For example, Carvalho, Azevedo, and Cruz-Machado (2012) proposed a structure for creating SCRes and illustrated its positive effect on SCP. Resilience is both a proactive and reactive capability, meaning that resilience can help mitigate the impact of disruptions in addition to helping recover to previous performance levels after the interfering event has occurred (Wieland et al. 2013). A resilient SC is agile (i.e. the ability to absorb and respond to change, and to monitor uncertainty), which enables organisations to sustain high levels of performance (Hendry et al. 2019). The recent Covid-19 pandemic revealed that organisations that failed to develop SCRes suffered partial or complete stoppage to their operations (Belhadi, Mani, et al. 2021). Previous research has indicated that in non-agricultural supply chains, improved SCRes can enable organisations to achieve long-lasting performance (Belhadi, Mani, et al. 2021). Post Covid-19 studies confirmed the influence of SCRES on financial performance, especially when assessed in the long term (El Baz, Ruel, and Fozouni Ardekani 2023). This study argues that the need for SCRes in AFSCs is heightened due the many actors involved in AFSCs (Le 2023) and the perishable nature of goods (Shukla and Jharkharia 2013). Thus, we hypothesise:

H2. Supply chain resilience significantly and positively affects supply chain performance.

3.3. The mediating role of organisational mindfulness and organisational flexibility

Organisations must proactively prepare for disruptions and have the capability to quickly and efficiently implement decisions to sustain performance during turbulent periods (Remko van 2020). This study theorises that AI-based information processing can lead to the development of SCRes. The literature highlights that OMIN and OFLEX are key elements for identifying and actualising insights generated from information processing technologies to build SCRes Hendry et al. (2019); Reb, Allen, and Vogus (2020); Dennehy et al. (2021). Hence, this study proposes a mediation effect from OMIN and OFLEX to enabling SCRes driven by AI-based information processing capabilities (Dubey, Gunasekaran, Childe, Roubaud, et al. 2019 a, b).

As supply chains are inherently complex, and unpredictable, there is a significantly high degree of uncertainty (D. Q. Chen, Preston, and Swink 2015; Dubey et al. 2020; Wong et al. 2020), which greatly increases the complexity of developing and scrutinising organisations expectations. Therefore, increasing available information and minimising uncertainty are critical for the effective adoption of OMIN. Recent studies have illustrated the ability of AI to (i) improve information processing and reduce uncertainty (e.g. (Belhadi, Mani, et al. 2021; Haefner et al. 2021), (ii) provide reliable forecasts and near real-time visibility of operations giving organisation a platform to continuously analyse their existing expectations (Baryannis et al. 2019; Hendry et al. 2019), and (iii) provide learnings from past events and its external environment, enabling organisations to manage expectations (Grover, Kar, and Dwivedi 2020). Dernbecher and Beck (2017) posit that technological infrastructure is at the core organisational capabilities for performance and mindfulness technology infrastructure is central to organisational capabilities for mindfulness and performance. Thus, we hypothesise:

H3a. AI-based information processing has a significant and positive effect on OMIN.

SCRes place a large emphasis on recovery and adaptability during times of crisis (Ambulkar, Blackhurst, and Grawe 2015; Craighead et al. 2007). Mindful organisations continuously adjust their resources during turbulent periods to attain desired levels of adaptability and responsiveness of the SC (Burnard, Bhamra, and Tsinopoulos 2018); moreover, contingency planning allows them to proactively prepare for disruptions (Mandal 2019). Mindful organisations operate in complex conditions while avoiding failures due to their highly reliable human processes and relationships (Hendry et al. 2019; Weick and Sutcliffe 2006). OMIN principles and practices align with supply chain organisations seeking to develop resilience, as the principles and practices of OMIN help avoid disruptions and to recover after disruptions (Sawyerr and Harrison 2020). OMIN provides a foundation for better information processing, which can explain how organisations can leverage the insights from AI-based informaiton processing to develop SCRes (Hendry et al. 2019; Reb, Allen, and Vogus 2020). Thus, we hypothesise:

H3b. OMIN mediates the relationship between AI-based information processing and SCRes.

The literature suggests that AI-based information processing can provide meaningful insights into external market conditions (Belhadi, Mani, et al. 2021). OFLEX requires organisations to possess the ability to effectively deploy and adjust resources in response to turbulent market conditions (Upton 1994). Hence, this study argues that AI-based information processing can provide the necessary information for organisations to utilise the adaptive capabilities of OFLEX. Thus, we hypothesise:

H4a. AI-based information processing has a significant and positive effect on OFLEX.

Organisations with superior OFLEX are better able to handle turbulent environments (Sreedevi and Saranga 2017). Previous studies have highlighted that SC organisations that achieved increased flexibility have resulted in improved SCRes (Dubey, Gunasekaran, Childe, Roubaud, et al. 2019; Ivanov, Sokolov, and Dolgui 2014). AI-based information processing can provide the necessary insights into SC operations and market conditions to strengthen SCRes; however, the ability of an organisation to make the necessary adjustments to actualise these insights is explained through OFLEX. Thus, we hypothesise:

H4b. OFLEX mediates the relationship between AI and SCRes.

4. Research design

4.1. Instrument development

The survey was developed according to guidelines proposed by Malhotra and Grover (1998), where measures which have been established in literature were used with small adjustments to item wordings. Additionally, following procedures outlined by Sudman (1983), 14 people were selected based on their professional or academic experience to pre-test the survey to uncover any shortcomings and to provide feedback on the overall survey design as well as the measures used to assess the constructs (Vanpoucke and Ellis 2019). Survey items were adapted from prior SC and resilience studies (e.g. Dubey et al. 2020) and pre-tested with 14 AFSC experts to ensure relevance to AFSC-specific issues such as spoilage, traceability, and logistical disruptions. We have included examples of this adaptation in Appendix A and clarified it in the instrument development section. The items were measured on a seven-point Likert scale with extreme points ranging from 1 = strongly disagree to 7 = strongly agree. The survey constructs, their indicators, and citation source are listed in the Appendix. All constructs were deployed as reflective constructs.

4.2. Sampling method and data collection

The empirical context of the study is the AFSC industry. A total of 147 complete responses were collected using Qualtrics. The questionnaire was responded to by employees of agri-food supply chain organisations with at least 2 years' experience in AFSC industry. The profile of respondents is summarised in Table 1. The non-response bias was tested following Armstrong and Overton (1977) procedure, where responses of early respondents (first 25%), late respondents (last 25%), and a sample of non-respondents were compared. This resulted in all items returning a $p > 0.3$, indicating that there was no statistically significant difference between early, late, and non-respondents. Participants were selected based on their minimum 2 years of experience in agri-food SC roles, ensuring familiarity with operational and strategic decisions. Our sample covers diverse roles (procurement, logistics, quality) across Europe, providing a cross-sectional representation of the AFSC domain.

Table 1. Profile of respondents.

Parameters	Details	Frequency	Percentage (%)
Gender	Male	106	72.11
	Female	36	24.49
	Prefer not to say	5	3.40
Years of agri-food supply chain industry experience	2–5	18	12.24
	6–10	42	28.57
	11–15	34	23.13
	16–20	9	6.12
	20+	44	29.94
Geographic area of the respondent's organisation	Europe	116	78.91
	North America	14	9.53
	South America	2	1.36
	Asia	9	6.12
	Africa	3	2.04
	Australia	3	2.04
Total		147	100

5. Data analysis and results

Data analysis was conducted using Structural Equation Modelling (SEM) as it provides statistical procedures for testing measurements and causal hypotheses (Jin, Vegelius, and Yang-Wallentin 2020). SEM includes a set of regression analyses making it suitable for examining interrelationships between independent and dependent variables (Belhadi, Mani, et al. 2021; Dubey et al. 2020). Following the guidelines of Hair et al. (2014) this study utilises PLS-SEM for model prediction. All the PLS-SEM computations were performed using SmartPLS 3.0.

5.1. Measurement validation

Table 2 contains the factor loadings and descriptive statistics of the items. The factor loadings for all items exceeded the proposed cut-off of 0.60 at $p < 0.001$, indicating construct validity (Hair, Ringle, and Sarstedt 2013).

The construct correlations and discriminate validity results (see Table 3) suggest that the study's measurements are reliable and the latent construct account for a minimum of 50% of the item variance (cf. Benitez et al. 2020). The threshold for HTMT is construct values that must be below 0.9, hence this model possesses discriminant validity. HTMT values are presented in Table 3. The overall model fit can be assessed by analysing the standardised root mean squared residual (SRMR) of the model, a value smaller than 0.080 indicates acceptable model fit (Benitez et al. 2020). The SRMR of this model is 0.069.

Testing and controlling endogeneity is a vital part of SEM analysis (Huit et al. 2018). Endogeneity can occur due to several reasons; however, it typically occurs when variables excluded from the regression model correspond to independent and dependent variable(s) in the model (Rossi 2014). The presence of endogeneity in the study can undermine the reliability of the results due to biased parameter estimates (Sande and Ghosh 2018). Endogeneity can be controlled through the control function approach (De Blander 2010), the control variable approach (Germann, Ebbes, and Grewal 2015), or the instrumental approach (Sande and Ghosh 2018). In this study we selected the instrumental approach as it is the most common approach in PLS-SEM (Sande and Ghosh 2018). Endogeneity was tested on the latent variable SCRes because it has both direct and indirect predictors. An additional predictor of SCRes, iv_SCRes, was added to the model to test for endogeneity through its path coefficient and significance using WarpPLS 7.0, which is a popular PLS techniques used in SEM analysis (Kock 2021). The path coefficient (iv_SCRes) was $B = 0.01$ and $p = 0.43$, indicating that the effect of endogeneity was non-significant.

5.2. Common method bias

It is necessary to account for common method bias (CMB) as the data was collected using the same method (Dubey et al. 2020), meaning the measurements in the study could share some common method variation (CMV). Additionally, there is a tendency for respondents to answer questions in a similar fashion which can

Table 2. Descriptive analysis of measurement scales.

	Mean	SD	Factor Loadings	Min	Max
AI_1	4.347	1.768	0.864	1	7
AI_2	3.946	1.84	0.891	1	7
AI_3	3.98	1.886	0.842	1	7
AI_4	3.932	1.923	0.82	1	7
OrgFlex_1	4.728	1.623	0.781	1	7
OrgFlex_2	4.646	1.502	0.857	1	7
OrgFlex_3	4.769	1.57	0.778	1	7
OrgMind_1	4.946	1.573	0.813	1	7
OrgMind_2	5.075	1.48	0.755	1	7
OrgMind_3	5.122	1.493	0.718	1	7
OrgMind_4	5.293	1.41	0.833	1	7
OrgMind_5	5.714	1.201	0.625	1	7
OrgMind_6	5.374	1.321	0.657	1	7
SCPer_1	5.265	1.396	0.711	1	7
SCPer_2	5.463	1.269	0.73	1	7
SCPer_3	5.286	1.438	0.669	1	7
SCPer_4	4.837	1.345	0.824	1	7
SCPer_5	4.823	1.446	0.771	1	7
SCPer_6	4.966	1.327	0.787	1	7
SCRes_1	5.095	1.491	0.732	1	7
SCRes_2	5.061	1.41	0.857	1	7
SCRes_3	5.211	1.381	0.714	1	7
SCRes_4	5.313	1.428	0.765	1	7

Table 3. Construct correlations and discriminant validity results.

				HTMT Values				
Constructs	*a*	CR	AVE	AI	OrgFlex	OrgMind	SCP	SCRes
AI	0.916	0.916	0.731					
OrgFlex	0.846	0.847	0.65	0.847				
OrgMind	0.878	0.876	0.544	0.704	0.816			
SCP	0.884	0.884	0.563	0.771	0.853	0.876		
SCRes	0.852	0.852	0.591	0.6	0.868	0.829	0.859	

also result in CMV (Podsakoff et al. 2003). To mitigate the impact of CMB, statistical analyses were conducted following the guidelines of (Podsakoff et al. 2003). Firstly, a conservative version of Harman's one-factor test was performed. The results demonstrated that CMB is not a significant concern as the test showed that the single factor explains 45.7% of the total variance, which is below the 50% threshold. To address the concern that Harman's one-factor test is not a robust assessment of CMB (Hendry et al. 2019), in this study, a partial correlation technique (Lindell and Whitney 2001) was performed. As no significant differences were detected, it indicates that CMB has no substantial impact on the study results. Hence, we can infer that CMB is not a serious issue in this study.

5.3. Hypotheses testing

The significant paths and the standardised coefficients in the structural model are presented in Figure 2.

The standardised path coefficients and p-values (see Table 4) explain a significant variance for the endogenous constructs. Notably, the explained variance (R^2) of the framework on OMIN is $R^2 = 0.37$, OFLEX is $R^2 = 0.55$, SCRes is $R^2 = 0.77$, and SCP is $R^2 = 0.57$ (Figure 2). The link AI→SCRes ($\beta = -0.3$; $p < 0.01$) is negatively related, while the combined paths for mediation effect of OMIN and OFLEX on the path connecting AI and SCRes, (AI→OMIN ($\beta = 0.61$; $p < 0.01$), OMIN→SCRes ($\beta = 0.39$; $p < 0.01$) and AI→OFLEX ($\beta = 0.74$; $p < 0.01$), OFLEX→SCRes ($\beta = 0.34$; $p < 0.01$)) are found to be positively linked. Therefore, we can deduce that OMIN and OFLEX fully mediate the path linking AI and SCRes. Moreover, the link between SCRes→SCP ($\beta = 0.76$; $p < 0.01$) are positively related. Thus, we make the case that based on beta values and

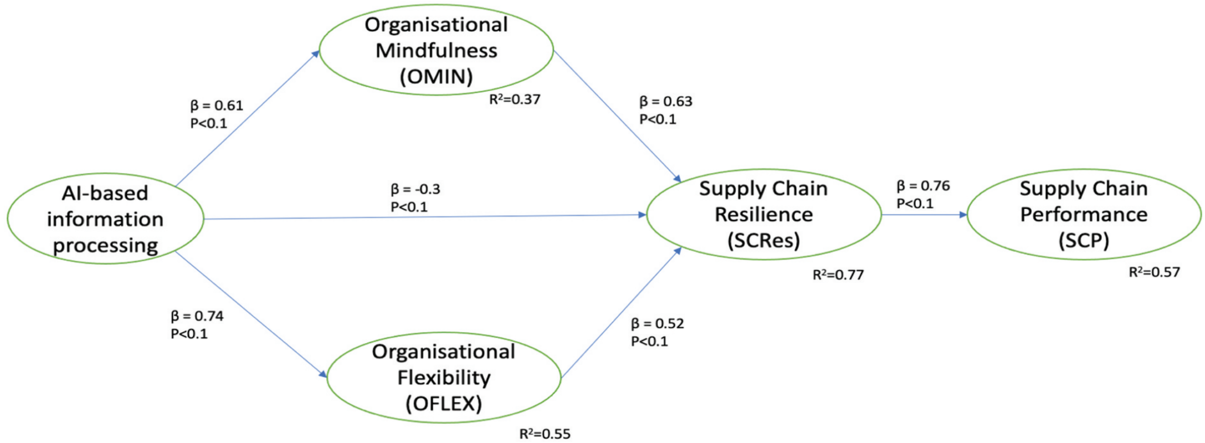

Figure 2. Research model.

Table 4. Structural estimates.

Hypothesis	Path	Path coefficient	*p* value	Result
H1	AI- > SCRes	−0.3	>0.01	Not supported
H2	SCRes- > SCP	0.76	<0.01	Supported
H3a	AI-OMIN	0.61	<0.01	Supported
H3b	OMIN- > SCRes	0.63	<0.01	Supported
H4a	AI- > OFLEX	0.74	<0.01	Supported
H4b	OFLEX-SCRes	0.52	<0.01	Supported

their corresponding *p* values that hypotheses H2, H3a, H3b, H4a, and H4b are supported, while H1 is not supported.

The structural model results offer important insights into the mechanisms linking AI-based information processing to supply chain resilience (SCRes). Notably, the direct path from AI to SCRes was negative and significant ($\beta = -0.30$, $p < 0.01$), indicating that AI alone may not directly enhance resilience. However, both organisational mindfulness (OMIN) and organisational flexibility (OFLEX) fully mediated this relationship, with strong and positive path coefficients from AI to OFLEX ($\beta = 0.74$, $p < 0.01$) and from OMIN to SCRes ($\beta = 0.39$, $p < 0.01$). These findings suggest that the value of AI in AFSCs depends critically on an organisation's ability to interpret data mindfully and act adaptively, supporting the idea that human and structural capabilities are essential for realising the resilience benefits of digital technologies (Dubey, Gunasekaran, Childe, Roubaud, et al. 2019; Hendry et al. 2019). The high explanatory power of SCRes ($R^2 = 0.77$) further underscores the central role these mediators play in translating AI insights into resilient outcomes.

6. Discussion

The current study uses a novel perspective to understand how AFSCs can deploy AI-enabled information processing, utilising the organisational competencies of mindfulness and flexibility, to achieve supply chain resilience and performance. Overall, our results indicate that AI-enabled information processing is not sufficient alone to achieve SCRES but is importantly mediated and enhanced by organisational factors. In the context of AFSC, there is a clear synergistic relationship between AI systems gathering, detecting and learning from the external environment and the mindful, sensing capabilities of employees, interpreting data, creating opportunities and honing the ability to respond to unpredicted events and take rapid, corrective action. This critical link between successfully implementing AI technology and organisational factors is reflected in recent studies on organisational mindfulness and digital transformation (H. Li et al. 2021).

While valuable contributions have been made about AI-based information processing in manufacturing SCs (Issa, Jabbouri, and Palmer 2022), there is limited knowledge about AI-based information processing in context of AFSCs. Our findings identify important organisational factors that utilise AI technologies to achieve SCRes as a tool for reducing food waste in AFSCs, therefore improving sustainability. Previous research that examined AI technologies for sustainability in AFSCs viewed AI as a tool to improve traceability and transparency (N. Tsolakis et al. 2022) or for reducing energy consumption (Kopka and Grashof 2022). This study demonstrates that AI-enabled information processing can build resilience in agri-food supply chains, thereby reducing food waste and improving food security, through the important mediating effects of OMIN and OFLEX, which ultimately lead to improved SCP.

As such, an important theoretical contribution of this study is the significant influence of OMIN and OFLEX as mediators in the relationship between AI-based information processing and SCRes. This contributes to our understanding of the inter-relationships between AI-based information processing, OMIN, OFLEX, and SCRes and highlights the need to explore the effect of organisational competencies on the application of AI-based information processing in the management of resilient SCs. Specifically, the effect of AI on SCRes is negative and insignificant when tested with mediators OMIN and OFLEX, contradicting prior research that indicates AI directly leads to SCRes (Modgil et al. 2022). In our study, the influence of AI on SCRes was fully and significantly mediated by the presence of OMIN and OFLEX. This is a critical finding as it demonstrates that AFSC organisations cannot simply implement AI-based information processing and expect to achieve SCRes, challenging the assumption that AI-based information processing will itself lead to a resilient AFSC.

Previously, Dennehy et al. (2021) utilised OMIN as a mediator between big data analytics and SCRes, while Dubey, Gunasekaran, and Childe (2019) employed OFLEX between data analytics and SCRes. Interestingly, both these studies returned partial mediation, indicating that AI differs from other analytical technologies. In this study, the influence of OMIN and OFLEX is examined commensurately and reveal important organisational competencies that strongly influence information processing capabilities and the resulting impact on resilience.

This study differs from existing literature on non-food supply chains by examining how AI-based information processing interacts with organisational mindfulness (OMIN) and organisational flexibility (OFLEX) to build resilience in agri-food supply chains (AFSCs). While prior studies in manufacturing or industrial contexts (e.g. Dubey, Gunasekaran, Childe, Fosso Wamba, et al. 2019; Belhadi, Mani, et al. 2021) highlight the direct impact of AI and data analytics on agility and performance, they often overlook the mediating role of organisational capabilities in more volatile, perishable environments. Unlike non-food supply chains, AFSCs operate under severe time constraints, biological variability, and regulatory pressures, making them more susceptible to disruption and waste.

Our findings reveal that AI alone does not directly enhance resilience in AFSCs; rather, its effectiveness depends on how organisations interpret insights through mindfulness and act on them through flexibility. This mediation model is distinct from prior work where AI is typically framed as a direct enabler of resilience or performance. By focusing on the human and structural capabilities required to unlock AI's potential in food systems, our study addresses a critical gap in the supply chain resilience literature.

AI-enabled information processing supports waste reduction and performance improvement in agri-food supply chains by enhancing visibility, prediction, and responsiveness. For example, AI can forecast weather disruptions or demand fluctuations, enabling timely harvesting and adaptive distribution to prevent spoilage (Belhadi, Mani, et al. 2021; Grover, Kar, and Dwivedi 2022). However, our findings show that these benefits are not achieved through AI alone. Organisational mindfulness (OMIN) helps interpret AI-generated insights in dynamic environments, while organisational flexibility (OFLEX) enables rapid resource reconfiguration in response to disruptions (Dubey, Gunasekaran, Childe, Roubaud, et al. 2019; Hendry et al. 2019). Together, these capabilities allow firms to transform AI insights into effective actions, reducing food waste and sustaining supply chain performance under uncertainty.

The findings show that OMIN displayed a stronger effect on SCRes with an effect size of (*f*-squared) of 0.795. when compared to OFLEX. In doing so, this study contributes to literature on antecedents of SCRes and intelligent systems and their impact on SCP (Belhadi, Mani, et al. 2021), by understanding how organisations can maintain and enhance SCP during turbulent periods. The findings of this study further suggest that developing SCRes will result in improved SCP in the context of AFSCs. This supports claims that organisations that can effectively develop readiness prior to disruptions, implement a swift response during the disruption, and an efficient recovery from the disruption have a higher chance of maintaining long-lasting SCP (Belhadi, Mani, et al. 2021; Datta 2017).

6.1. Implications for AFSC research

This research advances theory required by the SC research community (e.g. Dennehy et al. 2021; Dubey et al. 2021) into a deeper understanding about how AI-enabled information processing effects SCRes, particularly in the context of AFSCs. This study provides evidence that AI-enabled information processing can develop SCRes and therefore improve sustainability and SCP of AFSCs, when certain organisational competencies are present. While previous studies have provided insight into how the adoption of AI-enabled information processing can develop SCRes in a manufacturing setting (Belhadi, Mani, et al. 2021), this study highlights the mindful practices of an organisation in the adoption of AI-enabled information processing in AFSCs. Through the lens of OIPT, we explain how AI-enabled information processing can improve SCRes, sustainability and SCP through the enablers of OMIN and OFLEX.

This study highlights the importance of organisational competencies when seeking to develop supply chain resilience. AI tools have been shown to directly improve metrics such as, cost or efficiency (Fosso Belhadi, Mani, et al. 2021; Wamba et al. 2020), meaning that AI can directly enhance supply chain factors such as, performance or competitive advantage (Belhadi, Mani, et al. 2021; Hendry et al. 2019). However, supply chain resilience differs from these supply chain attributes. Developing resilience requires continuous scrutiny of the organisation's environment, in addition to possessing the ability to adjust operations to address an organisation's changing environment (Dennehy et al. 2021; Dubey et al. 2021; Hendry et al. 2019). While AI can provide a strong platform for supporting the monitoring of an organisation's internal and external environment and can support decision-making to help swiftly adjust operations, organisational factors are still required to fully meet the requirements of developing supply chain resilience.

Developing supply chain resilience, therefore, requires strong situational awareness in addition to having a controllable organisational structure (Dubey, Gunasekaran, and Childe 2019; Hendry et al. 2019). AI tools can provide detailed insights into an organisation's internal and external environments (Hendry et al. 2019); however, if an organisation lacks the capability to identify looming threats or opportunities, the value of these insights goes to waste. The principles and practices of OMIN develop the capability to effectively assess data and information to find valuable clues about an organisation's environment (Lee 2021), cultivating high situational awareness. OMIN in AFSCs enables a heightened situational awareness necessary to navigate perishability, seasonality, and regulatory variability challenges less pronounced in non-food SCs (Dennehy et al. 2021; Hendry et al. 2019). Our study shows that OMIN allows for better sensemaking of AI outputs, facilitating quicker and contextually appropriate responses to disruptions is critical in food systems where decision speed directly impacts waste and quality. AFSCs require failure-preoccupation and sensitivity to operations, two core aspects of OMIN, to monitor spoilage rates, adapt to weather shifts, or sudden logistical failures.

However, there is a gap between identifying the right information for a decision and implementing that decision. This research argues that OFLEX can bridge this gap. OFLEX promotes the ability of management to make the necessary decisions swiftly, in addition to ensuring the controllability and changeability of the organisational structure (Dubey et al. 2021; Volberda 1996). Collectively, both OMIN and OFLEX explain how organisations can transform the information generated from AI tools into concrete supply chain improvements, reiterating the importance of organisational factors in developing AFSC resilience.

AI-enabled information processing was found to be positively associated with SCRes through the mediation of OMIN and OFLEX but negatively associated when directly tested. This aligns with existing research on AI-based information processing, which employed other key enablers of SCRes (adaptive capabilities and supply chain collaboration) to explain how SCRes are achieved. However, this also challenges existing research which have found other analytical technologies (Dubey et al. 2021) to directly improve SCRes.

Finally, our findings indicate that to effectively leverage the insights generated from AI-based information processing, organisations must also transform their mindset, structure and managerial practices. This study demonstrates the importance of organisational competencies in this regard however, further empirical research is required to explore the connection between mindfulness and flexibility with AI information processing more fully. Identifying such measures is currently a major research gap in developing long-term approaches to SCRes (Gebhardt et al. 2022), although the identification of OMIN and OFLEX offers a fruitful line of enquiry.

6.2. Implications for AFSC practice

This study has important implications for managers seeking to operate under a high degree of uncertainty in the context of AFSCs. First, to maintain or even improve SCP while managing uncertainties and disruptive events, practitioners should focus on the development of SCRes. In doing so, they should recognise the role of AI-based information processing to develop OMIN and OFLEX capabilities, which will ultimately lead to improved sustainability and performance. Developing both organisational mindfulness and flexibility is an integral part to dealing with and responding to uncertain environments and disruptions.

AFSC organisations that can recognise and acquire external information and capable of assimilating, transforming, and exploiting this information will profit from increased resiliency and performance (Belhadi, Mani, et al. 2021; Dzhengiz and Niesten 2020). Indeed, previous studies (e.g. Dubey, Gunasekaran, and Childe 2019; Wieland et al. 2013) have made important contributions to advance understanding about the role of relationship theory for developing trust among SC partners, which can lead to better coordination. In contrast, this study outlines an alternative method of developing vertical information systems which can enhance information processing capability with minimal resource costs. This is an important implication for the AFSC industry as it is dominated by SMEs, accounting for over 80% of firms (Zhao et al. 2023). Specifically, this research emphasises the connection between information processing and organisational mindfulness and flexibility, hence, incorporating mindful management techniques tailored for the organisation and its information processing characteristics will be critical. Previous research has identified the need to 'fit' the organisation type with an approach to information processing – similar approaches will be required in this case (Moser, Kuklinski, and Srivastava 2017). Such mindful approaches to organisations have been demonstrated to be extremely useful especially for high reliability organisations (HROs) (Hales and Chakravorty 2016).

While AI-enabled information processing offers promising benefits for improving resilience and reducing food waste in AFSCs, several practical challenges must be considered. Implementing AI solutions often involves significant costs, including investment in digital infrastructure, specialised talent, and ongoing system maintenance, which can be especially burdensome for small and medium-sized enterprises that dominate the agri-food sector (Zhao et al. 2023). In addition, data fragmentation and interoperability issues are prevalent, as AFSCs typically comprise diverse stakeholders with varying levels of digital maturity and often lack integrated data systems (Kamble, Gunasekaran, and Gawankar 2020; Papetti et al. 2012). Ethical concerns such as data privacy, algorithmic bias, and exclusion of small producers also create barriers to adoption (Grover, Kar, and Dwivedi 2022). To address these issues, organisations should consider beginning with targeted AI applications (e.g. forecasting or monitoring) that generate early value, while simultaneously investing in organisational practices that promote mindfulness and flexibility. Encouraging cross-functional communication, scenario planning, and agile decision-making structures can help ensure AI insights are effectively interpreted and acted upon. Equally important is the establishment of robust data governance protocols and trust-based relationships across the supply chain to facilitate secure and ethical information sharing.

Rather than viewing AI as a plug-and-play technology, organisations should approach implementation as a process of capability-building. This includes fostering organisational mindfulness, such as developing heightened situational awareness, proactive monitoring, and strengthening flexibility through adaptable workflows and agile structures. AI tools should be integrated into existing decision-making routines, ensuring that human judgement remains central to interpreting and acting on AI insights. Additionally, cultivating a culture of experimentation and continuous learning can help organisations adapt to the evolving capabilities of AI. Ensuring the ethical use of AI and fostering inter-organisational collaboration for secure data sharing are also essential to maximise value while mitigating risk. These practices collectively provide a foundation for responsible and effective AI adoption in the context of complex, perishable, and often fragmented agri-food systems.

This research also has meaningful implications for policymakers, especially in the context of sustainability goals such as the EU's target to halve food waste by 2030. The study shows that achieving supply chain resilience through AI adoption is not solely a technological challenge but requires parallel development of organisational competencies. Policymakers can support this transition by investing in digital infrastructure and promoting standardised platforms that facilitate interoperability and data sharing across agri-food networks. Additionally, policy interventions could encourage training programs focused on adaptive management and digital literacy, especially targeted at small and medium-sized enterprises. Establishing clear ethical frameworks and guidelines for AI use in food systems will also be critical to build trust and ensure inclusive participation. By aligning technological innovation with organisational development and regulatory support, our framework can serve as a guide for designing policy instruments that promote both resilience and sustainability in agri-food supply chains.

7. Limitations and conclusions

We acknowledge this study has limitations, which also provide opportunities for future research. First, survey-based research on the role of AI in AFSC resilience and performance is a multifarious and multifaceted phenomenon which may not be entirely captured using this approach. Second, we grounded our survey items in extant literature, surveys are not exact measurements and are vulnerable to informants not sharing their true thoughts and feelings (Groves et al. 2011). Thirdly, 147 responses may appear modest, it exceeds the minimum threshold for PLS-SEM (Hair et al. 2014) and includes diverse roles and geographies. We acknowledge limitations in generalisability but assert that this sample provides robust exploratory insights into AFSC dynamics. Future research could adopt a mixed-method approach that may provide rich insights about the tensions and contradictions of AI and its use in the AFSC industry. Also, future research could build on our findings by exploring additional organisational capabilities that may influence the relationship between AI-based information processing and supply chain resilience. While this study focused on mindfulness and flexibility, other factors such as organisational learning, digital maturity, or absorptive capacity may also mediate or moderate these effects. Longitudinal studies would be particularly valuable to assess how these capabilities evolve over time and how sustained AI adoption impacts resilience during repeated or prolonged disruptions.

Furthermore, comparative research across different types of agri-food organisations, such as smallholders versus large processors, or across regional supply chains could uncover contextual factors that shape the effectiveness of AI implementation. Finally, there is a need for qualitative or mixed-method research to complement our findings and provide deeper insights into how decision-makers interpret and operationalise AI-driven insights in real-world AFSC environments. These avenues offer promising directions to refine and extend theoretical understanding of digital resilience in complex, perishable supply chains.

This study set out to advance understanding about the role of AI-enabled systems to either directly or indirectly build resilience in AFSC and improve sustainability and performance. By drawing on organisational information processing theory, the study advances understanding about AI-enabled information processing in the context of agri-food supply chains. Our results highlight the important role of AI-based information processing as a complementary capability of an organisation. This study showed that AI-based information processing could develop the organisational concepts of OMIN and OFLEX that assist in the development of SCRes which is needed to operate in disruptive and uncertain environments. In doing so, both the technical characteristics of AI-enabled information processing and the state of organisational mindfulness and flexibility must be considered by actors in the AFSC network.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Ali, I., Arslan, A., Khan, Z., and Tarba, S. Y. 2021. "The Role of Industry 4.0 Technologies in Mitigating Supply Chain Disruption: Empirical Evidence from the Australian Food Processing Industry." IEEE Transactions on Engineering Management, 1–11. IEEE.

Ali, I., A. Arslan, Z. Khan, and S. Y. Tarba. 2024. "The Role of Industry 4.0 Technologies in Mitigating Supply Chain Disruption: Empirical Evidence from the Australian Food Processing Industry." *IEEE Transactions on Engineering Management* 71:10600–10610. https://doi.org/10.1109/TEM.2021.3088518.

Ambulkar, S., J. Blackhurst, and S. Grawe. 2015. "Firm's Resilience to Supply Chain Disruptions: Scale Development and Empirical Examination." *Journal of Operations Management Elsevier BV* 33–34 (1): 111–122. https://doi.org/10.1016/j.jom.2014.11.002.

Armstrong, J. S., and T. S. Overton. 1977. "Estimating Nonresponse Bias in Mail Surveys." *Journal of Marketing Research* 14 (3): 396. https://doi.org/10.1177/002224377701400320.

Bai, C., and J. Sarkis. 2022. "The Water, Energy, Food, and Sustainability Nexus Decision Environment: A Multistakeholder Transdisciplinary Approach." *IEEE Transactions on Engineering Management* 69 (3): 656–670. https://doi.org/10.1109/TEM.2019.2946756.

Balezentis, T., A. Zickiene, A. Volkov, D. Streimikiene, M. Morkunas, V. Dabkiene, and E. Ribasauskiene. 2023. "Measures for the Viable Agri-Food Supply Chains: A Multi-Criteria Approach." *Journal of Business Research* 155 (PA): 113417. https://doi.org/10.1016/j.jbusres.2022.113417.

Baryannis, G., S. Validi, S. Dani, and G. Antoniou. 2019. "Supply Chain Risk Management and Artificial Intelligence: State of the Art and Future Research Directions." *International Journal of Production Research* 57 (7): 2179–2202. https://doi.org/10.1080/00207543.2018.1530476.

Belhadi, A., S. Kamble, Fosso Wamba, and M. M. Queiroz. 2021. "Building Supply-Chain Resilience: An Artificial Intelligence-Based Technique and Decision-Making Framework." *International Journal of Production Research* 60 (14): 4487–4507. https://doi.org/10.1080/00207543.2021.1950935 .

Belhadi, A., V. Mani, S. S. Kamble, S. A. R. Khan, and S. Verma. 2021. "Artificial Intelligence-Driven Innovation for Enhancing Supply Chain Resilience and Performance Under the Effect of Supply Chain Dynamism: An Empirical Investigation." *Annals of Operations Research*. Springer US, (333 (2–3): 0123456789. https://doi.org/10.1007/s10479-021-03956-x.

Belhadi, A., K. Zkik, A. Cherrafi, S. M. Yusof, and S. El Fezazi. 2019. "Understanding Big Data Analytics for Manufacturing Processes: Insights from Literature Review and Multiple Case Studies." *Computers and Industrial Engineering Elsevier Ltd* 137:106099. https://doi.org/10.1016/j.cie.2019.106099.

Benitez, J., J. Henseler, A. Castillo, and F. Schuberth. 2020. "How to Perform and Report an Impactful Analysis Using Partial Least Squares: Guidelines for Confirmatory and Explanatory Is Research." *Information and Management Elsevier* 57 (2): 103168. https://doi.org/10.1016/j.im.2019.05.003.

Bottani, E., P. Centobelli, M. Gallo, M. A. Kaviani, V. Jain, and T. Murino. 2019. "Modelling Wholesale Distribution Operations: An Artificial Intelligence Framework." *Industrial Management and Data Systems* 119 (4): 698–718. https://doi.org/10.1108/IMDS-04-2018-0164.

Braunscheidel, M. J., and N. C. Suresh. 2009. "The Organizational Antecedents of a Firm's Supply Chain Agility for Risk Mitigation and Response." *Journal of Operations Management* 27 (2): 119–140. https://doi.org/10.1016/j.jom.2008.09.006.

Burnard, K., R. Bhamra, and C. Tsinopoulos. 2018. "Building Organizational Resilience: Four Configurations." *IEEE Transactions on Engineering Management* 65 (3): 351–362. https://doi.org/10.1109/TEM.2018.2796181.

Carvalho, H., S. G. Azevedo, and V. Cruz-Machado. 2012. "Agile and Resilient Approaches to Supply Chain Management: Influence on Performance and Competitiveness." *Logistics Research* 4 (1–2): 49–62. https://doi.org/10.1007/s12159-012-0064-2.

Cavalcante, I. M., E. M. Frazzon, F. A. Forcellini, and D. Ivanov. 2019. "A Supervised Machine Learning Approach to Data-Driven Simulation of Resilient Supplier Selection in Digital Manufacturing." *International Journal of Information Management* 49:86–97. https://doi.org/10.1016/j.ijinfomgt.2019.03.004.

Chen, D. Q., D. S. Preston, and M. Swink. 2015. "How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management." *Journal of Management Information Systems* 32 (4): 4–39. https://doi.org/10.1080/07421222.2015.1138364.

Chen, I. J., and A. Paulraj. 2004. "Towards a Theory of Supply Chain Management: The Constructs and Measurements." *Journal of Operations Management* 22 (2): 119–150. https://doi.org/10.1016/j.jom.2003.12.007.

Choudhary, N., M. Ramkumar, T. Schoenherr, and N. P. Rana. 2021. "Assessing Supply Chain Resilience During the Pandemic Using Network Analysis." *IEEE Transactions on Engineering Management* 71:12297–12310. https://doi.org/10.1109/TEM.2021.3124027.

Chowdhury, M. M. H., M. Quaddus, and R. Agarwal. 2019. "Supply Chain Resilience for Performance: Role of Relational Practices and Network Complexities." *Supply Chain Management* 24 (5): 659–676. https://doi.org/10.1108/SCM-09-2018-0332.

Christopher, M., and H. Peck. 2004. "Building the Resilient Supply Chain." *The International Journal of Logistics Management* 15 (2): 1–14. https://doi.org/10.1108/09574090410700275.

Craighead, C. W., J. Blackhurst, M. J. Rungtusanatham, and R. B. Handfield. 2007. "The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities." *Decision Sciences* 38 (1): 131–156. https://doi.org/10.1111/j.1540-5915.2007.00151.x.

Datta, P. 2017. "Supply Network Resilience: A Systematic Literature Review and Future Research." *The International Journal of Logistics Management* 28 (4): 1387–1424. https://doi.org/10.1108/IJLM-03-2016-0064.

De Blander, R. 2010. "A Simple Estimator for the Correlated Random Coefficient Model." *Economics Letters* 106 (3): 158–161. https://doi.org/10.1016/j.econlet.2009.11.007.

Dennehy, D., J. Oredo, K. Spanaki, S. Despoudi, and M. Fitzgibbon. 2021. "Supply Chain Resilience in Mindful Humanitarian Aid Organizations: The Role of Big Data Analytics." *International Journal of Operations & Production Management* 41 (9): 1417–1441. https://doi.org/10.1108/IJOPM-12-2020-0871.

Dernbecher, S., and R. Beck. 2017. "The Concept of Mindfulness in Information Systems Research: A Multi-Dimensional Analysis." *European Journal of Information Systems Palgrave Macmillan UK* 26 (2): 121–142. https://doi.org/10.1057/s41303-016-0032-z.

Dhamija, P., and S. Bag. 2020. "Role of Artificial Intelligence in Operations Environment: A Review and Bibliometric Analysis." *The TQM Journal* 32 (4): 869–896. https://doi.org/10.1108/TQM-10-2019-0243.

Dubey, R., D. J. Bryde, Y. K. Dwivedi, G. Graham, and C. Foropon. 2022. "Impact of Artificial Intelligence-Driven Big Data Analytics Culture on Agility and Resilience in Humanitarian Supply Chain: A Practice-Based View." *International Journal of Production Economics Elsevier BV* 250 (July): 108618. https://doi.org/10.1016/j.ijpe.2022.108618.

Dubey, R., A. Gunasekaran, and S. J. Childe. 2019. "Big Data Analytics Capability in Supply Chain Agility: The Moderating Effect of Organizational Flexibility." *Management Decision* 57 (8): 2092–2112. https://doi.org/10.1108/MD-01-2018-0119.

Dubey, R., A. Gunasekaran, S. J. Childe, D. J. Bryde, M. Giannakis, C. Foropon, D. Roubaud, and B. T. Hazen. 2020. "Big Data Analytics and Artificial Intelligence Pathway to Operational Performance Under the Effects of Entrepreneurial Orientation and Environmental Dynamism: A Study of Manufacturing Organisations." *International Journal of Production Economics Elsevier BV* 226 (October 2019): 107599. https://doi.org/10.1016/j.ijpe.2019.107599.

Dubey, R., A. Gunasekaran, S. J. Childe, S. Fosso Wamba, S. Fosso Wamba, M. Giannakis, and C. Foropon. 2019. "Empirical Investigation of Data Analytics Capability and Organizational Flexibility as Complements to Supply Chain Resilience." *International Journal of Production Research* 210:120–136. https://doi.org/10.1016/j.ijpe.2019.01.023.

Dubey, R., A. Gunasekaran, S. J. Childe, S. Fosso Wamba, D. Roubaud, and C. Foropon. 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. https://doi.org/10.1080/00207543.2019.1582820.

Dubey, R., A. Gunasekaran, S. J. Childe, D. Roubaud, S. Fosso Wamba, M. Giannakis, and C. Foropon. 2019. "Big Data Analytics and Organizational Culture as Complements to Swift Trust and Collaborative Performance in the Humanitarian Supply Chain." *International Journal of Production Economics Elsevier BV* 210 (January): 120–136. https://doi.org/10.1016/j.ijpe.2019.01.023/.

Dzhengiz, T., and E. Niesten. 2020. "Competences for Environmental Sustainability: A Systematic Review on the Impact of Absorptive Capacity and Capabilities." *Journal of Business Ethics Springer Netherlands* 162 (4): 881–906. https://doi.org/10.1007/s10551-019-04360-z.

El Baz, J., and S. Ruel. 2021. "Can Supply Chain Risk Management Practices Mitigate the Disruption Impacts on Supply Chains' Resilience and Robustness? Evidence from an Empirical Survey in a COVID-19 Outbreak Era." *International Journal of Production Economics* 233 (October) 2020. 107972. https://doi.org/10.1016/j.ijpe.2020.107972.

El Baz, J., S. Ruel, and Z. Fozouni Ardekani. 2023. "Predicting the Effects of Supply Chain Resilience and Robustness on COVID-19 Impacts and Performance: Empirical Investigation Through Resources Orchestration Perspective." *Journal of Business Research* 164 (April). https://doi.org/10.1016/j.jbusres.2023.114025.

Elhoone, H., T. Zhang, M. Anwar, and S. Desai. 2020. "Cyber-Based Design for Additive Manufacturing Using Artificial Neural Networks for Industry 4.0." *International Journal of Production Research Taylor & Francis* 58 (9): 2841–2861. https://doi.org/10.1080/00207543.2019.1671627.

Estampe, D., S. Lamouri, J.-L. Paris, and S. Brahim-Djelloul. 2013. "A Framework for Analysing Supply Chain Performance Evaluation Models." *International Journal of Production Economics Elsevier* 142 (2): 247–258. https://doi.org/10.1016/j.ijpe.2010.11.024.

European Commission. 2017. *EU Platform on Food Losses and Food Waste'*, Denmark 1–2.

European Environment Agency. 2019. "*EEA Signals 2019-Land and Soil in Europe*." *European Environment Agency*.

Fahimnia, B., and A. Jabbarzadeh. 2016. "Marrying Supply Chain Sustainability and Resilience: A Match Made in Heaven." *Transportation Research Part E: Logistics and Transportation Review Elsevier Ltd* 91:306–324. https://doi.org/10.1016/j.tre.2016.02.007.

FAO. 2022. "The State of Food Security and Nutrition in the World." In *Repurposing Food and Agricultural Policies to Make Healthy Diets more Affordable*. Rome: FAO. https://doi.org/10.4060/cc0639en.

Galbraith, J.R, 1977. *Organization Design*. Reading, Mass, pp. 243–380.

Gebhardt, M., A. Spieske, M. Kopyto, and H. Birkel. 2022. "Increasing Global Supply Chains' Resilience After the COVID-19 Pandemic: Empirical Results from a Delphi Study." *Journal of Business Research* 150 (February 2021): 59–72. https://doi.org/10.1016/j.jbusres.2022.06.008.

Germann, F., P. Ebbes, and R. Grewal. 2015. "The Chief Marketing Officer Matters!" *Journal of Marketing* 79 (3): 1–22. https://doi.org/10.1509/jm.14.0244.

Gonzálvez-Gallego, N., F. J. Molina-Castillo, P. Soto-Acosta, J. Varajao, and A. Trigo. 2015. "Using Integrated Information Systems in Supply Chain Management." *Enterprise Information Systems* 9 (2): 210–232. https://doi.org/10.1080/17517575.2013.879209.

Grover, P., A. K. Kar, and Y. K. Dwivedi. 2020. "Understanding Artificial Intelligence Adoption in Operations Management: Insights from the Review of Academic Literature and Social Media Discussions." *Annals of Operations Research*. Springer US. 308 (1–2): 177–213. https://doi.org/10.1007/s10479-020-03683-9/.

Grover, P., A. K. Kar, and Y. K. Dwivedi. 2022. "Understanding Artificial Intelligence Adoption in Operations Management: Insights from the Review of Academic Literature and Social Media Discussions." *Annals of Operations Research* 308 (1–2): 177–213. https://doi.org/10.1007/s10479-020-03683-9.

Groves, R. M., Fowler Jr, F.J., Couper, M.P., Lepkowski, J.M., Singer, E. and Tourangeau, R 2011. *Survey Methodology*. John Wiley & Sons. John Wiley & Sons

Gupta, S., Modgil, S., Meissonier, R., and Dwivedi, Y. K 2021. *Artificial Intelligence and Information System Resilience to Cope with Supply Chain Disruption*, 1–11. IEEE.

Gupta, S., S. Modgil, R. Meissonier, and Y. K. Dwivedi. 2024. "Artificial Intelligence and Information System Resilience to Cope with Supply Chain Disruption." *IEEE Transactions on Engineering Management* 71:10496–10506. https://doi.org/10.1109/TEM.2021.3116770.

Haefner, N., J. Wincent, V. Parida, and O. Gassmann. 2021. "Artificial Intelligence and Innovation Management: A Review, Framework, and Research Agenda." *Technological Forecasting and Social Change Elsevier* 162 (June 2020): 120392. https://doi.org/10.1016/j.techfore.2020.120392.

Hair, J. F., C. M. Ringle, and M. Sarstedt. 2013. "Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance." *Long Range Planning* 46 (1–2): 1–12. https://doi.org/10.1016/j.lrp.2013.01.001.

Hair, J. F., M. Sarstedt, L. Hopkins, and V. G Kuppelwieser. 2014. "Partial Least Squares Structural Equation Modeling (PLS-SEM): An Emerging Tool in Business Research." *European Business Review* 26 (2): 106–121. https://doi.org/10.1108/EBR-10-2013-0128.

Hales, D. N., and S. S. Chakravorty. 2016. "Creating High Reliability Organizations Using Mindfulness." *Journal of Business Research* 69 (8): 2873–2881. https://doi.org/10.1016/j.jbusres.2015.12.056.

Hendry, L. C., M. Stevenson, J. MacBryde, P. Ball, M. Sayed, and L. Liu. 2019. "Local Food Supply Chain Resilience to Constitutional Change: The Brexit Effect." *International Journal of Operations & Production Management* 39 (3): 429–453. https://doi.org/10.1108/IJOPM-03-2018-0184.

Hohenstein, N.-O., E. Feisel, E. Hartmann, and L. Giunipero. 2015. "Research on the Phenomenon of Supply Chain Resilience." *International Journal of Physical Distribution & Logistics Management* 45 (1/2): 90–117. https://doi.org/10.1108/IJPDLM-05-2013-0128.

Hosseini, S., and D. Ivanov. 2020. "Bayesian Networks for Supply Chain Risk, Resilience and Ripple Effect Analysis: A Literature Review." *Expert Systems with Applications* 161:161. https://doi.org/10.1016/j.eswa.2020.113649.

Huit, G. T. M., J. F. Hair, D. Proksch, M. Sarstedt, A. Pinkwart, and C. M. Ringle. 2018. "Addressing Endogeneity in International Marketing Applications of Partial Least Squares Structural Equation Modeling." *Journal of International Marketing* 26 (3): 1–21. https://doi.org/10.1509/jim.17.0151.

Issa, H., R. Jabbouri, and M. Palmer. 2022. "An Artificial Intelligence (AI)-Readiness and Adoption Framework for Agritech Firms." *Technological Forecasting and Social Change Elsevier Inc* 182 (July): 121874. https://doi.org/10.1016/j.techfore.2022.121874.

Ivanov, D., and A. Dolgui. 2021. "Or-Methods for Coping with the Ripple Effect in Supply Chains During COVID-19 Pandemic: Managerial Insights and Research Implications." *International Journal of Production Economics Elsevier BV* 232 (September 2020): 107921. https://doi.org/10.1016/j.ijpe.2020.107921.

Ivanov, D., B. Sokolov, and A. Dolgui. 2014. "The Ripple Effect in Supply Chains: Trade-Off "Efficiency-Flexibility-Resilience" in Disruption Management." *International Journal of Production Research* 52 (7): 2154–2172. https://doi.org/10.1080/00207543.2013.858836.

Jin, S., J. Vegelius, and F. Yang-Wallentin. 2020. "A Marginal Maximum Likelihood Approach for Extended Quadratic Structural Equation Modeling with Ordinal Data." *Structural Equation Modeling: A Multidisciplinary Journal* 27 (6): 864–873. https://doi.org/10.1080/10705511.2020.1712552.

Jraisat, L. E., and I. H. Sawalha. 2013. "Quality Control and Supply Chain Management: A Contextual Perspective and a Case Study." *Supply Chain Management: An International Journal* 18 (2): 194–207. https://doi.org/10.1108/13598541311318827.

Kamble, S. S., A. Gunasekaran, and S. A. Gawankar. 2020. "Achieving Sustainable Performance in a Data-Driven Agriculture Supply Chain: A Review for Research and Applications." *International Journal of Production Economics Elsevier BV* 219 (May 2019): 179–194. https://doi.org/10.1016/j.ijpe.2019.05.022.

Khan, K., B. Bakkappa, B. A. Metri, and B. S. Sahay. 2009. "Impact of Agile Supply Chains' Delivery Practices on Firms' Performance: Cluster Analysis and Validation." *Supply Chain Management* 14 (1): 41–48. https://doi.org/10.1108/13598540910927296.

Kock, N. 2021. "WarpPLS User Manual: Version 8." 0'. https://doi.org/10.1016/j.ijinfomgt.2021.102350/.

Kopka, A., and N. Grashof. 2022. "Artificial Intelligence: Catalyst or Barrier on the Path to Sustainability?" *Technological Forecasting and Social Change Elsevier Inc* 175 (April 2021): 121318. https://doi.org/10.1016/j.techfore.2021.121318.

Kumar, Z., A. K. Agrawal, and D. Rahman. 2017. "An ISM Approach for Modelling the Enablers of Sustainability in Market-Oriented Firms." *International Journal of Business Excellence* 12 (1): 23. https://doi.org/10.1504/IJBEX.2017.083331.

Latino, M. E., A. Corallo, M. Menegoli, and B. Nuzzo. 2023. "Agriculture 4.0 as Enabler of Sustainable Agri-Food: A Proposed Taxonomy." *IEEE Transactions on Engineering Management* 70 (10): 3678–3696. https://doi.org/10.1109/TEM.2021.3101548.

Le, T. T. 2023. "How Do Food Supply Chain Performance Measures Contribute to Sustainable Corporate Performance During Disruptions from the Covid-19 Pandemic Emergency?" *International Journal of Quality & Reliability Management* 40 (5): 1233–1258. https://doi.org/10.1108/IJQRM-03-2022-0089.

Le, T. T., and A. Behl. 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. https://doi.org/10.1109/TEM.2023.3348274.

Leat, P., and C. Revoredo-Giha. 2013. "Risk and Resilience in Agri-Food Supply Chains: The Case of the ASDA Porklink Supply Chain in Scotland." *Supply Chain Management* 18 (2): 219–231. https://doi.org/10.1108/13598541311318845.

Lee, N. C. A. 2021. "Reconciling Integration and Reconfiguration Management Approaches in the Supply Chain." *International Journal of Production Economics Elsevier BV* 242 (May): 108288. https://doi.org/10.1016/j.ijpe.2021.108288.

Li, H., Y. Wu, D. Cao, and Y. Wang. 2021. "Organizational Mindfulness Towards Digital Transformation as a Prerequisite of Information Processing Capability to Achieve Market Agility." *Journal of Business Research* 122 (February 2019): 700–712. https://doi.org/10.1016/j.jbusres.2019.10.036.

Li, L. 2012. "Effects of Enterprise Technology on Supply Chain Collaboration: Analysis of China-Linked Supply Chain." *Enterprise Information Systems* 6 (1): 55–77. https://doi.org/10.1080/17517575.2011.639904.

Li, S., and B. Lin. 2006. "Accessing Information Sharing and Information Quality in Supply Chain Management." *Decision Support Systems* 42 (3): 1641–1656. https://doi.org/10.1016/j.dss.2006.02.011.

Li, X., X. Zhao, H. L. Lee, and C. Voss. 2023b. "Building Responsive and Resilient Supply Chains: Lessons from the COVID-19 Disruption." *Journal of Operations Management* 69 (3): 352–358. https://doi.org/10.1002/joom.1250.

Lindell, M. K., and D. J. Whitney. 2001. "Accounting for Common Method Variance in Cross-Sectional Research Designs." *Journal of Applied Psychology* 86 (1): 114–121. https://doi.org/10.1037/0021-9010.86.1.114.

Liu, Y., X. Ma, L. Shu, G. P. Hancke, and A. M. Abu-Mahfouz. 2021. "From Industry 4.0 to Agriculture 4.0: Current Status, Enabling Technologies, and Research Challenges." *IEEE Transactions on Industrial Informatics* 17 (6): 4322–4334. https://doi.org/10.1109/TII.2020.3003910.

Maheshwari, S., P. Gautam, and C. K. Jaggi. 2021. "Role of Big Data Analytics in Supply Chain Management: Current Trends and Future Perspectives." *International Journal of Production Research* 59 (6): 1875–1900. https://doi.org/10.1080/00207543.2020.1793011.

Maitlis, S., and M. Christianson. 2014. "Sensemaking in Organizations: Taking Stock and Moving Forward." *Academy of Management Annals Taylor & Francis* 8 (1): 57–125. https://doi.org/10.5465/19416520.2014.873177.

Malhotra, M. K., and V. Grover. 1998. "An Assessment of Survey Research in POM: From Constructs to Theory." *Journal of Operations Management* 16 (4): 407–425. https://doi.org/10.1016/S0272-6963(98)00021-7.

Mandal, S. 2019. "The Influence of Big Data Analytics Management Capabilities on Supply Chain Preparedness, Alertness and Agility: An Empirical Investigation." *Information Technology and People* 32 (2): 297–318. https://doi.org/10.1108/ITP-11-2017-0386.

Min, Q., Y. Lu, Z. Liu, C. Su, and B. Wang. 2019. "Machine Learning Based Digital Twin Framework for Production Optimization in Petrochemical Industry." *International Journal of Information Management Elsevier* 49 (May): 502–519. https://doi.org/10.1016/j.ijinfomgt.2019.05.020.

Modgil, S., S. Gupta, R. Stekelorum, and I. Laguir. 2022. "AI Technologies and Their Impact on Supply Chain Resilience During -19." *International Journal of Physical Distribution & Logistics Management* 52 (2): 130–149. https://doi.org/10.1108/IJPDLM-12-2020-0434.

Moser, R., C. P. J. W. Kuklinski, and M. Srivastava. 2017. "Information Processing Fit in the Context of Emerging Markets: An Analysis of Foreign SBUs in China." *Journal of Business Research* 70:234–247. https://doi.org/10.1016/j.jbusres.2016.08.015.

Müller, J., K. Hoberg, and J. C. Fransoo. 2022. "Realizing Supply Chain Agility Under Time Pressure: Ad Hoc Supply Chains During the covid-19 Pandemic." *Journal of Operations Management* 69 (3): 426–449. May. https://doi.org/10.1002/joom.1210.

Muravev, D., H. Hu, A. Rakhmangulov, and P. Mishkurov. 2021. "Multi-Agent Optimization of the Intermodal Terminal Main Parameters by Using AnyLogic Simulation Platform: Case Study on the Ningbo-Zhoushan Port." *International Journal of Information Management Elsevier* 57 (April): 102133. https://doi.org/10.1016/j.ijinfomgt.2020.102133.

Olan, F., E. Ogiemwonyi Arakpogun, J. Suklan, F. Nakpodia, N. Damij, and U. Jayawickrama. 2022. "Artificial Intelligence and Knowledge Sharing: Contributing Factors to Organizational Performance." *Journal of Business Research* 145 (February): 605–615. https://doi.org/10.1016/j.jbusres.2022.03.008.

Papetti, P., C. Costa, F. Antonucci, S. Figorilli, S. Solaini, and P. Menesatti. 2012. “A RFID Web-Based Infotracing System for the Artisanal Italian Cheese Quality Traceability.” *Food Control* 27 (1): 234–241. https://doi.org/10.1016/j.foodcont.2012.03.025.

Paul, S. K., P. Chowdhury, M. A. Moktadir, and K. H. Lau. 2021. “Supply Chain Recovery Challenges in the Wake of COVID-19 Pandemic.” *Journal of Business Research* 136 (July): 316–329. https://doi.org/10.1016/j.jbusres.2021.07.056.

Peng, D. X., G. R. Heim, and D. N. Mallick. 2014. “Collaborative Product Development: The Effect of Project Complexity on the Use of Information Technology Tools and New Product Development Practices.” *Production & Operations Management* 23 (8): 1421–1438. https://doi.org/10.1111/j.1937-5956.2012.01383.x.

Podsakoff, P. M., S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff. 2003. “Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies.” *Journal of Applied Psychology* 88 (5): 879–903. https://doi.org/10.1037/0021-9010.88.5.879.

Priore, P., B. Ponte, R. Rosillo, and D. de la Fuente. 2019. “Applying Machine Learning to the Dynamic Selection of Replenishment Policies in Fast-Changing Supply Chain Environments.” *International Journal of Production Research* 57 (11): 3663–3677. https://doi.org/10.1080/00207543.2018.1552369.

Reb, J., T. Allen, and T. J. Vogus. 2020. “Mindfulness Arrives at Work: Deepening Our Understanding of Mindfulness in Organizations.” *Organizational Behavior and Human Decision Processes Elsevier* 159 (May): 1–7. https://doi.org/10.1016/j.obhdp.2020.04.001.

Remko van, H. 2020. “Research Opportunities for a More Resilient Post-COVID-19 Supply Chain – Closing the Gap Between Research Findings and Industry Practice.” *International Journal of Operations & Production Management* 40 (4): 341–355. https://doi.org/10.1108/IJOPM-03-2020-0165.

Rossi, P. E. 2014. “Even the Rich Can Make Themselves Poor: A Critical Examination of IV Methods in Marketing Applications.” *Marketing Science* 33 (5): 655–672. https://doi.org/10.1287/mksc.2014.0860.

Sande, J. B., and M. Ghosh. 2018. “Endogeneity in Survey Research.” *International Journal of Research in Marketing Elsevier BV* 35 (2): 185–204. https://doi.org/10.1016/j.ijresmar.2018.01.005.

Sawyerr, E., and C. Harrison. 2020. “Developing Resilient Supply Chains: Lessons from High-Reliability Organisations.” *Supply Chain Management* 25 (1): 77–100. https://doi.org/10.1108/SCM-09-2018-0329.

Schniederjans, D. G., C. Curado, and M. Khalajhedayati. 2020. “Supply Chain Digitisation Trends: An Integration of Knowledge Management.” *International Journal of Production Economics Elsevier BV* 220 (June 2019): 107439. https://doi.org/10.1016/j.ijpe.2019.07.012.

Sharma, M. K., Shusil, P. K. Jain. 2010. “Revisiting Flexibility in Organizations.” *Global Journal of Flexible Systems Management* 11 (3): 51–68. https://doi.org/10.1007/BF03396587.

Sharma, R., S. Kamble, V. Mani, and A. Belhadi. 2022. “An Empirical Investigation of the Influence of Industry 4.0 Technology Capabilities on Agriculture Supply Chain Integration and Sustainable Performance.” *IEEE Transactions on Engineering Management* 71:12364–12384. https://doi.org/10.1109/TEM.2022.3192537.

Shen, Z. M., and Y. Sun. 2023. “Strengthening Supply Chain Resilience During COVID-19: A Case Study of JD.com.” *Journal of Operations Management* 69 (3): 359–383. https://doi.org/10.1002/joom.1161.

Shukla, M., and S. Jharkharia. 2013. “Agri-Fresh Produce Supply Chain Management: A State-of-the-Art Literature Review.” *International Journal of Operations & Production Management* 33 (2): 114–158. https://doi.org/10.1108/01443571311295608.

Song, H., M. Li, and K. Yu. 2021. “Big Data Analytics in Digital Platforms: How Do Financial Service Providers Customise Supply Chain Finance?” *International Journal of Operations & Production Management* 41 (4): 410–435. https://doi.org/10.1108/IJOPM-07-2020-0485.

Spanaki, K., E. Karafili, and S. Despoudi. 2021. “AI Applications of Data Sharing in Agriculture 4.0: A Framework for Role-Based Data Access Control.” *International Journal of Information Management* 59:102350. https://doi.org/10.1016/j.ijinfomgt.2021.102350.

Spring, M., J. Faulconbridge, and A. Sarwar. 2022. “How Information Technology Automates and Augments Processes: Insights from Artificial-Intelligence-Based Systems in Professional Service Operations.” *Journal of Operations Management* 68 (6–7): 592–618. https://doi.org/10.1002/joom.1215.

Sreedevi, R., and H. Saranga. 2017. “Uncertainty and Supply Chain Risk: The Moderating Role of Supply Chain Flexibility in Risk Mitigation.” *International Journal of Production Economics Elsevier BV* 193:332–342. https://doi.org/10.1016/j.ijpe.2017.07.024.

Srinivasan, R., and M. Swink. 2018. “An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics: An Organizational Information Processing Theory Perspective.” *Production & Operations Management* 27 (10): 1849–1867. https://doi.org/10.1111/poms.12746.

Stone, J., and S. Rahimifard. 2018. “Resilience in Agri-Food Supply Chains: A Critical Analysis of the Literature and Synthesis of a Novel Framework.” *Supply Chain Management* 23 (3): 207–238. https://doi.org/10.1108/SCM-06-2017-0201.

Sudman, S. 1983. “Survey Research and Technological Change Hispanic Journal of Behavioral Sciences.” *Sociological Methods & Research* 12 (2): 217–320. http://hjb.sagepub.com.proxy.lib.umich.edu/content/9/2/183.full.pdf+html.

Teece, D. J., G. Pisano, and A. Shuen. 1997. “Dynamic Capabilities and Strategic Management.” *Strategic Management Journal* 18 (March): 77–116. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z.

Thomassey, S. 2010. “Sales Forecasts in Clothing Industry: The Key Success Factor of the Supply Chain Management.” *International Journal of Production Economics* 128 (2): 470–483. https://doi.org/10.1016/j.ijpe.2010.07.018.

Toorajipour, R., V. Sohrabpour, A. Nazarpour, P. Oghazi, and M. Fischl. 2021. “Artificial Intelligence in Supply Chain Management: A Systematic Literature Review.” *Journal of Business Research* 122 (May 2020): 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009.

Trevisan, C., and M. Formentini. 2023. “Digital Technologies for Food Loss and Waste Prevention and Reduction in Agri-Food Supply Chains: A Systematic Literature Review and Research Agenda.” *IEEE Transactions on Engineering Management* 71:12326–12345. https://doi.org/10.1109/TEM.2023.3273110.

Tsolakis, N., et al. 2022. *Artificial Intelligence and Blockchain Implementation in Supply Chains: A Pathway to Sustainability and Data Monetisation? Annals of Operations Research*. London, UK: Springer US.

Tsolakis, N. K., C. A. Keramydas, A. K. Toka, D. A. Aidonis, and E. T. Iakovou. 2014. “Agrifood Supply Chain Management: A Comprehensive Hierarchical Decision-Making Framework and a Critical Taxonomy.” *Biosystems Engineering* 120:47–64. https://doi.org/10.1016/j.biosystemseng.2013.10.014.

Tushman, M. L., and D. A. Nadler. 1978. “Information Processing as an Integrating Concept in Organizational Design.” *Academy of Management Review* 3 (3): 613–624. https://doi.org/10.2307/257550.

United Nations. 2022. “The Sustainable Development Goals Report 2019. *United Nations Publication Issued by the Department of Economic and Social Affairs*, p. 64. https://unstats.un.org/sdgs/report/2022/%0Ahttps://www.un-ilibrary.org/content/books/9789210018098.

Upton, D. M. 1994. “The Management of Manufacturing Flexibility.” *California Management Review* 36 (2): 72–89. https://doi.org/10.2307/41165745.

Vanpoucke, E., and S. C. Ellis. 2019. “Building Supply-Side Resilience – A Behavioural View.” *International Journal of Operations & Production Management* 40 (1): 11–33. https://doi.org/10.1108/IJOPM-09-2017-0562.

Volberda, H. W. 1996. “Toward the Flexible Form: How to Remain Vital in Hypercompetitive Environments.” *Organization Science* 7 (4): 359–374. https://doi.org/10.1287/orsc.7.4.359.

Wamba, S. F., R. Dubey, A. Gunasekaran, and S. Akter. 2020. “The Performance Effects of Big Data Analytics and Supply Chain Ambidexterity: The Moderating Effect of Environmental Dynamism.” *International Journal of Production Economics*. Elsevier B.V. 222. 222:107498. https://doi.org/10.1016/j.ijpe.2019.09.019.

Weick, K. E., and K. M. Sutcliffe. 2006. “Mindfulness and the Quality of Organizational Attention.” *Organization Science* 17 (4): 514–524. https://doi.org/10.1287/orsc.1060.0196.

Wieland, A., C. M. Wallenburg, H. L. Töyli, H. L. Töyli, and J. Lauri Ojala. 2013. “The Influence of Relational Competencies on Supply Chain Resilience: A Relational View.” *International Journal of Physical Distribution & Logistics Management* 43 (4): 300–320. https://doi.org/10.1108/IJPDLM-08-2012-0243.

Williams, B. D., J. Roh, T. Tokar, and M. Swink. 2013. “Leveraging Supply Chain Visibility for Responsiveness: The Moderating Role of Internal Integration.” *Journal of Operations Management Elsevier BV* 31 (7–8): 543–554. https://doi.org/10.1016/j.jom.2013.09.003.

Wong, C. W. Y., T.-C. Lirn, C.-C. Yang, and K.-C. Shang. 2020. “Supply Chain and External Conditions Under Which Supply Chain Resilience Pays: An Organizational Information Processing Theorization.” *International Journal of Production Economics*. Elsevier B.V. 226. 226:107610. https://doi.org/10.1016/j.ijpe.2019.107610.

Yan, B., C. Yan, C. Ke, and X. Tan. 2016. “Information Sharing in Supply Chain of Agricultural Products Based on the Internet of Things.” In *Industrial Management & Data Systems*. Leeds, UK: Emerald Publisher.

Yu, W., M. A. Jacobs, R. Chavez, and J. Yang. 2019. “Dynamism, Disruption Orientation, and Resilience in the Supply Chain and the Impacts on Financial Performance: A Dynamic Capabilities Perspective.” *International Journal of Production Economics Elsevier BV* 218:352–362. https://doi.org/10.1016/j.ijpe.2019.07.013.

Zhao, G., H. Chen, S. Liu, D. Dennehy, P. Jones, and C. Lopez. 2023. “Analysis of Factors Affecting Cross-Boundary Knowledge Mobilization in Agri-Food Supply Chains: An Integrated Approach.” *Journal of Business Research* 164 (April): 114006. https://doi.org/10.1016/j.jbusres.2023.114006.

Zhong, R. Y., K. Tan, and G. Bhaskaran. 2017. “Guest Editorial.” *Industrial Management and Data Systems* 117 (9): 1779–1781. https://doi.org/10.1108/IMDS-06-2017-0269.

Zhu, S., J. Song, B. T. Hazen, K. Lee, and C. Cegielski. 2018. “How Supply Chain Analytics Enables Operational Supply Chain Transparency: An Organizational Information Processing Theory Perspective.” *International Journal of Physical Distribution & Logistics Management* 48 (1): 47–68. https://doi.org/10.1108/IJPDLM-11-2017-0341.

Zissis, D., E. Aktas, and M. Bourlakis. 2017. “A New Process Model for Urban Transport of Food in the UK.” *Transportation Research Rocedia* 22:588–597. https://doi.org/10.1016/j.trpro.2017.03.048.