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Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis

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ABSTRACT

This study posits that the use of artificial intelligence (AI) enables supply chains (SCs) to dynamically react to volatile environments, and alleviate potentially costly decision-makings for small-medium enterprises (SMEs). Building on a resource-based view, this work examines the impact of AI on SC risk management for SMEs. A structural model comprising of AI-risk management capabilities, SC re-engineering capabilities and supply chain agility (SCA) was developed and tested based on data collected from executives, managers and senior managers of SMEs The main methodological approach used in this study is partial least squares-based structural equation modelling (PLS-SEM) and artificial neural network (ANN). The results identified the use of AI for risk management influences SC re-engineering capabilities and agility. Re-engineering capabilities further affect and mediate agility. PLS-SEM and ANN were compared and the results revealed consistency for models A and B. Current levels of demand uncertainties in the SC challenges managers in making complex trade-off decisions that require huge management resources in very limited time. With AI, it is possible to model various scenarios to answer crucial questions that archaic infrastructures are not able to. This study combines a multi-construct agility concept and identified non-linear relationships in the model.

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Supply chain agility; re-engineering capabilities; risk management; artificial intelligence; ANN; PLS-SEM

1. Introduction

In the context of the supply chain (SC), agility can refer to the firm's ability to (1) calibrate tactics and operations within its SC in response or adapt to fluctuations, opportunities or environmental threats (D. M. Gligor, Holcomb, and Stank 2013); (2) respond to short-term market fluctuations (Aslam et al. 2018); (3) and exploit opportunities while addressing risks through market sensitivity, network-based flexibility and process integration (Brusset 2016). These fluctuations include demand patterns change such as quality, quantity and variety and supply patterns change like shortages and disruptions (Blome, Schoenherr, and Rexhausen 2013). According to Choudhary and Sangwan (2018), managers are pressured to instil agility to ensure sustained SC performance. Improved SC performance is crucial as competition has shifted to SCs (Abdallah, Abdullah, and Mahmoud Saleh 2017; D. Gligor et al. 2019; Queiroz et al. 2021) and firms must oversee the sustainability of their SCs (Carter, Kaufmann, and Ketchen 2020). Despite having received vast attention among scholars, there does not exist a universally accepted concept for supply chain agility (SCA) (D. M. Gligor, Holcomb, and Stank 2013; D. Gligor et al. 2019; D. Z. Zhang 2011). The theoretical understanding of SCA is fragmented due to its broad and multidimensional concept that spans multiple disciplines. Earlier research concentrated on firms' ability to succeed in an environment of continuous and uncertainties. This concept evolved into a paradigmatic view of firms' capability to respond to customers' dynamic demands and has expanded to multiple business challenges of turbulent environments. Other researchers have defined agility in terms of a network of different integrated companies to streamline material, information and financial flow (Costantino et al. 2011). The focus then was on flexibility and performance while Braunscheidel and Suresh

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(2009) defined agility as a multi-dimensional construct of demand response, joint planning, customer responsiveness and visibility.

However, a firm's ability to acquire timely, relevant and up-to-date information can ensure enhanced SC visibility, agility, performance and competitiveness (Baah et al. 2021). On the contrary, poor information sharing creates conflicts and can lead to inferior performance (Singh, Acharya, and Modgil 2020). A flexible SC needs to be able to sense external stimuli and decide on the appropriate response in a timely manner. And to carry out these, the SC relies on the presence of the right metrics to inform stimulus, availability of strategic responses and scalability of resources and to measure the effectiveness of responses. Information sharing thus is essential to inform SC coordination activities for overcoming SC dynamics and flexibility performance (Chan and Chan 2008; Huo, Haq, and Gu 2020). Untimely sharing of information creates uncertainty in operations due to ambiguity about materials supply, supply capacity (G. Zhang, Shang, and Li 2011) and lead time (Osman and Demirli 2012), as well as internal operations. Many studies have found that timely information sharing greatly impacts SC performance particularly in reducing the bullwhip effect via better coordination (Jeong and Hong 2017; Ouyang 2007; Tang et al. 2021) and allow firms to better manage their decision-makings leading to improved resource utilisation and lower supply costs. To date, SCA is considered one of the main issues of present-day SC management and is the suggested means by which firms master market turbulence and handle disruptions (D. Gligor et al. 2019).

In this regard, various studies have examined the effects of disruptions on the SCs; particularly, the COVID-19 pandemic has been extensively studied by scholars (Ivanov and Dolgui 2020b; Queiroz et al. 2020; Nikolopoulos et al. 2020; Chowdhury et al. 2021; Ivanov 2020; Gupta et al. 2021). However, existing research has yet to consider how small-medium enterprises (SMEs) can identify appropriate strategies during disruptions and assess the effectiveness of their strategies in the context of the firm's capabilities (Gruber, Kim, and Brinckmann 2015; Papadopoulos, Baltas, and Balta 2020). Despite the significance of SMEs, there is scant information on SME disaster planning and recovery (Helgeson et al. 2020; Papadopoulos, Baltas, and Balta 2020). Yet, the pressure to remain efficient amid the demands of frugal capacity management persists. The challenge is, therefore, for SME managers to ensure SC resilience while maintaining their competitiveness and to develop new strategies in their future SC that allow firms to prepare for and build both medium- and long-term SC resilience.

The use of Industry 4.0 technologies such as artificial intelligence (AI), big-data analytics, cloud computing, distributed ledgers can bring about SC efficiencies in many ways (Hastig and Sodhi 2020; Sundarakani, Ajaykumar, and Gunasekaran 2021; Akter et al. 2020; Belhadi, Mani, et al. 2021). For example, AI enables predictive approaches for risk assessment and minimisation of disruptive events throughout the SC (Riahi et al. 2021), develops models to enable managers to discover improvement areas (Ni, Xiao, and Lim 2019) and in the case of Alibaba (2020), a digitalised cloud-based production SC powered by AI technologies can allow SMEs to identify new opportunities in the shift of customer preference and predict risks through data analytics capabilities. For this to work, two main components are essential: live data and feedback loop (Leavy, 2019). The value chain is re-configured and modularised into technologically optimised networks and retail activities are coordinated real-time with machine-made operational decisions through the use of machine learning (ML) techniques (Leavy 2019). All business activities such as sales, marketing and production are decentralised, scalable and optimised. Data generated can be collected continuously from real-time interactions and online processes for an ongoing feedback loop into the system providing 'more context, greater opportunities for stakeholders' for innovative purposes (Dwivedi et al. 2017, 198). Through AI technologies, customer issues can be diagnosed and fixed automatically with customer confirmation (Ming 2018; Kumar, Singh, and Dwivedi 2020). Trends and sales forecasts can be generated fast to provide much-needed insights into customer preferences and this enables businesses to react timely to meet customer personalisation demands. In this manner, firms can adapt dynamically and rapidly in response to market changes. Business decisions become smarter (Leavy, 2019). Additionally, manufacturers can reduce inventory levels and minimise wastage including improving profit margin. And in the case of Taobao, credit risk assessments for the small businesses using the Alibaba platform are decidedly hard (Zeng 2018). Here, AI-powered algorithms are trained based on transaction data to gauge the competitiveness of the business offerings and determine the credit ratings of these small businesses. In this manner, the financing needs of an ecosystem are taken care of via automatic analysis of all actions taken on the platform. At the same time, these algorithms continuously learn and improve the quality of decisions. The result is a highly successful micro-lending business fuelled by live data and automated decision-making. However, these emerging technologies are often underexploited or neglected by SMEs (Hansen and Bøgh 2020; Moeuf et al. 2018) due to various resources and financial constraints, especially during a disruption (L. W. Wong, Leong, et al. 2020; Papadopoulos, Baltas, and Balta 2020; Kumar, Singh, and Dwivedi 2020). Despite the challenges, SMEs can also explore new opportunities and develop business continuity strategies because of their relatively smaller size and greater flexibility. But for many, producing economically meant the ability to counter fast-changing trends and customer demand, all of which require speed and accuracy in decision-making. Without the ability to reinvent and adapt their business model, it will be hard for SMEs to ensure business continuity. Although the role of technologies has long been studied as a capability, securing competitive advantage during disruptions depends on how resources are configured and re-configured. And this is done via 'sensing', 'seizing' and 'orchestrating' resources and capabilities for business continuity (Papadopoulos, Baltas, and Balta 2020, 3). Grounded on the resource-based view (RBV), the objective of this study henceforth is to examine the interplay between the use of AI technologies for risk management, SC Re-engineering capabilities and SC Agility; as well as to further examine the effect of SC Re-engineering capability on SCA.

This study begins with a discussion of extant literature followed by the conceptual model and hypothesis development in the following sections. Subsequently, the analysis of data and findings are presented. The final sections of this work include a discussion of the results and also a review of managerial and practical implications. Lastly, this work concludes with a few general outlines for future research.

2. Literature Review

2.1. RBV and dynamic capabilities

The RBV is grounded on the view that firms in possession of valuable and rare resources that are non-imitable can achieve sustainable competitive advantage by strategically leveraging these resources (Yu et al. 2018). Many scholars have considered RBV in the context of operations and SC management (Shibin et al. 2020; Y. Yang, Jia, and Xu 2019; Huo, Han, and Prajogo 2016; Yu et al. 2018; Barney 2001) due to its suitability in explaining how organisation strategic resources can enable organisations to gain competitive advantage (Shibin et al. 2020). The RBV affords superior performance resulting from effective use of resources and organisational capabilities to build strategic relationships with customers, SC partners; and flexible and speedy responses to market demands (Yu et al. 2018). In general, resources can be tangible or intangible (Kwak, Seo, and Mason 2018); and capabilities indicate the firm's capacity to employ its resources and processes to attain desired outcomes (Huo, Han, and Prajogo 2016).

Within the context of capabilities, scholars have considered operational capabilities (Kim 2006; Brusset and Teller 2017) from dynamic capabilities (S. F. Wamba et al. 2017; Blome, Schoenherr, and Rexhausen 2013) where superior performance can be attained (Cepeda and Vera 2007). Operational capabilities are processes and routines related to knowledge (Cepeda and Vera 2007) that allow firms to respond to unexpected events affecting the SC performance (Barreto 2010). Here, resilience is an operational capability critical to maintaining continuity of operations (Brusset and Teller 2017) that allows the SC to absorb or recover from disruptions (Bhamra, Dani, and Burnard 2011). By contrast, the dynamic capability is context-dependent and is a learned pattern of cooperative activities and strategic procedures that enabled firms to accomplish new resource configurations and improve competitiveness (Teece 2007). In other words, dynamic capabilities indicate the firm's integration and reconfiguration abilities in addressing rapid changes both within and outside the firm (Huo, Han, and Prajogo 2016). According to Brusset and Teller (2017), dynamic capabilities enable firms to characterise operational capabilities that they wish to augment and across SCs. Similarly, Brusset (2016) considered how agility could be enhanced based on practices and processes. Taken together, RBV provides a theoretical angle to comprehend how firms can leverage their reserves and capabilities to enhance the performance of SCs during disruptions (Queiroz et al. 2020).

Despite RBV being widely employed in SC management theorising, RBV has also been heavily criticised. First, RBV is considered to be lacking in terms of managerial implications and operational validity (Kraaijenbrink, Spender, and Groen 2009). Managerial leaders are informed of the resources to acquire and develop; however, there is no information on how the resources should be acquired. This creates a gap between what is theorised to be useful and a prescription on how managers should go about obtaining the resources (Lado et al. 2006). A second criticism arises in regard to its limited applicability. A resource that is rare, inimitable and nonsubstitutable denies the firms any potential to generalise the resource. Further, this could lead to an infinite search for the ultimate resources and capabilities in the quest for a sustainable advantage that exceeds other firms' capacity to replicate (Priem and Butler 2001). The critiques mainly concern the lack of demarcation and definition of resource and value, in addition to a narrow explanation of sustained competitive advantage (Kraaijenbrink, Spender, and Groen 2009). Without an appropriate emphasis on bundling resources and involving humans in assessing and creating value, the essence of competitiveness would not be sufficiently captured. Additionally, resources development and deployment should be conceptualised as integrations and applications (actions/process) instead of capacities owned. Kraaijenbrink, Spender and Groen (2009) further suggested distinguishing capacity building (includes resources and capabilities) and capacity deployment processes so that a more practical resource-based theory can be developed. Oliver (1997) argues that RBV lacks consideration for social contexts within which resources are sourced. To address the limitations, the authors proposed a theoretical framework integrating the RBV with the institutional theory that provides a better explanation of the motivation for the adoption of technology that stemmed from legitimacy (Shibin et al., 2020). In the context of this study, RBV is the natural fit theoretical base to understand capacity building for subsequent capacity deployment as the focus excludes legitimacy generated through the inclusion of stakeholders and experts.

2.2. AI for risk management

The role of digital technologies in SC research has been considered by scholars in various areas from enhancing forecasting, to production flexibility and SC visibility (Dubey et al. 2019; Baryannis et al. 2019; Ivanov and Dolgui 2020a; Belhadi, Kamble, et al. 2021). According to Baryannis et al. (2019), an approach is artificially intelligent if it can autonomously determine the course of action that can successfully achieve risk management objectives despite not having complete information on the SC environment. The authors considered knowledge-based symbolic AI, fuzzy systems, statistical AI, as well as ML-based risk management methods, among others. They further noted the nascent stage of AI predictive and learning capabilities in the sphere of SC risk management and the most common application of AI-driven risk management (AIRM) is stochastic parameters for modelling. Riahi et al. (2021) considered the distribution of AI techniques across supply chain operations reference (SCOR) areas reported genetic algorithms were mostly used in the planning process followed by neural networks. Belhadi, Mani, et al. (2021) investigated AI's impact on short-term SC performance during the influence of uncertainty. Ni, Xiao and Lim (2019) showed that the use of ML in SC management is in a developmental stage and there are insufficient publications. None of these works was specifically targeted at SMEs and thus further studies are required to extend the generalisability of the findings on AI's applicability to SMEs. Other researchers have used network-based approaches to understand the different states, outcomes and possible transitions of SC. These include the use of reasoning Petri Nets and its variants (Rossi and Pero 2012; Asar et al. 2006; Blackhurst, (Teresa) Wu, and Craighead 2008) and Bayesian Belief Networks (Qazi et al. 2018; Nepal and Yadav 2015) to estimate probability distributions of SC loses due to disruptions. More recently, Lima-Junior and Carpinetti (2020) adapted a network-based fuzzy inference system to evaluate the performance of SC based on SCOR metrics. Their work demonstrated greater prediction accuracy, learning ability from historical data and suitability to decision-making under uncertainty.

Additionally, scholars have also used big-data analytics in close relation to AIRM for risk identification and management. According to Yang et al. (2020), unlike large enterprises, credit-related attributes for SMEs are usually insufficient and hard to acquire. The social relations between SMR owners, transactions between SMEs or between SMEs and consumers provide abundant interactive data that could help to predict SMEs' future credit status. Intuitively, these data contain effective information that can provide insights on these firms' financial risks, or it can also be very noisy that the data can be irrelevant to analysis. However, exploring SC relationships can help to comprehensively model the SMEs which could subsequently improve financial risk analysis for SMEs. Using neural networks, the authors modelled the credit topological structure and temporal variations of SMEs and proposed an innovative method of SC mining in a semi-supervised link prediction manner to mine SC relationships using a supervised node classification manner to predict loan defaulters. Overall, their work demonstrates that SC relationships improve the accuracy of predictions significantly. Other scholars such as, Cavalcante et al. (2019) employed a hybrid approach of simulation and ML to analyse supplier performance risk profiles under uncertainty. Their work, which eliminated the need to estimate the likelihood of disruptions and forecasting performance impacts uses the k-NN algorithm and Logistic Regression classifiers to optimise the selection of suppliers with the best chance of timely delivery based on past data categorised as either on-time or late. The authors utilised the data analytics capability of digital manufacturing to explore the conditions of resilient supplier performance. Applying k-NN, the authors mapped suppliers' performance according to date and order quantity while Logistic regressions are applied to estimate the probability of supplier on-time delivery. In this manner, the risk profiles or suppliers are determined according to the probabilities of success in regard to on-time delivery. Their results suggested that a combination of supervised ML and simulation can improve delivery reliability by creating digital SC twins.

Artificial intelligence-driven risk management is promising for optimising SC and augmenting its resilience (Riahi et al. 2021). Despite this, the use of big-data analytics and AI remains largely untapped potential and has received little attention in SC disruption (Xu et al. 2020; Ivanov and Dolgui 2020a). AI technologies can 'monitor and control processes in real-time', enhancing human capabilities rather than replacing it (Dwivedi et al. 2021). The gap was also echoed by Dolgui, Ivanov, and Sokolov (2018), which envisioned a cyber-SC that overarches traditional SC analytics and several other studies (S. Wamba and Akter 2019; Akter et al. 2020; Belhadi, Mani, et al. 2021).

2.3. SC re-engineering

The consideration of SCs' ability to recover from unexpected disruptions is grounded on the notion that some risks cannot be averted (Jüttner and Maklan 2011). During the onset of disruption, it would be too late to develop preventive solutions and incorporate preparedness for an efficient response that will allow resources to be deployed in a manner such that the outcome is as planned (Scholten, Scott, and Fynes 2014; Tomasini and Van Wassenhove 2009). According to Schleper et al. (2021), SCs need to be prepared for unexpected disruptions and environmental fluctuations. The need to rethink conventional SC wisdom and foster future SCs with heightened ability to adapt to abrupt disruptions through digitalisation (F. Li 2020), absorb and withstand shocks with resilience and sustainability (Ivanov 2020) is imminent. Thus, both robust (proactive) and agile (reactive) SC strategies are required to enhance a firm's sustenance capability by preventing risks and enabling resistance to change (Wieland and Marcus Wallenburg 2012). In a reactive approach, SC changes can be monitored and strategies relating to customer needs, competitors and techniques. A proactive approach can help identify potential risks and minimise impact before it occurs (Abeysekara, Wang, and Kuruppuarachchi 2019)

According to Soni et al. (2014), past literature had proposed diverse measurements of SCs adaptive capability to tackle temporary disruptions; however, there is inconsistency regarding the variables that constitute these measures (Jüttner and Maklan 2011; Liu et al. 2018). For instance, some studies considered agility and robustness (Wieland and Marcus Wallenburg 2012) while others have considered knowledge-management (Scholten, Scott, and Fynes 2014), SC re-engineering (Scholten, Scott, and Fynes 2014), flexibility, redundancy, velocity (Azadeh et al. 2014). While the list presented here is not exhaustive, researchers have outlined the need for firms to employ fitting policies and actions to continually assess risks and coordinate efforts of the SC network (Scholten, Scott, and Fynes 2014; Liu et al. 2018). Re-adjustment, re-designing and re-shuffling SCs to integrate resilience in SCs are referred to as re-engineering (Christopher and Peck 2004). SC re-engineering comprises the integration of processes and activities that are required to optimise product and service flow (Liu et al. 2018). SC re-engineering approaches that are widely adopted include (i) incorporating viable alternatives in various situations and having flexibilities that can strengthen the firm and (ii) storing a safety stockpile and having backup suppliers to create a capacity surplus.

2.4. Supply chain agility

Supply chain agility is a 'broad and multi-dimensional concept' that bridges many disciplines (D. M. Gligor and Holcomb 2014, 161). According to Yang (2014), there are two avenues where SCA can be examined: (1) speed and responsiveness to uncertain markets (Van Hoek, Harrison, and Christopher 2001; Swafford, Ghosh, and Murthy 2008); and (2) information-driven relationships (Huo, Han, and Prajogo 2016). In the work of Van Hoek et al. (2001), agility encompasses a firm's responsiveness to dynamic and turbulent market and customer needs. Swafford et al. (2008) identified agility as an outwardly facing capability that reflects the speed at which firms adapt to evolving markets. Firms with agile SCs are better able to respond to unforeseen circumstances. Other researchers defined agility in integrating various companies into streamlined material and how flexible information flow and performance (Costantino et al. 2012). Li et al. (2009) characterised SCA based on factors surrounding strategic response, operational response, episodic response as two broad dimensions of alertness and capability.

Despite lacking a consensus in the definition of agility, research in SC management has outlined the importance of developing agility to manage disruption risks and ensure service continuity (Braunscheidel and Suresh 2009; C. J. Chen 2019) for firms to take better advantage of changes and synchronise supply with demand. In differentiating the concepts of agility and resilience. In summary, agility is a key strategy for firms facing arduous, low probability risk situations because SCs are required to respond quickly (Abeysekara, Wang, and Kuruppuarachchi 2019). Combined, the dimensions of decisiveness, visibility, demand response and customer responsiveness form the components of SCA in the context of this study.

3. Research model and hypothesis

Small-medium enterprises need to leverage technologies that allow them to respond to customer requirements and improve goods and service quality better to tap into opportunities afforded via seamless and global platforms (L. W. Wong, Tan, et al. 2020). During the onset of disruption, managing risks are not only crucial but more challenging. This study conceptualises the use of AIRM for two reasons. First, as discussed in earlier sections, using AI helps firms establish knowledge creation during disruptions. Specifically, AI can help firms reduce uncertainty by providing insights into firm SC for better predictability and decision-making (Baryannis et al. 2019). Secondly, innovation practices that affect SC structure can be employed as a means of re-engineering that affects the SC performance and is a key factor in SC management (Sabri, Micheli, and Nuur 2018). Therefore, AIRM is a capability that affords SMEs capabilities to re-engineer SCs (RP) when necessary and enhances SCA.

3.1. AI-risk management and SCA

According to Chen et al. (2015), firms can capitalise on dynamic capabilities to produce 'cutting-edge knowledge' (8) amid a dynamic situation. In their work, firms' analytics capabilities can be considered an avenue through which firms can enhance their capability to process information. This capability enables them to gather, understand and inform appropriate decisions. This view is also concurred by Dubey, Bryde, et al. (2020) in their study on big-data analytics powered by AI. By synthesising information from various sources, AIRM can provide complete visibility with predictive data that can significantly reduce cold chain logistics and foster better resource allocation (Myers 2020). Further, insights generated through AI allow firms to better model and predict demand, be more decisive with allocating resources with margin-optimisation, can reduce uncertainty against capacities and supply availability to mitigate shortages (D. Q. Chen, Preston, and Swink 2015). Analytics capabilities used within SC practices are, therefore, the strategic routes through which firms achieve new resource configurations. Similarly, this study suggests that the use of AIRM offers insights and opportunities for firms to reconfigure resources to adapt to dynamic conditions (Duan, Edwards, and Dwivedi 2019). Collectively, the use of AIRM can potentially lead to enhanced SCA. Thus, this paper hypothesises that:

> **H1:** AIRM has a significant and positive relationship with SCA.

3.2. AI-risk management and SC re-engineering capabilities

Firms need to have the knowledge and understanding of their SC structures to establish a resilient SC that can respond efficiently and effectively to events (Soni, Jain, and Kumar 2014; Liu et al. 2018). The ability to detect or forecast a potential disruption in advance to reduce its negative impact (Sheffi 2015). According to Jüttner (2005), effective precautions before the onset of disruption are possible if risk assessment tools are used to identify weak areas of an SC in advance of a disruption. Along this line, this study suggests that the use of AIRM to enhance awareness of risk situations in SC at times of uncertainties enables firms to undertake radical redesigns such as integration of processes and activities that can augment and optimise product and service flow. Further, re-engineering leads to the creation of flexibility and redundancy that helps firms recover from disruptions and build competitiveness (Sheffi 2015; Abeysekara, Wang, and Kuruppuarachchi 2019). Potential disruptions are typically characterised based on the magnitude of impact, the likelihood of occurrence and detection lead time (Sheffi 2015). The earlier the warning of an upcoming disruption, the more a firm can prepare such as relocation of assets, securing backup supplies and in many cases, a sudden disruption such as that of a pandemic may take weeks for the disruption to hit the firm. Thus, this paper hypothesises that the use of AIRM can potentially lead to better SC RP.

> **H2:** AIRM has a significant and positive relationship with RP.

3.3. SC re-engineering capabilities and SCA

According to Wong and Arlbjørn (2008), managing SC uncertainties requires firms to be agile, flexible, reliable and fast. Firms that can react and respond to frequently demands change while continually meeting customer demands are considered agile. And to be responsive and adaptable, firms need to have the ability to develop flexible practices and operations (Yauch 2011). Gligor (2015) offered five dimensions of agility, namely (i) the ability to quickly detect changes, opportunities and threats, (ii) rapid data accessibility within SCs, (iii) resolute decisiveness in response to changes, (iv) rapid implementation of decisions and (v) the ability to 'modify its range of tactics and operations' to implement its strategy. All of these abilities are congruent with the definition of SC re-engineering offered by Christopher and Peck (2004). Earlier sections have also defined RP in the light of flexibility and redundancy through AIRM. In this context, RP efforts can be undertaken to identify and manage SC uncertainties (C. Y. Wong and Arlbjørn 2008) and accordingly, this study hypothesises that:

> **H3:** RP has a significant and positive relationship with SCA.

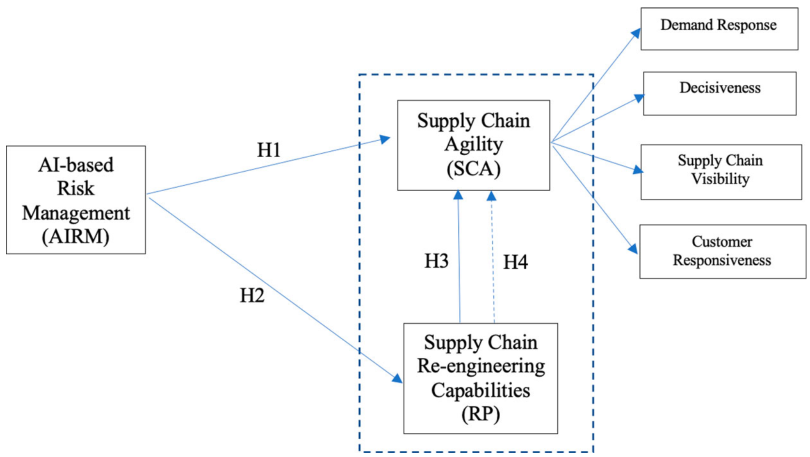

Figure 1. Conceptual model.

H4: RP has a significant and positive mediating effect between SCA and RP.

The conceptual model representing the above hypotheses is presented in Figure 1 below.

4. Methodology

4.1. Data collection and sampling method

The online survey questionnaires were distributed randomly to Malaysian manufacturing firms listed in the Companies Commission of Malaysia (also known as Suruhanjaya Syarikat Malaysia (SSM)) directory between September and October 2020 using a team of experienced data collectors due to COVID-19 restrictions. SSM is an agency responsible for sharing and registering incorporated companies and businesses to the public. Klang Valley, which lies between the state of Selangor and Kuala Lumpur, the capital city of Malaysia, was chosen as the sampling location because the region contributed to the most income of Malaysia's Gross Domestic Product and has been regarded as the most advanced region for the manufacturing sector (Tan et al. 2018; L. W. Wong, Tan, et al. 2020). All respondents were required to evaluate the questionnaire using a seven Likert scale ranging from strongly agree to strongly disagree. Out of the 400 questionnaires distributed, 270 responded and after omitting incomplete data and straight-lining responses, only 252 valid questionnaires were used for this analysis. Thus this translates to a response rate of 93.3%. Prior to data distribution, the survey instrument was also evaluated for content and face validity with 10 industry practitioners who were experts in SC and AI. Some modifications were made to the questionnaire based on the feedback such as the removal of jargon and vogue statements.

4.2. Measurement instrument

The measurement items were adapted based on established scales from past literatures with some minor wording changes to accommodate the context of the study. The questionnaire items were scored on a seven-point Likert-type scale (1 = strongly disagree and 7 = strongly agree). All constructs were adapted from past studies: six items for AIRM are adapted from Dubey, Bryde, et al. (2020). The construct of SCA is comprised of (i) four items on decisiveness adapted from Gligor et al. (2013), (ii) five items on demand response, and four items on customer responsiveness adapted from Braunscheidel and Suresh (2009), (iii) two items each on visibility adapted from Braunscheidel and Suresh (2009) as well as Abeysekara, Wang, and Kuruppuarachchi (2019). Last but not least, five items for RP are adapted from Abeysekara, Wang, and Kuruppuarachchi (2019).

5. Data analysis

5.1. Respondents' profile

The profile of the respondents is presented in Table 1.

5.2. Statistical analysis

For this purpose of study, partial least squares-structural equation modelling (PLS-SEM) was adopted through SmartPLS version 3.2.8. The choice of using PLS-SEM is mainly due to the unfulfilment of normal data distribution. One-sample Kolmogorov–Smirnov test shows that all *p*-values of the indicator construct are less than .05 which shows that the distribution of data is non-normal (Dalvi-Esfahani et al. 2020; Tew et al. 2021). Additionally, PLS-SEM is also suitable for the complicated model with the presence of second-order constructs (Ooi, Hew, and Lin 2018). Since SCA is modelled as a second-order

Table 1. Demographic analysis.

Demographic characteristics		Frequency	Per cent
Gender	Female	131	52.0
	Male	121	48.0
Age (years)	30 and below	90	35.7
	Between 31 and 40	107	42.5
	Between 41 and 50	45	17.9
	51 and above	10	4.00
Number of years with organisation (years)	Less than 1	17	6.70
	1–2	65	25.8
	3–5	88	34.9
	6–10	45	17.9
	11–20	22	8.70
	Above 20 Years	15	6.00
Job position	Executive (e.g. Officer, Accountant, Senior Accountant, Engineer, Senior Engineer, Staff Engineer, System Analyst, Assistant Manager, etc.)	127	50.4
	Senior Staff Engineer/Principal Engineer/Manager/Senior Manager/Head of Department	86	34.1
	General Manager/Director/Senior Director/Executive Director/Managing Director/Chief Executive Officer/Vice President/President/Chairman	20	7.90
	Other	19	7.50
Age of firm (years)	< 5 Years	22	8.70
	$5 \leq$ Years < 10 Years	75	29.8
	> 10 Years	154	61.1
Category of organisation product	Electrical and electronics	48	19.0
	Chemical	19	7.50
	Textile	17	6.70
	Food	63	24.9
	Rubber and plastic	34	13.4
	Machinery and hardware	34	13.4
	Others	38	15.0
Number of employees	Less than 5	26	10.3
	5 to < 75	134	53.0
	75 to ≤ 200	57	22.5
	> 200	36	14.2%

construct with DR, DE, VI and CR as its first-order construct, the suitability of PLS-SEM is warranted in this study. G∗Power was further employed to estimate the minimum sample size using an effect size, f^2 of 0.15, probability of error, $\alpha = .05$ and power level, $(1 - \beta) = .8$ with 2 as the number of predictors. The actual sample size of 252 was more than the minimum sample size of 68 to assess the proposed conceptual framework.

5.3. Common method bias

Since the data were collected via a self-reported questionnaire and in particular, the exogenous and endogenous constructs were measured by respondents' perceptual judgement, common method bias (CMB) was performed statistically through the approach developed by Liang et al., (2007) as shown in Table 2. Since the majority of the method, factor loading (FL) is insignificant and the substantive variance higher than the corresponding method variance, the results indicated that CMB does not pose a problem (Lee et al. 2020). Several procedural remedies were also adopted to restrain CMB such as using simple language, assuring maximum confidentiality and anonymity of participants, informing that there are no right or wrong answers and listing the exogenous construct items before the endogenous construct items during the development and administration of the questionnaire (Philip M. Podasakoff et al. 2003; Adhikari and Panda 2020).

5.4. Assessing the outer measurement model

Dijkstra Henseler's (rho_A) and composite reliability (CR) were used to measure internal reliability. In Table 3, all rho_A and CR values for the first- and second-order constructs were above the limit of 0.60, exhibiting strong internal reliability (Cachón Rodríguez, Prado Román, and Zúñiga-Vicente 2019; Loh et al. 2020; Bawack, Wamba, and Carillo 2021). Convergent validity (CA) is assessed by FL and average variance extracted (AVE). All FL shown in Table 3 is greater than the threshold of 0.70 except for RP1, RP4, CR4, DR5 and VI2 (Loh et al. 2022). Hair et al., (2017) concluded that FL values ranging between 0.40 and 0.70 are acceptable if AVE > 0.5 and CR > 0.70 and should be considered for removal if the values are below 0.40. RP1 and RP4 FL were removed from Table 3 due to poor-loading CR4, DR5 and VI2 on the other hand were retained as the FL can explain about 50% of the AVE and above the minimum threshold of 0.70 for CR. Additionally, AVE for each construct ranged from 0.533 and 0.715 for both first- and second-order and has exceeded the minimum threshold of 0.50 (L. W. Wong, Tan, et al. 2020; Dubey et al. 2021). Both criteria denote that the measurement model has a good CV. Next, the discriminant validity (DV) was assessed by the means of the Hetero-Trait-Mono-Trait (HTMT) ratio of correlations. Tables 4 and 5 show that all HTMT values for first- and second-order are below the minimum value of 0.85. In addition, the HTMT inference test in Tables 4 and 5 has also been established as the results show the confidence interval did not show a value of 1 for any of the constructs for both 2.5% (lower bound) and 07.25% (higher bound) suggesting that there is adequate DV throughout the model (Henseler, Ringle, and Sarstedt 2015).

Table 2. Common method factor analysis.

Latent Construct	Indicators	Substantive factor loading (Ra)	Ra^2	Method factor loading (Rb)	Rb^2
AIRM	AIRM1	0.65***	0.42	0.19*	0.04
	AIRM2	0.87***	0.76	-0.09^{NS}	0.01
	AIRM3	0.95***	0.90	−0.17**	0.03
	AIRM4	0.99***	0.98	−0.17*	0.03
	AIRM5	0.78***	0.61	0.04^{NS}	0.00
	AIRM6	0.57***	0.32	0.20^{NS}	0.04
CR	CR1	0.83***	0.68	0.02^{NS}	0.00
	CR2	0.83***	0.69	-0.02^{NS}	0.00
	CR3	0.90***	0.81	-0.09^{NS}	0.01
	CR4	0.48***	0.23	0.13^{NS}	0.02
DE	DE1	0.67***	0.45	0.12^{NS}	0.01
	DE2	0.95***	0.91	−0.14*	0.02
	DE3	0.86***	0.74	-0.01^{NS}	0.00
	DE4	0.77***	0.60	0.04^{NS}	0.00
DR	DR1	0.75***	0.57	0.05^{NS}	0.00
	DR2	0.39***	0.16	0.37***	0.14
	DR3	0.86***	0.75	−0.15*	0.02
	DR4	0.91***	0.82	−0.14*	0.02
	DR5	0.72***	0.52	-0.13^{NS}	0.02
RP	RP2	0.72***	0.51	0.08^{NS}	0.01
	RP3	0.86***	0.73	−0.09*	0.01
	RP5	0.76***	0.57	0.00^{NS}	0.00
VI	VI1	0.89***	0.79	-0.11^{NS}	0.01
	VI2	0.70***	0.48	-0.07^{NS}	0.00
	VI3	0.70***	0.50	0.11^{NS}	0.01
	VI4	0.730***	0.53	0.05^{NS}	0.00
	Average	0.77	0.62	0.00	0.02

Note: ***$p < .001$; **$p < .01$; *$p < .05$, ^{NS}insignificant.

5.5. Inspecting the inner structural model

The model fit was measured using the standardised root mean square residual (SRMR) value (Hair et al. 2017). Since the SRMR value for both saturated and estimated models was below 0.08, Hu and Bentler (1999) indicate that the model has a good fit. Further, multicollinearity was not a concern as all the inner variance inflation factor (VIF) values for both first- and second-order constructs were below 5.00 which indicates that the problem of multicollinearity is not a concern (Cao et al., 2021; Lew et al., 2020). The hypotheses in the structural model were tested using a bias-corrected and accelerated (BCa) bootstrap procedure with 5000 sub-samples. Figure 2 and Table 6 show that AIRM ($\beta = .416, p < .001$) has a direct positive relationship with RP thus supporting H2. Similarly, AIRM ($\beta = .545$, $p < .001$) and RP ($\beta = .400$, $p < .001$) are positive and significant with SCA, hence supporting H1 and H3. Table 7 also ascertained that RP partially mediates the path between AIRM and SCA in a complementary manner (Hew et al. 2018). This outcome support H4. The coefficient of determination, R^2 in Table 8 shows that 63.9% of the variance in SCA is explained by RP and AIRM.

5.6. The predictive relevance and effect size

The f^2 effect size was further assessed using Cohen's f^2 whereby the intensity is represented by small, medium and large effects for values above 0.02, 0.15 and 0.35, respectively (Cohen 1988; Hew et al., 2018). The results of the f^2 effect sizes are summarised in Table 8 with values ranging from 0.209 to 0.683 indicating medium and large effects on the predictor construct RP and SCA. The predictive relevance of the structural model was further accessed using Stone–Geisser's Q^2 value (Yuan et al. 2021; Yan et al. 2021). Table 9 illustrated that both endogenous construct RP and SCA showed predictive accuracy of the model with Q^2 values greater than zero.

5.7. Artificial neural network analysis

In view of the limitation of PLS-SEM that can only capture compensatory and linear studies (Lim et al. 2021), the study further complements the PL-SEM analysis by adopting the artificial neural network (ANN) analysis as ANN is able to capture non-linear relationship in this study and therefore useful in decision-making (Ooi, Hew, and Lin 2018; Wan et al. 2021). Two ANN models were constructed for SCA and RP. In order to determine the predictive accuracy of models A and B, the root mean squared error (RMSE) is calculated for the 10 neural networks (Wang et al. 2022). Table 10 shows that all the RMSE value shows high prediction accuracy as they are relatively small with values ranging from 0.079 to 1.996 (Lee et al., 2020). Additionally, the study also ranks the exogenous based on the

Table 3. Loadings, composite reliability, Dijkstra Henseler and average variance extracted.

Constructs	Items	Loadings (*p*-levels)	Dijkstra Henseler's (rho_A)	Composite reliability (CR)	Average variance extracted (AVE)
First order					
AIRM	AIRM1	0.812 ($p < .001$)	0.891	0.915	0.643
	AIRM2	0.792 ($p < .001$)			
	AIRM3	0.796 ($p < .001$)			
	AIRM4	0.837 ($p < .001$)			
	AIRM5	0.824 ($p < .001$)			
	AIRM6	0.748 ($p < .001$)			
RP	RP2	0.788 ($p < .001$)	0.670	0.818	0.600
	RP3	0.772 ($p < .001$)			
	RP5	0.763 ($p < .001$)			
CR	CR1	0.835 ($p < .001$)	0.781	0.854	0.596
	CR2	0.816 ($p < .001$)			
	CR3	0.806 ($p < .001$)			
	CR4	0.610 ($p < .001$)			
DE	DE1	0.782 ($p < .001$)	0.833	0.889	0.667
	DE2	0.832 ($p < .001$)			
	DE3	0.845 ($p < .001$)			
	DE4	0.806 ($p < .001$)			
DR	DR1	0.797 ($p < .001$)	0.793	0.850	0.533
	DR2	0.725 ($p < .001$)			
	DR3	0.733 ($p < .001$)			
	DR4	0.783 ($p < .001$)			
	DR5	0.596 ($p < .001$)			
VI	VI1	0.798 ($p < .001$)	0.751	0.838	0.566
	VI2	0.649 ($p < .001$)			
	VI3	0.799 ($p < .001$)			
	VI4	0.754 ($p < .001$)			
Second order					
AIRM∗				1.000	1.000
AIRM∗		1.000			
SCA			0.868	0.909	0.715
CR		0.831 ($p < .001$)			
DE		0.857 ($p < .001$)			
DR		0.838 ($p < .001$)			
VI		0.857 ($p < .001$)			
RP∗				1.000	1.000
RP∗		1.000			

Note: ∗Single-item constructs were excluded from this analysis.

Table 4. Hetero-Trait-Mono-Trait Assessment (HTMT) for first-order constructs.

Latent construct	AIRM	CR	DE	DR	RP	VI
AIRM						
CR	0.761 [0.653, 0.862]					
DE	0.68 [0.529, 0.809]	0.752 [0.631, 0.88]				
DR	0.609 [0.487, 0.715]	0.731 [0.618, 0.826]	0.812 [0.711, 0.897]			
RP	0.528 [0.348, 0.682]	0.61 [0.485, 0.747]	0.76 [0.635, 0.873]	0.839 [0.742, 0.934]		
VI	0.792 [0.700, 0.871]	0.849 [0.673, 1.027]	0.796 [0.618, 0.948]	0.788 [0.636, 0.921]	0.741 [0.532, 0.933]	

Note: The values in the brackets represent the lower and the upper bounds of the 95% confidence interval.

Table 5. Hetero-Trait-Mono-Trait Assessment ($HTMT_{.85}$) for second-order constructs.

Latent construct	AIRM	RP	SCA
AIRM			
RP	0.416 [0.277, 0.537]		
SCA	0.763 [0.691, 0.822]	0.673 [0.582, 0.75]	

Note: The values in the brackets represent the lower and the upper bounds of the 95% confidence interval.

normalised relative importance towards the endogenous variable in Table 11 (Lim et al. 2021). In ANN model A, AIRM is the most important (100% normalised relative importance) predictor of SCA while RP is ranked the second most important predictor of SCA. While there is only one single neuron model for ANN model B, the sensitivity analysis shows a 100% of normalised importance. Results between PLS-SEM and ANN were compared using patch coefficient and normalised relative importance, respectively (Ng et al. 2022), and Table 12 shows that both results are consistent for ANN model A and B.

6. Discussion and implication

The results of this study suggest that AIRM is a significant determinant of RP and SCA. This finding supports past

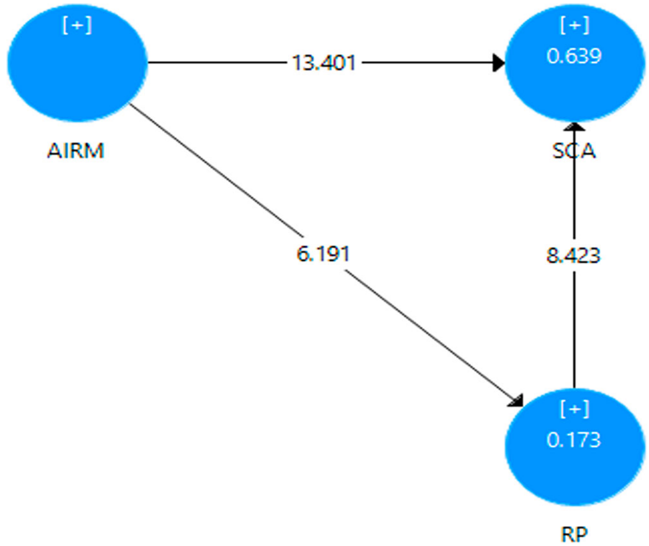

Figure 2. Result of hypotheses testing.

literature on the potential benefits of AIRM (Baryannis et al. 2019; Hosseini and Ivanov 2020) and SMEs (Hansen and Bøgh 2020; S. Yang et al. 2020). AI technology is a critical integration to firms which includes better coordination in an uncertain environment, understanding and predicting consumer habits, developing personalised profiles of customers, trust building (Dwivedi et al. 2021; Dubey, Bryde, et al. 2020) and supplier management for decision-making (Borges et al. 2021). The adaptive capability of SC in dealing with disturbances, responding to disruptions and subsequently recovering by means of maintaining continuity of operations can be greatly enhanced through the use of AI and increased information processing capability. The enhanced operational SC transparency as per Dubey, Gunasekaran, Bryde, et al. (2020) by means of proactive communication among stakeholders leads to better visibility and traceability in SC operations. Here, we can say that AIRM is a potent instrument for firms to address the opportunities and constraints of operations, understand relationships, provide visibility into operations and support decision-making. Further, the findings of this study also resonate with the work of Liu et al. (2018) which suggests that risk management performance is essential in generating positive RP and SCA outcomes; and risk management culture positively affects the RP and SCA capability of SCs (Abeysekara, Wang, and Kuruppuarachchi 2019). An earlier work by Wieland and Marcus Wallenburg (2012) also concluded that SCA is essential to deal with customer-related risks.

According to Christopher and Peck (2004), SCA comprises two key ingredients: visibility and velocity. Simply put, the analytics capabilities of SC driven by big data, AI or machine capabilities provide insights for real-time decision-making (S. Wamba and Akter 2019). The use of AIRM, therefore, allows firms to not only enhance firm performance but is also a driver for accelerating firm performance through robust agility in operations. Managing SC agility requires real-time visibility. Utilising AIRM to harness fast and big data enable managers to rapidly predict risks via identification and quantification from past impact and prescribe mitigating strategies tailored to the particular scenario (Dwivedi et al. 2021). The use

Table 8. Effect size (f^2).

Predictor constructs/dependent constructs	RP	SCA
AIRM	0.209	0.682
RP		0.367
SCA		

Table 9. Predictive relevance (Q^2) and R^2.

Endogenous construct	Q^2	Predictive relevance	R^2
RP	0.169	Q2 > 0	0.173
SCA	0.451	Q2 > 0	0.639

Table 6. Outcome of the structural model examination.

PLS path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P-values	Bias-corrected confidence intervals		Remarks
AIRM → RP***	0.416	0.415	0.067	6.191	0	0.277	0.536	Supported
AIRM → SCA***	0.545	0.545	0.041	13.401	0	0.464	0.624	Supported
RP → SCA***	0.400	0.402	0.048	8.423	0	0.302	0.486	Supported

Notes: ***Significant at $p < .001$ level.

Table 7. Mediation analysis.

	Direct effect	95% CIs of the direct effect	t-Value	Significant ($p < .05$)?	Indirect effect	95% CIs of the indirect effect	t-Value	Significant ($p < .05$)?	Mediation type
Paths	Algorithm	Bootstrapping			Algorithm	Bootstrapping			Types of mediation
AIRM → SCA via RP	0.545	(0.464, 0.624)	13.401	Yes	0.166	(0.116, 0.229)	5.798	Yes	Complementary (partial mediation)

Table 10. RMSE values for SCA and RP.

	Model A		Model B	
	Input: AIRM, RP		Input: AIRM	
	Output: SCA		Output: RP	
	Training	Testing	Training	Testing
Neural network	RMSE	RMSE	RMSE	RMSE
ANN1	0.079	0.079	0.123	2.219
ANN2	0.077	0.081	0.120	2.492
ANN3	0.079	0.086	0.121	1.387
ANN4	0.079	0.085	0.119	2.457
ANN5	0.080	0.087	0.121	2.339
ANN6	0.078	0.091	0.123	1.354
ANN7	0.081	0.058	0.123	1.967
ANN8	0.080	0.071	0.126	1.534
ANN9	0.093	0.074	0.124	2.588
ANN10	0.080	0.079	0.126	1.623
Mean	0.081	0.079	0.123	1.996
SD	0.004	0.010	0.002	0.485

Table 11. Sensitivity analysis.

	Model A (Output: SCA)		Model B (Output: RP)
Neural network	AIRM	RP	AIRM
ANN1	0.536	0.464	1.000
ANN2	0.539	0.461	1.000
ANN3	0.510	0.490	1.000
ANN4	0.537	0.463	1.000
ANN5	0.560	0.440	1.000
ANN6	0.555	0.445	1.000
ANN7	0.478	0.522	1.000
ANN8	0.505	0.495	1.000
ANN9	0.490	0.510	1.000
ANN10	0.476	0.524	1.000
Average relative importance	0.519	0.481	1.000
Normalised relative importance (%)	100.000	92.827	100.000

of AI has also been shown to improve SCA within stakeholder collaborative relationships (Dubey, Bryde, et al. 2020). Alter (2021) differentiates four categories of smartness for devices according to specific capabilities. These are information processing, internal regulation, knowledge acquisition and action outside the organisations where capabilities such as sensing, actuation, coordination, communication and control may be augmented by AI applications. According to the author, every information processing is present in a work system and includes internal regulation to recognise its state and respond accordingly. Subsequently, actions are deployed through engagement with users and knowledge is acquired from it. While these are standard processes, AIRM offers speed and possibly better suggestions by analysing a much more comprehensive range of past scenarios, live data and form a feedback loop to the system. It was also observed that SC re-engineering capability is significantly related to SCA and mediates the relationship. Leung et al. (2018) demonstrated that the use of a smart system to re-engineer e-order fulfilment processes can successfully mitigate irregular order arrival patterns, limited time for order processing and overcome logistics challenges thereby preserving customer satisfaction. However, this study deviates from Abeysekara, Wang, and Kuruppuarachchi (2019), whose work considered both RP and SCA as distinct factors of SC resilience and the work of Liu et al. (2018) which outlined that SCA and RP need to be transformed through risk management performance for excellent firm performance. According to Abeysekara, Wang, and Kuruppuarachchi (2019), the capacity for adapting to and coping with uncertainties while ensuring operations continuity by means of fast adjustments is referred to as SC resilience. This term is mainly used to characterise low probability chronic disruptions while smaller but more frequent disruptions such as logistics deliveries, machine and technology caused disruptions such as in-house disruptions are only recently considered in resilience literature. But there exists neither a consensus on the definition of resilience nor a focus on the decisive factors of resilience. Abeysekara, Wang, and Kuruppuarachchi (2019) conceptualised SC resilience as comprising of re-engineering, agility, collaboration and risk management culture (Christopher and Peck, 2004) with risk management culture being the pre-requirement for resilience following Liu et al (2018). This work focuses on the agile SC that pursues faster responses fuelled by live data and feedback loop powered by AI technologies to 'create the ability to respond rapidly and cost-effectively to unpredictable changes in markets and environmental turbulences' (Carvalho, Azevedo, and Cruz-Machado 2012, 50). An agile management approach entails consideration of the following parameters: market sensitivity, customer satisfaction, quality improvement, use of technologies among others.

Table 12. Comparison between PLS-SEM and ANN results.

PLS path	Original sample (O)/Path Coefficient	ANN results: Normalised relative importance (%)	Ranking (PLS-SEM) [based on Path coefficient]	Ranking (ANN) [based on normalised relative importance (%)]	Remark
Model A (Output: SCA)					
AIRM → SCA	0.545	100.000	1	1	Match
RP → SCA	0.400	92.827	2	2	Match
Model B (Output: RP)					
AIRM → RP	0.416	100.000	1	1	Match

6.1. Theoretical implications

As described earlier, RBV has been criticised for its lack of applicability as theoretical grounding. This work contributes to RBV theory development. The study identified that an SC must exhibit characteristics of agility to sense, reconfigure and transform in response to uncertainties. The inclusion of AIRM characterised by the use of live data and feedback loop necessarily complements the resources of firms in terms of pursuing faster responses to dynamic situations. This is in line with transforming resources accordingly to address SC uncertainties. Resources remain the core elements of firms to survive disruptions.

This study extends the existing literature on the use of AIRM and its implications on RP and SCA. Further, the concept of SCA is studied as a composition of four dimensions, namely customer responsiveness, visibility, demand responsiveness and decisiveness. Extant literature has highlighted the multi-dimensional perspectives of agility and the unavailability of a standardised conceptualisation of agility (Abeysekara, Wang, and Kuruppuarachchi 2019; D. Gligor et al. 2019). In this manner, this study contributed further to the understanding of the agility concept in the context of managing risks through the use of AI. In response to RQ1 and RQ2, the findings show that the use of AI for SC risk management is a strong predictor of SC re-engineering RP and SCA. Further, there is a mediating effect between SC RP and SCA. This work adds empirical evidence to the potentially beneficial use of AI for SC risk management as highlighted from extant reviews (Ni, Xiao, and Lim 2019; Riahi et al. 2021; Akter et al. 2020; Belhadi, Mani, et al. 2021). AI algorithms such as neural networks, genetic algorithms and support vector machines can address complex SC management problems such as demand/sales estimation and can accurately predict retailer demands with time lags (Ni, Xiao, and Lim, 2019). The forecasting models built using methods such as neural networks, fuzzy logic and data mining are more reliable than traditional models did. According to Riahi et al. (2021), the application of AI in SCs has been studied in diverse sectors – retail, automotive, manufacturing, healthcare and several other sectors. However, the majority of the papers studied in their work considered a simulation-based approach and does not focus on real case application. One explanation for this is that AI requires a vast amount of existing data for learning and to achieve the potential of AI-first requires the use of big-data and applying analytics for subsequent prediction (Akter et al., 2020). This means successful AI transformation hinges on a good data ecosystem with strong data governance, business value use cases, analytics capabilities and tools among others.

Researchers have considered SMEs in a juncture of either not having the capability and technological infrastructure to undertake technological interventions (L. W. Wong, Leong, et al. 2020), or having the flexibility to change and adapt due to size (Shepherd and Williams 2018). There are four ways in which SMEs need to focus on in order to be more resilient (Bak et al. 2020). First, is the role of collaboration. Collaboration with a network or specialised partners allows SMEs to maintain the focus on their core competencies so that they can withstand disturbances. Close relationships with customers and partners can help SMEs to strengthen their technological base, and broaden the adoption of technologies while investing in building strategic and complementary relationships. Second, the smaller size of SMEs allows for greater agility, flexibility and quick response at times of disturbances thereby overcoming the lack of capabilities by being more resilient through diverse customer portfolios and seamless communication systems. Thirdly, by developing a shared pool of technical content and market knowledge, SMEs can enhance their abilities to withstand turbulence and respond to external changes. According to Papadopoulos et al. (2020), aligning SME's business strategy with technologies constitutes a research avenue and whether the technological alignment is at par with business strategy or an indication of SME's technological investments. Further, high costs and unclear return-on-investments may hinder SMEs from adopting technologies but on the same aspect (Agrawal, Pandit, and Menon 2012), SMEs may overcome their financing limitations through the use of technologies as explained earlier in the case of Taobao. Therefore, it is pertinent that SMEs understand the impact of technologies on their businesses and innovativeness. SMEs need to consider if they have a clear and actionable roadmap to achieve the alignment. Is there a clear understanding of and ability to govern the infrastructure? Along this vein, future research could also consider the formidable issue of technological debt and its implications on competitiveness in the face of ever-changing business realities that demand higher agility.

6.2. Managerial implications

Supply chain risk management remains a significant challenge that affects firms' performance (Brusset and Teller 2017) and in particular, SMEs need to be at the forefront of adopting new technologies if they wish to remain competitive. However, the complexity of AI is a challenge for

SMEs that lack the knowledge and resources to exploit the benefits of technology despite being aware of its benefits (Hansen and Bøgh 2020). That said, the challenge for SMEs in navigating uncertainties and disruptions goes beyond technological affordability. Calling managers to be open-minded towards emerging technologies (L. W. Wong et al. 2021), cautioned that there are often pre-conceived notions about specific technology and users tend to reject innovations without due consideration or their potential. Thus, understanding AI is critical for acceptance and subsequently, SMEs need to reassess and formulate the right strategies that will see them through these challenging times. Practical implications are provided below based on the findings of this study:

(i) Transitioning to the use of AIRM requires managers to adopt a proactive, risk-taking and innovative mindset (Dubey, Gunasekaran, Childe, et al. 2020). Managers need to learn from the disruptions and take appropriate measures. They must make rapid decisions and take immediate actions to maintain business operations. They must be careful in identifying opportunities from threats addressing issues that could slow or cripple the SC. Echoing Wong et al. (2021), SCs generally involve multiple stakeholders and a prime challenge for managers implies that they must first understand the benefits of any emerging technologies in order to persuade adoption before any benefits can be reaped.

(ii) Agility and re-engineering capabilities need to be architected into SCs. The use of technologies enables scenario planning to help managers anticipate expected and worst-case situations to ensure supply and demand alignment. With the use of AI and analytical tools, control towers can highlight situations where disruptions will result in difficulty meeting demands. SC visibility, especially during disruptions is important for firms to see how SC is affected and takes appropriate actions.

(iii) Finally, the use of AIRM requires the presence of data. SMEs need to understand and embrace the notion that digital transformation is the way forward. Therefore, it is important that all levels of stakeholders fully understand the implications and issues surrounding the adoption of AIRM. Management needs to take the pivot role in encouraging and spearheading the transformation. This may mean moving from traditional manual-based recording to digital capture of data and putting in place an appropriate infrastructure to support the technology. And as with any digitalisation initiatives, management needs to be prepared for various governance and protection issues arising therewith. Where necessary, SMEs need to explore opportunities for assistance (both educational and financial) that are available to them from various entities and plan the journey for adoption. Integrating AIRM is a journey that requires careful consideration and planning; an effort that goes beyond a mere upgrade or a patch.

7. Conclusion

The purpose of this study was to investigate the use of AIRM for enhancing SCA and RP for securing business continuity. The hypothesis that AIRM enhances SC RP and SCA is all supported; the mediating effect of RP and SCA is also supported. Thus, the use of AIRM allows SMEs to better cope with the changes caused by disruptions. This means SMEs exploring opportunities for improving SCA and RP may find AIRM a strong driver. Nevertheless, some limitations remain. This study is conducted using AIRM in SCs for SMEs in a specific region. Generalisability may be problematic although the literature has presented sufficient support for the model as discussed in earlier sections. The model in this study is also tested with encouraging outcomes. However, this is also an opportunity for future work to consider a broader base of respondents. Further, the model did not include other influences of technological adoption such as culture, management commitment and technological readiness. We recommend future studies consider these factors in understanding the adoption of AI for SC risk management. As per Li, (2020, 812), 'in today's unpredictable digital environment, it is no longer viable to develop a new strategy and then execute it over many years'. There is a mismatch between traditional business models and digital future – strategies must be recalibrated through execution, for digital transformation is an ongoing process. Likewise, emerging technologies and their applicability call for new research work to be continually conceptualised and validated to be of significance. Along with this, future research can also consider incorporating the moderating effects of disruptions and performance outcomes in the research. Finally, the AI ecosystem is a 'family of overlapping aspects, technologies and techniques' (Stahl 2022) that raises several governance-related challenges. Future research may consider incorporating policy and governance aspects to help organisations decide on the adoption of responsible AI algorithms as well as security and data privacy concerns that are characteristics of AI techniques and big-data applications. Despite these limitations, AI-enabled systems are powerful and promise firms better usage of their data, optimisation of processes and innovate businesses.

Disclosure statement

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

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author Y. K. D. upon reasonable request.

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