Modelling Supply Chain Visibility, Digital Technologies, Environmental Dynamism and Healthcare Supply Chain Resilience: An Organisation Information Processing Theory Perspective

Abstract

The healthcare sector is a complex and critical industry that requires a resilient supply chain to ensure patients receive the care they need. However, the pandemic and geopolitical crises have highlighted the need for a more comprehensive understanding of healthcare supply chain resilience. To address this, healthcare providers and policymakers increasingly recognise the importance of digital technology in enhancing their supply chain resilience. Despite this recognition, there is a lack of empirical studies that have explored the relationship between supply chain visibility, digital capabilities, and environmental dynamism in the healthcare sector. Therefore, our study aimed to fill this gap by utilising organisational information processing theory (OIPT) to explain the relationship between these factors. Our analysis of 137 survey responses revealed that supply chain visibility is a foundational resource for digital capabilities. Moreover, digital capabilities are vital in enhancing healthcare supply chain resilience in highly turbulent environments. Our research expands the concept of the OIPT to offer a more comprehensive explanation of how supply chain visibility is a crucial factor for the effective functioning of digital technologies, particularly in highly uncertain environments. Our findings also provide useful insights for healthcare managers and policymakers who wish to enhance their supply chain's resilience and leverage digital technologies to achieve this objective.

Keywords: *Supply Chain Visibility, Digital Technologies, Environmental Dynamism, Healthcare Supply Chain Resilience, Information Processing Theory, SDG 3: Good health and well-being*

1. Introduction

The pandemic has caused significant disruptions in healthcare operations, affecting hospitals and clinics in various ways (Kovacs & Falagara Sigala, 2021; Gupta et al., 2021; Queiroz et al., 2022a, b; Chervenkova & Ivanov, 2023). To ensure the safety of staff and patients, new protocols have been implemented, including social distancing measures, frequent and intense cleaning, and personal protective equipment (PPE) (Ivanov, 2020). The COVID-19 pandemic has increased the demand for healthcare services, especially testing and treatment (Chowdhury et al., 2021). This has strained healthcare resources, and providers seek new ways to manage patient care (Zamiela et al., 2022). Additionally, the pandemic has adversely affected the financial stability of the healthcare industry as many elective procedures have been postponed or cancelled, leading to a decrease in revenue (Dai et al., 2022; Choudhury et al., 2023). In conclusion, COVID-19 has posed unprecedented challenges to the healthcare sector, highlighting the need for resilience and innovation in adversity (Bergami et al., 2022).

The COVID-19 crisis has exposed the vulnerability of the healthcare sector, specifically in relation to its supply chain (Sodhi & Tang, 2021; Spieske et al., 2022; Xu et al., 2023). This has prompted policymakers to discuss building robust and resilient healthcare supply chains that can withstand future crises (Bag et al., 2021; Finkenstadt & Handfield, 2021a). The debate involves identifying potential weaknesses in current supply chains and exploring ways to address them, such as diversifying suppliers, increasing local production, and investing in new technologies (Ivanov & Dolgui, 2021). The main objective is to guarantee that healthcare providers have uninterrupted access to vital medical supplies and equipment to deliver quality patient care, even during unforeseen disruptions (Finkenstadt & Handfield, 2021b; Alexander et al., 2022).

During the onset of COVID-19 in early 2021, numerous healthcare organisations responded to the sudden surge in cases by taking decisive actions. For instance, Medicom, a Canadian-based firm, quickly established a new manufacturing unit aimed at producing melt-blown polypropylene. This raw material is crucial for the production of personal protective equipment (PPE), which was in high demand during the pandemic (Park et al., 2020). Similarly, Huaxi Hospital, a top-tier medical facility affiliated with Sichuan University in Western China, played a pivotal role in providing remote consultation services. These services were supported by 5G technology, which allowed patients to receive medical attention from the safety of their homes (Hong et al., 2020). Likewise, HCAH Limited, a prominent Indian healthcare organisation known for its home-based services, also played a significant role in combating the pandemic. The organisation leveraged digital technologies to ensure seamless coordination between patients and healthcare staff (Hebbar et al., 2020). These examples demonstrate how digital technologies, aided by adequate visibility and transparency at multiple levels, have helped healthcare organisations to effectively manage the disruptions caused by the pandemic.

Hence, we can argue that digital technologies (DT) have revolutionised how we approach supply chain management and have played a crucial role in enhancing the resilience of supply chains across various industries (Zouari et al., 2021; Raimo et al., 2023; Ghobakhloo et al., 2023). The healthcare sector has dramatically benefitted from integrating digital technologies into its supply chain management systems (Tortorella et al., 2022; Fursteanau et al., 2022; Govindan et al., 2023; Massaro, 2023). With the help of advanced analytics, automation, and real-time tracking, healthcare providers can now better manage inventory, monitor supply chain performance, and respond to disruptions promptly and effectively (Sodhi et al., 2023). These technologies have also enabled greater visibility and transparency across the supply chain, ensuring better stakeholder collaboration and coordination (Mandal, 2017a; Sodhi & Tang, 2019; Choi et al., 2022). As a result, healthcare supply chain resilience has improved, enabling healthcare providers to serve their patients and communities better (Shen & Sun, 2023; Garcia-Perez et al., 2023).

Considering recent events, the global healthcare community has shifted its focus towards implementing DT for tracking and tracing medical supplies (Zimmerling & Chen, 2021). Distributing critical items such as PPEs, medicines, and essentials requires better stakeholder visibility and coordination (Falagara Sigala et al., 2022; Dubey, 2023; Devi et al., 2023). With the help of DT, real-time data can be captured and analysed to understand better the availability and demand of these critical items (Hu et al., 2023). By adopting DT, healthcare providers can take proactive measures to prevent potential shortages of essential healthcare items. Additionally, this will ensure that all stakeholders are well-informed about the availability of these items and any possible shortages (Samadhiya et al., 2023). DT utilisation will also facilitate effective stakeholder coordination to optimise available resources (Falagara Sigala et al., 2022). This approach will improve the overall efficiency and effectiveness of the healthcare system, leading to better patient outcomes (Fosso et al., 2015; Marques et al., 2020; Iyanna et al., 2022).

Although the existing literature has extensively studied how DT can effectively and efficiently build healthcare supply chain resilience (HSCR) (van Hoek, 2020; Spieske et al., 2022; Choi, 2021; Siala & Wang, 2022), there is limited understanding regarding the processes and steps required to build the necessary capabilities. In recent years, many studies have been conducted to examine how Digital Technology (DT) can enhance visibility in the supply chain. However, these studies have failed to recognize that the current lack of transparency and visibility issues often limit the effectiveness of advanced digital tools that rely on quality data

(Srinivasan & Swink, 2018). The absence of end-to-end visibility in the supply chain means that Big Data analytics (BDA) and Artificial Intelligence (AI) tools often generate unreliable outcomes. As a result, the decision-making of supply chain managers is negatively affected, which can lead to serious consequences. Despite the well-known fact that the lack of transparency hinders the implementation of DT solutions in the healthcare industry, only a few studies have empirically validated these observations in the operations and supply chain literature. This research gap poses a significant challenge to the development and implementation of DT solutions in the healthcare industry, which could significantly improve healthcare delivery and ultimately lead to better patient outcomes. Therefore, it is necessary to conduct further research to identify the critical factors required to establish DT capabilities in healthcare organisations. In order to bridge this gap, we propose the following research question:

RQ1: What factors enable the implementation of DT in resilient healthcare systems?

Due to various uncertainties, operating in emerging markets can pose a significant challenge for healthcare managers (Raj et al., 2022). These uncertainties can take different forms, such as political instability, weak regulatory frameworks, and underdeveloped legal systems (Krammer & Kafouros, 2022). Thus, decision-making processes become more complex, and healthcare supply chain managers must engage in advanced information-gathering and processing activities to successfully navigate these challenges (Munir et al., 2020). These activities could include conducting comprehensive risk assessments, monitoring regulatory changes, and engaging with local communities and stakeholders to understand social and cultural contexts better (Shaw et al., 2021). Proficient handling of institutional uncertainty is critical for healthcare supply chain managers to succeed in the sector (Ahmad et al., 2023). By effectively managing this aspect, managers can ensure a smooth and efficient supply chain operation, enabling them to tackle uncertainties confidently. However, it is not clear how environmental uncertainties influence the information processing requirements and capabilities (Ifthikar et al., 2022; Cui et al., 2023; Wang et al., 2023) and how they may further affect the resilience of the healthcare supply chain (Yu et al., 2022). To address this gap, we propose the second research question:

RQ2: How do environmental uncertainties affect the path connecting DT and HSCR?

To address our research questions, we developed a theoretical framework based on the perspective of organisational information processing theory (OIPT). In the next section of the paper, we set out the theoretical background and explain the derivation of our hypotheses. We describe the importance of the OIPT and critical constructs in the healthcare supply chain: *supply chain visibility (SCV)*, *digital technologies (DT)*, and *healthcare supply chain resilience (HSCR)*. We grounded our theoretical perspective in the OIPT under the moderating influence of environmental dynamism. The following section details our research design, explaining how we operationalised the constructs and how our theoretical model was validated using the Partial Least Squared-Structured Equation Modelling analytical method with a dataset obtained via a survey of 137 practitioners with experience in implementing DT in healthcare organisations. Section four of the paper presents the data analysis and results. We present the test for common method bias, the measurement model, and tests of the hypotheses. The latter includes endogeneity testing and model estimation and analysis. In section five, we discuss the results, highlighting, , three key theory contributions: firstly, specific factors that play a critical role in effectively implementing DT in healthcare operations; secondly, how DT can enhance HSCR in environments characterised by high levels of volatility and unpredictability; thirdly, how taking a contingent view of OIPT can provide insights into how organisations adapt their information processing approaches to different situations. Section five also offers implications for policymakers and managers in healthcare organisations, highlighting the importance of DT to help ensure organisations are resilient to future shocks to their supply chains. Section five ends with a reflection on the limitations of our study. These would be met by further in-depth analysis, such as, gaining an additional understanding of the underlying factors driving HSCR and future research directions around different cultural contexts. In the paper's final section, we provide our conclusions.

2. Theoretical Background and Hypotheses Development

2.1 Organisational Information Processing Theory (OIPT)

OIPT argues that organisations must use information derived from data effectively and efficiently, mainly when they operate in high levels of environmental uncertainty (Galbraith, 2014; Srinivas & Swink, 2018; Li et al., 2022). The theory aims to explain how organisations process information and make decisions based on that information (Moser et al., 2017). It emphasises that firms must have a well-organised and structured system for acquiring, storing, and utilising information to achieve their goals. To accomplish this, firms have two options (Galbraith, 1974). Firstly, they can reduce their need for information by simplifying their tasks, limiting the scope of their operations, or narrowing their focus. Secondly, firms can increase their information processing capabilities by investing in better technology, hiring more skilled workers, or improving existing processes. Overall, OIPT emphasises the crucial role that information plays in the success of firms and highlights the need for firms to be proactive in managing information to remain competitive and effective.

Organisations are complex entities that interact with their external environment in various ways. OIPT assumes an organisation is an open system, continuously exchanging information with the environment to sense and respond to outside changes (Moser et al., 2017). This helps organisations adapt their strategies and operations to meet their stakeholders' evolving needs and expectations promptly and effectively (Tushman & Nadler, 1978). Effective coordination is essential for organisations to achieve their objectives. The exchange of information within and outside the organisation is critical to achieving effective coordination (Galbraith, 1974). By functioning as open systems, organisations can leverage the power of communication and collaboration with their stakeholders to accomplish tasks and achieve their goals (Galbraith, 1974; Moser et al., 2017). This approach enables organisations to tap into their stakeholders' collective knowledge and expertise, leading to better decision-making, innovation, and overall success (Srinivasan & Swink, 2015).

Management scholars across various disciplines have extensively studied OIPT. It is studied in supply chain management, product development, marketing, and information management. Studies show that OIPT helps organisations improve their information processing capabilities, giving them an edge in uncertain situations. For instance, research conducted by Srinivasan & Swink (2018) in supply chain management found that OIPT described how organisations coordinate their activities effectively and quickly respond to market changes. Similarly, in the field of new product development, Song et al. (2005) demonstrated that OIPT could help organisations understand how to identify customer needs and preferences and develop products that meet those needs. In strategic management, Tuggle and Gerwin (1980) and Rogers et al. (1999) showed that OIPT encompasses how organisations scan the environment, identify opportunities and threats, and make decisions accordingly. Tybout et al. (1981) and Clark et al. (2006) found that OIPT could help explain how organisations analyse customer behaviour and preferences and develop marketing strategies tailored to their needs. Gattiker & Goodhue (2004) and Hann et al. (2007) demonstrated that the theory covers how organisations manage and process information effectively, improving their decision-making capabilities. Hence, we argue that OIPT is a useful theoretical lens for understanding how organisations process information and make decisions. Its application highlights its usefulness in improving information processing and decision-making capabilities for a competitive advantage. In healthcare supply chains, DT are vital in building resilience during crises. OIPT offers a comprehensive understanding of how DT can be integrated into healthcare supply chain management to enhance resilience.

2.2 Need for the OIPT in Healthcare Supply Chain

During the COVID-19 crisis, healthcare managers had to process large amounts of information to make decisions that would reduce costs and increase the availability of necessary healthcare items. One of the critical aspects of the healthcare supply chain is the procurement of medical supplies, pharmaceuticals, and equipment (Lega et al., 2013; Moons et al., 2019; Altay et al., 2023). This process requires careful planning and coordination to ensure that the right products are sourced at the right time and at the best possible price (Narayana et al., 2014; Patil et al., 2019). Historically, healthcare sectors have manually handled data stored in data warehouses to obtain insights (Kaplan & Porter, 2011; Böhme et al., 2013). Healthcare organisations are increasingly relying on the accuracy of information and the speed with which organisations can obtain information from data (Kwon et al., 2016; García-Villarreal et al., 2019) to reduce uncertainty, especially when facing high levels of demand and supply uncertainties, and highly complex operational tasks (i.e., highly interdependent). Managing these processes can be explained using OIPT (Galbraith, 2014; Srinivasan & Swink, 2018). The present research on digital capabilities has predominantly concentrated on the amalgamation of technologies that involve information, computing, communication, and connectivity (Warner & Wager, 2019; Sousa-Zomer et al., 2020). However, we suggest broadening the definition of digital capabilities to encompass the organisation's role in developing visibility and transparency. By doing so, the organisation can facilitate the processing of large and intricate data, which can ultimately lead to better decision-making capabilities. This approach emphasises the significance of organisational factors in achieving digital success, rather than just focusing on the technological aspects. The healthcare supply chain includes the management of inventory, which involves tracking the availability and usage of medical supplies and equipment (Zamiela et al., 2022). This information is essential for forecasting future demand and ensuring that there is always an adequate supply of products to meet the needs of patients (Mustaffa & Potter, 2009). Thus, the critical challenge that healthcare supply chains face is the proper storage of medical supplies and equipment to ensure their safety and efficacy, which involves proper maintenance, monitoring, and handling. Transportation and distribution must also be well-coordinated to ensure the products reach their destination on time and in good condition (Bhakoo et al., 2012).

Overall, the healthcare supply chain is a critical component of the healthcare system, and it plays a vital role in ensuring that patients receive the care they need (Ward et al., 2014). The system includes exchanging information between different parties involved in the healthcare delivery process, such as patients, healthcare professionals, suppliers, and insurers (Dobrzykowski, 2019). The effective management of the healthcare supply chain is crucial for ensuring that patients receive the care they need in a timely and efficient manner, whilst minimising costs and waste (Sinha & Kohnke, 2009). The COVID-19 pandemic has caused a ripple effect across the healthcare supply chain, with an increased demand for medical supplies, equipment, and personnel (Leite et al., 2020; Sindhwani et al., 2023). Hospitals and healthcare facilities have had to adapt to new protocols and guidelines for safety and sanitation, leading to delays and disruptions in procuring and delivering critical items (Forman et al., 2021). As a result, there has been a heightened awareness of the importance of supply chain management and the need for greater resilience and flexibility in the face of unexpected crises (Gunessee & Subramanian, 2020; Yang et al., 2021a). Therefore, in uncertain healthcare environments, healthcare organisations must be capable of organising and utilising information effectively, particularly when they need to rely on complex tasks (Bag et al., 2021; Lebovitz et al., 2022). In such scenarios, OIPT provides a suitable perspective for analysing the complex aspects of the healthcare supply chain.

2.3 Supply Chain Visibility (SCV)

SCV is essential for managing and optimising supply chain operations (Barratt & Oke, 2007; Caridi et al., 2010; Juttner & Maklan, 2011; Srinivasan & Swink, 2018). It involves collaborating with external partners and sharing information across the supply chain network to gain real-time insights into inventory levels, production schedules, and transportation status (Wang & Wei, 2007; Kalaiarasan et al., 2022). With complete visibility across the supply chain, companies can proactively identify potential disruptions and take timely actions to mitigate risks, reduce costs, and improve customer satisfaction (Pfahl & Moxham, 2014; Kraft et al., 2022). Therefore, investing in solutions to enhance SCV is crucial for businesses looking to operate efficiently, increase agility, and maintain a competitive edge in today's dynamic markets (Williams et al., 2013; Sodhi & Tang, 2019). SCV is a critical aspect of supply chain management that involves collecting, analysing, and disseminating information on various supply chain stages (Somapa et al., 2018). Managers gather and analyse data on the flow of materials, services, and information from multiple stakeholders in the supply chain, including suppliers, patients, distributors, and retailers (Kalairasan et al., 2023).

In healthcare supply chain management, it is crucial to enhance the visibility of demand and supply by improving the quality and availability of information (Privett & Gonsalvez, 2014; Moons et al., 2019; Spieske et al., 2022). This visibility is critical in ensuring the timely and efficient delivery of healthcare services to patients (Mandal et al., 2017a). Healthcare organisations that seek to improve visibility may invest in digital capabilities such as electronic health records (EHRs) and other digital solutions (Kohli & Tan, 2016). EHRs are a vital tool for healthcare providers in managing patient information, and they can also be used to track inventory levels and monitor supply chain operations (Jussupow et al., 2021). Healthcare organisations can benefit significantly from digital solutions to gain real-time visibility into their supply chain. This can help them make informed decisions and optimise their operations (Yadav, 2015). The resource-based or dynamic capability view argues that SCV is a source of competitive advantage, as stated by Barratt & Oke (2007) and Brandon-Jones et al. (2014). Following the OIPT (Galbraith, 2014), we believe that investing in digital capabilities can be a smart move for healthcare organisations that want to improve supply and demand visibility in their operations. This can lead to better patient care, streamlined supply chain operations, and reduced costs. It's worth noting that despite the potential benefits, Big Data-enabled or AI-based tools may fail to provide better results if they lack visibility or reliable information, as highlighted by Trautmann et al. (2022). Hence, we can argue that increased visibility allows for a more comprehensive understanding of the supply chain, better decision-making, and, ultimately, the resilience of the healthcare supply chain (Friday et al., 2021). Developing and implementing digital capabilities can enhance the information processing capabilities within the healthcare supply chain.

2.4 Digital Technologies (DT)

The advancements in DT over the past few years have brought about a significant revolution in how we live our lives (Zaki, 2019). Smartphones and artificial intelligence have transformed how we communicate, obtain information, and solve problems (Ciarli et al., 2021). With the help of digital technologies, tasks that were once considered impossible are now easily achievable, such as real-time communication with people from different parts of the world and retrieving vast amounts of data in seconds (Papadopoulos et al., 2020). DT have played a crucial role in shaping and enhancing our daily lives in ways we could not have imagined (Leonardi, 2021; Parra et al., 2022). For instance, using DT has facilitated the creation of new products and services, significantly improving our quality of life (Ivanov et al., 2019). Additionally, DT have enabled us to access information quickly, making it easier to conduct research and make informed decisions (Martinez-Caro et al., 2021).

In particular, "*digital technologies (which are combinations of information, computing, communication, and connectivity technologies) are fundamentally transforming business strategies, processes, firm capabilities, products, and services, as well as key interfirm relationships in extended business networks*" (Bharadwaj et al., 2013, p. 471). DT has been advancing rapidly since 2013. Machine learning, integrated DT, advanced robots, mobile robots, and generative AI have improved human abilities to process complex data and derive information, thus enhancing decision-making abilities in complex settings (Gupta & George, 2016; Ciarli et al., 2021; Mikalef & Gupta, 2021). This scope of definition remains well within the definition offered by Bhardwaj et al. (2013). The ever-evolving landscape of DT has undergone a significant transformation with the emergence of cutting-edge technologies like big data analytics (Gupta & George, 2016), machine learning (Mikalef & Gupta, 2021; Alvarenga et al., 2023) and Generative AI (Fosso Wamba et al., 2023). These advanced technologies have broadened the scope of digital technologies, presenting many opportunities for industries to explore while posing new challenges that must be addressed. We adopted Alvarenga et al. (2023) to effectively operationalise the construct at hand. By doing so, we aim to ensure that our approach remains consistent with established practices in the field, thereby enhancing the validity and reliability of our results (Warner & Wager, 2019; Sousa-Zomer et al., 2020; Mikalef & Gupta, 2021).

DT provide real-time data and insights to help healthcare providers make informed decisions and optimise their supply chain operations (Betcheva et al., 2021; Sharma & Kshetri, 2020; Nguyen et al., 2022; Cadden et al., 2022). Thus, it is evident that DT has revolutionised the healthcare supply chain by reducing inefficiencies, improving transparency, and enhancing patient care (Beaulieu & Bentahar, 2021). Moreover, DT has played a key role in addressing healthcare crises resulting from COVID-19, especially in countries with limited resources to tackle the pandemic (Budd et al., 2020). The use of DT in healthcare has facilitated remote consultations, telemedicine, and remote monitoring of patients, which has significantly improved the quality and accessibility of healthcare services (LeRouge et al., 2019; Bokolo, 2021). Improving visibility within the healthcare supply chain can enhance information processing capability; enabling . healthcare providers to better respond to any disruptions or challenges that may arise, ensuring that patients receive the care they need in a timely and efficient manner (Mandal, 2017a).

2.5 Healthcare Supply Chain Resilience (HSCR)

Due to globalisation, supply chains have become more connected, making them more vulnerable to disruptions. Studies by Juttner & Maklan (2011) and Chowdhury & Quaddus (2017) show that such disruptions have led to significant economic losses in recent years. External factors such as natural disasters (Craighead et al., 2007; Saglam et al., 2022; Aghajani et al., 2023), global outsourcing (Bakshi & Kleindorfer, 2009), shorter product lifecycles (Sodhi, 2005), and pandemics (Craighead et al., 2020) have further increased the risks faced by supply chains (Sodhi & Tang, 2021). The COVID-19 pandemic has highlighted the critical importance of resilient supply chains, especially in the healthcare sector. Scholars such as Harland et al. (2021), Senna et al. (2023a,b), and Zamiela et al. (2022) have noted that the pandemic has put immense pressure on healthcare supply chains, leading to a decline in the quality of care provided to patients. Therefore, scholars emphasise the need for immediate action to build HSCR in response to the COVID-19 crisis (Friday et al., 2021; Spieske et al., 2022). This involves developing contingency plans, diversifying supply sources, and improving coordination among stakeholders to ensure that critical medical supplies are available when and where they are most needed (Mandal, 2017b). We suggest building HSCR (Scholten et al., 2020) by developing strategies to anticipate, prevent, and mitigate disruptions and ensuring the capability to recover quickly should disruptions occur through leveraging DT.

2.6 Environmental Dynamism (ED)

Organisations can adopt two strategies to gain a competitive advantage in an uncertain environment (Galbraith, 2014). The first strategy is to reduce their information needs. However, this option is not easy and may not help meet the customer's immediate needs (Peng et al., 2014). Additionally, it may cost the organisation extensively. The second strategy is to enhance their information processing capability by investing in collaborative relationships and vertical information systems (Srinivasan & Swink, 2018). However, the performance of information processing capability depends on the level of ED (Garg et al., 2003). Therefore, in this study, we suggest that the effect of DT on HSCR is contingent on ED.

2.7 Theoretical Model and Hypotheses

To answer our research questions, we derived a theoretical model (see Figure 1) based on the OIPT. In the remainder of this section, we set out the hypotheses to analyse the relationships between the four constructs in our model: SCV, DT, HSCR, and ED.

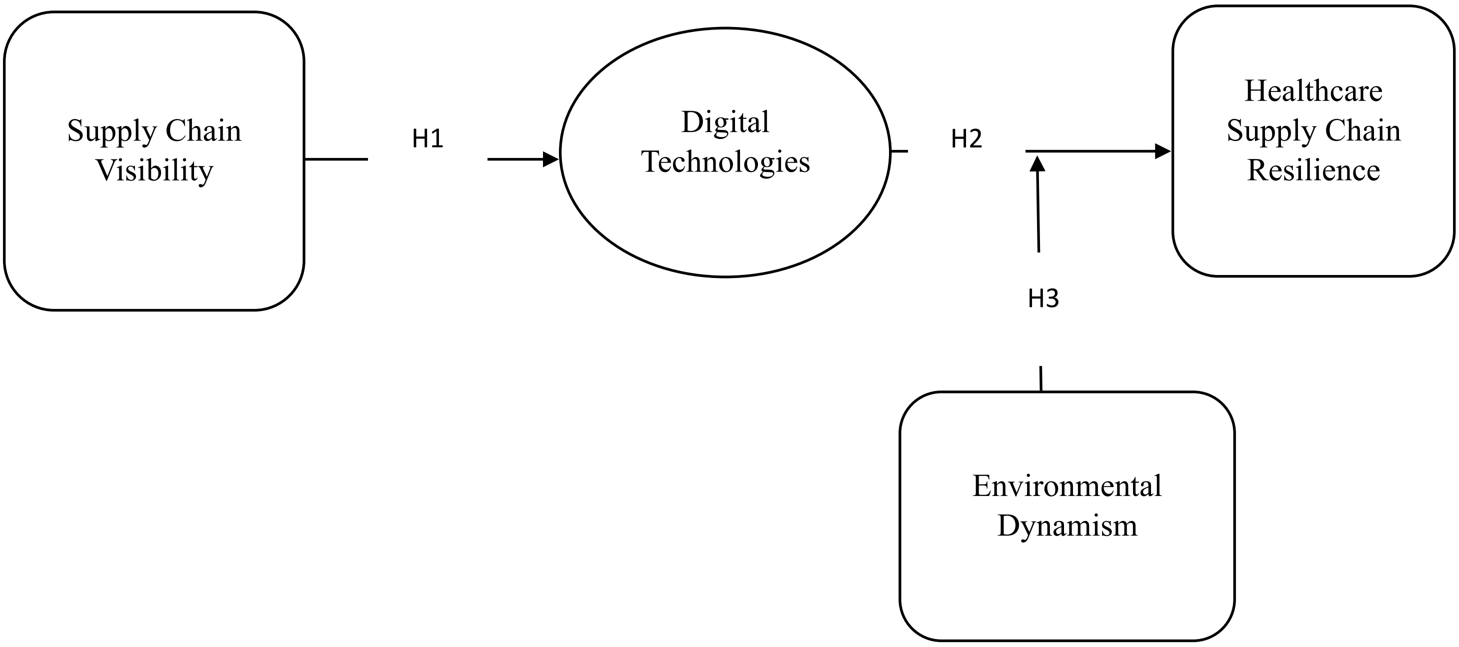

Figure 1: Theoretical model

2.7.1 Supply Chain Visibility (SCV) and Digital Technologies (DT)

According to Srinivasan & Swink (2018), organisations that prioritise increasing visibility in their demand and supply chains are more likely to succeed in adopting DT that supports various data analytics activities. Such technologies can be particularly effective in tracing inventory movement and monitoring dynamic situations (Santharm & Ramanathan, 2022). By investing in these technologies, healthcare organisations can gain a comprehensive understanding of their operational processes, which can help optimise supply chain management and enable more informed decisions about inventory management (Omar et al., 2022). Additionally, these technologies can improve the tracking and tracing of products, enabling healthcare organisations to provide better services to patients (Fursteanu et al., 2022).

The availability of real-time and accurate information through the supply chain plays a crucial role in influencing the performance of digital technologies. SCV helps to improve the efficiency of various digital systems (Dolgui & Ivanov, 2022; Hu et al., 2023), enabling healthcare organisations to make better-informed decisions, reduce errors, and enhance patient services (Marbouh et al., 2023). Furthermore, SCV gives healthcare organisations insights into the entire supply chain process. This allows them to identify areas for optimisation and improvement. By leveraging the power of SCV, healthcare organisations can use DT to tackle environmental uncertainties.

Visibility may be a necessary condition for the effective use of DT (Treem & Leonardi, 2013; Mandal, 2017a). Most studies argue that DT are crucial in building SCV (Yang et al., 2021b). Many operations and supply chain literature arguments are based on the resource-based view. According to the OIPT framework, having SCV is key to enabling success (Williams et al., 2013). Organisations can gain valuable insights into changing market conditions by acquiring data from their business partners regarding demand and supply (Srinivasan & Swink, 2018). Galbraith (1974) suggests building external lateral relationships can increase information processing capacity. Organisations can process and gain insights from accurate and timely data from external partners, making visibility crucial for efficient DT functioning (Kache & Seuring, 2017). For instance, machine learning algorithms and AI applications rely heavily on the availability of information visibility to perform their tasks effectively (Busuioc, 2021; Painuly et al., 2023). With access to real-time and up-to-date information, these technologies can make more informed decisions and optimise supply chain performance. Hence, we hypothesise that:

H1: The visibility of the supply chain positively affects the functioning of digital technologies.

2.7.2 Digital Technologies (DT) and Healthcare Supply Chain Resilience (HSCR)

Recent advancements in DT have revolutionised the healthcare industry, especially in improving the supply chain's resilience (Garcia-Perez et al., 2023). With the help of cloud computing, AI, and IoT, healthcare providers can effectively manage their operations, cut costs, and enhance patient outcomes (Stoumpos et al., 2023; Paul et al., 2023). Cloud computing enables healthcare organisations to securely store and access patient data from anywhere, while AI-powered tools can automate routine tasks and improve diagnostic accuracy (Polevikov, 2023). IoT has also significantly enhanced supply chain resilience by providing real-time visibility into inventory levels, shipments, and other crucial data through sensors and connected devices (Juned et al., 2022).

DT in healthcare have transformed the industry by providing efficient, effective, and patient-centric care (Bag et al., 2021; Tortorella et al., 2022). Additionally, digital tools and platforms enable healthcare providers to manage medical supplies, track inventory better, and coordinate the distribution of essential resources (Rapaccini et al., 2020; Tortorella et al., 2022), which ensures that patients receive the care they need, even during the most challenging circumstances. Furthermore, digital technologies facilitate remote consultations, enabling healthcare professionals to provide timely and efficient medical advice to patients who cannot access physical healthcare facilities (Gkeredakis et al., 2021). Overall, using DT is a potential game-changer in crisis management, providing vital support to healthcare systems and ensuring patients receive the care they need (Scala & Lindsay, 2022; Queiroz et al., 2023). Based on the preceding arguments, we propose the following research hypothesis:

H2: There is a positive association between digital technologies and the resilience of the healthcare supply chain.

2.7.3 Moderating Effect of Environmental Dynamism (ED)

Miller & Friesen (1983) argue that ED is characterised by volatility and unpredictability. This implies that the environment is constantly changing, and companies operating in such an environment must be agile and responsive to adapt to the changing circumstances. ED is essential in strategic management as it informs firms' decisions regarding resource allocation, competitive positioning, and innovation (Schilke, 2014). Environmental dynamism potentially affects the impact of DT on the HSCR (Katsaliaki et al., 2022). In turbulent environments with multiple disruptions, DT play a more significant role in enhancing HSCR compared to stable environments (Munir et al., 2022). Based on the above, we hypothesise that ED positively moderates the path to joining DT and the HSCR. Our hypothesis is as follows:

H3: Environmental dynamism positively moderates the path between digital technologies and the resilience of the healthcare supply chain.

2.7.4 Mediating Effect of Digital Technologies (DT) between Supply Chain Visibility (SCV) and Healthcare Supply Chain Resilience (HSCR)

We argued that SCV can directly impact resilience (Brandon-Jones et al., 2014). SCV is crucial in enhancing supply chain resilience (Zouari et al., 2021). It enables businesses to track and monitor their supply chain operations in real time, identifying potential disruptions and responding proactively (Modgil et al., 2022). While DT can indirectly influence the performance effects of SCV, the direct impact on supply chain resilience makes it an essential component of any efficient supply chain management system (Faruquee et al., 2021). Hence, we argue that DT are crucial in connecting SCV and HSCR. They act as an intermediary factor providing a seamless flow of information, enhancing the resilience of healthcare supply chains, leading to the following hypothesis:

H4: Digital technologies mediate the effect of supply chain visibility on healthcare supply chain resilience.

2.8 Control Variables

We incorporated two control variables to define our sampling unit and conduct an in-depth analysis of the differences among various healthcare organisations. These variables are 1) the size of the healthcare organisation, which is defined by the number of employees, patients, and facilities that the organisation manages (Raimo et al., 2023); and 2) the nature of ownership, which refers to whether the healthcare organisation is privately or publicly owned (Robert et al., 2009). We identified these three control variables based on existing literature that suggests they may impact the level of investment in digital capabilities. By including these control variables, we hope to understand better how they may influence investment decisions in digital healthcare.

3. Research Design

Following the recommendations of Malhotra and Grover (1998), we reviewed the existing literature. We made minor scale adjustments to create our survey instrument for healthcare organisations in India. We evaluated companies collaborating with private and government healthcare organisations to develop digital healthcare supply chain systems. We accessed a database from the Indian Brand Equity Foundation (IBEF) to gather data and implemented all constructs as reflective constructs in our model.

3.1 Construct Operationalisation

For any research study that uses surveys, the process of operationalising the constructs of the research model is a critical component (Malhotra & Grover, 1998; Wright et al., 2012). This involves defining and establishing the specific steps, procedures, and criteria that will be used to create the survey questions (Wright et al., 2012). By carefully planning and executing this process, researchers can ensure that their surveys are accurate, reliable, and effective in gathering the data they need to answer their research questions (Polites et al., 2012). Proper operationalisation can also help minimise bias and ensure the study results are valid and generalisable to the population of interest (Hulland et al., 2018). The following section discusses the operationalisation of SCV, DT, ED, and HSCR. All the items developed to measure each construct are provided in Appendix 1.

3.1.1 Supply Chain Visibility

Several methods have been suggested for measuring SCV in supply chain management. Two notable examples are the scales developed by Wang & Wei (2007) and Caridi et al. (2010). However, we found the measurement scale introduced by Williams et al. (2013) particularly suitable for our specific case. Therefore, to evaluate the level of SCV in our case, we have implemented a ten-item scale based on Williams et al. (2013), which we believe offers a comprehensive assessment of the visibility of our healthcare supply chain. Williams et al. (2013) used SCV as a construct to gain insights into how it influences responsiveness using organisational information processing theory, providing a deeper understanding of SCV's impact on organizational decision-making. Subsequently, Srinivasan & Swink (2018) employed the same scale and found it reliable in an empirical context. Our study also explored the concept of SCV from an OIPT perspective, and we determined that the scale produced reliable results, making it a valuable tool to use in our research. Therefore, we selected the same scale for our study to ensure a thorough and accurate investigation into the role of SCV using OIPT.

3.1.2 Digital Technologies

We extensively reviewed numerous studies to comprehensively understand how DT has been measured. Despite multiple studies being conducted on this topic, including those by Frank et al. (2019) and Alvarenga et al. (2023), we found a lack of research that explores the usage of DT within the healthcare supply chain context. As a result, we developed a five-item modified scale that is custom-tailored to fit our research context, providing a more descriptive approach to this underexplored topic.

3.1.3 Environmental Dynamism

We undertook an extensive literature review on ED, as listed in Priem et al. (1995) and Lepak et al. (2003), and utilised the five-item Schilke (2014) measurement scale as being most appropriate to our study.

3.1.4 Healthcare Supply Chain Resilience

We analysed the literature on HSCR(see Zamiela et al. 2022; Senna et al., 2023b) and, hence, employed Mandal's (2017b) five-item scale, which allowed us to evaluate various aspects of the supply chain and identify areas for improvement.

3.2 Data Collection

We obtained contact information for potential survey respondents from the IBEF database. The IBEF (India Brand Equity Foundation) is a trust established by the Department of Commerce and Industry in India. Its primary focus is benchmarking the best global practices to help Indian-based organisations become more competitive. The IBEF's support extends to all sectors, including healthcare. We collaborated with the IBEF to gather information on organisations that have contributed significantly to the digital transformation of the healthcare sector in India. To obtain better insights, we identified consultants who have spent significant time working with public and privately owned healthcare organisations in India. We selected these consulting organisations because they better understand the Indian healthcare sector. We also cross-checked information with key officers from the Ministry of Health and Family Welfare, Government of India, who have detailed knowledge of the status of digitalisation projects within the Indian healthcare sector.

We contacted various consultants via email based on the information provided by IBEF, ensuring anonymity. We sought diverse perspectives and requested recipients to pass on the survey to knowledgeable consultants from different departments or parts of the organisation. We did not record the exact number of consultants we approached but sent follow-up emails to increase the response rate. The survey was sent on May 7, 2023, and the data collection concluded on October 23, 2023. After two rounds of follow-up, we received 137 usable responses.

Our team thoroughly analysed the responses we received and established specific criteria for evaluating them. To ensure accuracy and consistency, we used a key-informant approach, which aligns with previous research by Kumar et al. (1993) and Srinivasan & Swink (2018). This approach involved removing responses from individuals in our sample who were not directly involved in implementing DT in the healthcare supply chain. As a result, we were left with respondents who held various supply chain positions such as partner, associate partner, engagement manager, associate, and analyst. More information on the positions held by our respondents is provided in Table 1.

Table 1: Profile of the Respondents

Designation	N	%
Partner	35	25.55
Associate Partner	47	34.30
Engagement Manager/ Project Manager	17	12.41
Analyst	38	27.74
TOTAL	137	100
Size of the Organisations		
Number of Employees	Number of Organisations	%
1-100	32	23.36
101-150	57	41.61
>150	48	35.04
Revenues (million dollars)		
1-50 million USD	35	25.55
51-100 million USD	87	63.50
>100 million USD	15	10.95

We received sufficient responses, which is noteworthy considering recent empirical research trends. For example, Liang et al. (2007) conducted their research with a sample size of N=77, whereas Eckstein et al. (2015) used N=143 to test their research hypotheses. Hence, our 137 usable responses are a reasonable sample size, which provides adequate statistical power and increases the likelihood of obtaining reliable results (Kock & Hadaya, 2018). To determine the minimum sample size for our study using the PLS-SEM tool, we referred to an article by Kock & Hadaya (2018). There are two methods to determine sample size: The inverse square root method and the Gamma exponential method. We used software based on these approaches and found that at 0.7 power level (0.5-0.99), the maximum sample size was (122, 110)= 122. Therefore, our sample size of 137 is sufficient for our analysis, and we obtained good results.

Therefore, we can be relatively confident in the generalisability of our findings and their ability to contribute to the existing body of knowledge (Sarstedt et al., 2020b, p. 295). Unfortunately, we cannot provide a response rate, as we cannot accurately determine the number of individuals we approached to participate in the survey.

To check for any bias in non-response, we followed the recommendations of Armstrong and Overton (1977). We compared the responses of the first 30% of respondents with those of the last 30%. This allowed us to assess if the late respondents were similar to the non-respondents. We carefully analysed the responses of each measurement item and found no statistically significant differences between the early and late respondents. Based on this analysis, we can confidently conclude that this study has no non-response bias.

4. Data Analysis and Results

As part of our data analysis process, we used a statistical tool that employs Partial Least Squares Structural Equation Modelling (PLS-SEM) techniques to test and validate our data rigorously (Peng & Lai, 2012; Akter et al. 2017; Benitez et al., 2020; Stekelorum et al., 2021; Saglam et al., 2022; Vincent et al., 2023). The PLS-SEM tool helps evaluate the relationships between various factors and variables in our data, identifying any potential errors or inaccuracies and ultimately ensuring the reliability and validity of our results (Henseler et al., 2014; Hair et al., 2017; Bag et al., 2023). We carefully considered various criticisms that have been raised concerning the use of PLS-SEM and took steps to address them. After a thorough evaluation, we concluded that PLS-SEM was suitable for testing the theoretical model (Ronkko et al., 2016). Our assessment was based on many factors, including its flexibility, robustness, and ability to handle complex models (Kock & Hadaya, 2018; Benitez et al., 2020).

4.1 Common Method Bias (CMB)

We administered a survey-based questionnaire to a single informant, which provided us with cross-sectional data. While this approach has limitations and there is a possibility of standard method bias (CMB), we took steps to minimise its potential impact on our findings (Podsakoff et al., 2003; Ketokivi & Schroeder, 2004; Podsakoff et al., 2024). By using reliable measures, we reduced the potential for bias and ensured the validity and reliability of our research (MacKenzie & Podsakoff, 2012). Podsakoff et al. (2024) argue that post hoc analyses that utilise Harman's one-factor test, unmeasured latent variable (UMLV), direct measured latent variable (DMLV), or marker variable (MV) statistical methods are inadequate for controlling common method bias (CMB). These statistical methods alone are, therefore, insufficient for addressing

CMB. Instead, procedural remedies are recommended as a more practical approach to reducing the CMB effect. We followed the recommendations of MacKenzie & Podsakoff (2012) and utilised procedural remedies.

Despite statistical methods' limitations, we conducted conservative and recommended tests to ensure a thorough analysis. Additionally, we conducted statistical analyses to examine the potential effects of CMB on our results. We began by performing Harman's one-factor test, which revealed that all four factors were present, and the most covariance explained by a single factor was 28.54 per cent. This indicates that CMB may not be a significant issue. However, there are some concerns about the reliability of Harman's test as a standalone method for assessing CMB (Hulland et al., 2018; Podsakoff et al., 2024), with some scholars suggesting that it may not accurately evaluate CMB. Hence, we conducted a thorough analysis to address this issue and used the correlation marker technique to identify potential bias. We also employed an unrelated variable to evaluate the significance of correlations arising from CMB. The equation provided by Lindell & Whitney (2001) was used to determine the importance of correlations in our study. Based on the results of these tests, we concluded that CMB is not a significant issue in our data.

4.2 Measurement Model

As shown in Table 2, each construct's scale composite reliability (CR) is more significant than 0.7, and each average variance extracted (AVE) is above 0.5. These values indicate that the measurements are reliable and that the latent construct can account for at least 50% of the variance in the items. Moreover, the factor loadings are well above 0.5, and the t-values suggest they are significant at the 5% confidence level. These results indicate that the constructs used in the model satisfy the convergent validity criteria, as noted by Fornell and Larcker (1981).

As per the recommendations of Fornell and Larcker (1981), we tested for discriminant validity, see Table 3. The values shown in bold represent the square root of the AVEs, which are higher than the correlation values in the same row and column. This suggests that the different constructs possess adequate discriminant validity. In addition to this, following Gefen et al's. (2000) suggestions, we prepared a cross-loading table (see Appendix 2). This table shows that each item loading is much higher on its assigned construct than on the other constructs, supporting the assumption of adequate convergent and discriminant validity.

Apart from conducting the tests above, we further incorporated the Heterotrait-Monotrait (HTMT) criterion into our analysis, as recommended by Henseler et al. (2015) (see

Table 4). This statistical measure assesses the similarity between latent variables in structural equation modelling (Benitez et al., 2020). It is a popular method for evaluating discriminant validity. In cases where the HTMT value is less than one, it is generally accepted that discriminant validity has been successfully established (Henseler et al., 2015). However, the threshold for acceptable HTMT values may vary depending on the field of study and the research context. In some practical situations, a threshold of 0.90 or lower is acceptable. Overall, HTMT is a valuable tool for evaluating the validity of measurement models and ensuring that constructs are not too similar. Our study's values are below 0.9, suggesting an adequate discriminant validity for all constructs.

Table 2: Convergent Validity (Factor Loadings, Composite Reliability, Average Variance Extracted)

Constructs	Indicators	λi (loadings of indicators)	Var (σ^2)	Measurement error ($1-\sigma^2$)	Scale Composite Reliability (CR)	Average Variance Extracted (AVE)
Supply Chain Visibility (SCV)	VISB1	0.86	0.74	0.26	0.97	0.74
	VISB2	0.86	0.74	0.26		
	VISB3	0.91	0.82	0.18		
	VISB4	0.84	0.71	0.29		
	VISB5	0.85	0.72	0.28		
	VISB6	0.82	0.67	0.33		
	VISB7	0.86	0.74	0.26		
	VISB8	0.86	0.73	0.27		
	VISB9	0.87	0.76	0.24		
	VISB10	0.89	0.80	0.20		
Digital Technologies (DT)	DT1	0.85	0.72	0.28	0.94	0.76
	DT2	0.91	0.82	0.18		
	DT3	0.88	0.77	0.23		
	DT4	0.84	0.70	0.30		
	DT5	0.88	0.78	0.22		
Healthcare Supply Chain Resilience (HSCR)	HSCR1	0.83	0.69	0.31	0.95	0.79
	HSCR2	0.90	0.82	0.18		
	HSCR3	0.91	0.83	0.17		
	HSCR4	0.88	0.78	0.22		
	HSCR5	0.91	0.82	0.18		
Environmental Dynamism (DYNM)	DYNM1	0.88	0.77	0.23	0.93	0.72
	DYNM2	0.86	0.74	0.26		
	DYNM3	0.80	0.65	0.35		
	DYNM4	0.86	0.74	0.26		
	DYNM5	0.84	0.71	0.29		

Table 3: Discriminant Validity

	SCV	DT	HSCR	ED
SCV	**0.86**			
DT	0.31***	**0.87**		
HSCR	0.58**	0.44***	**0.89**	
ED	0.49**	0.29***	0.51**	**0.85**

***p <0.001; **p<0.01; *p<0.05; AVEs are bold

Table 4: HTMT values

	SCV	DT	HSCR	ED
SCV	0.31			
DT	0.72	0.53		
HSCR	0.66	0.38	0.70	
ED	0.73	0.62	0.83	0.86

4.3 Hypothesis Testing

4.3.1 Endogeneity Testing

To ensure that our results were accurate and reliable, we conducted an endogeneity test before hypothesis testing, following the recommendation of Guide and Ketokivi (2015). This is a crucial step in hypothesis testing, especially when dealing with complex data and models. Endogeneity in PLS-SEM occurs when there is a correlation between a predictor construct and the dependent construct's error term (Sarstedt et al., 2020a). This can lead to biased or incorrect estimates of model parameters. Therefore, one must address this issue before proceeding with hypothesis testing.

According to Hult (2018, p. 8), the Gaussian Copula (GC) approach is suitable for addressing endogeneity in PLS-SEM. This considers the joint distribution of the endogenous variables and the error term. However, before adopting this approach, we need to test the assumptions of the endogenous variables, such as non-normality, as recommended by Becker et al. (2022). Testing these assumptions can help us to identify any violations of the assumptions and take appropriate measures to address them. The Becker et al. (2022) recommendation was quite helpful in our case. Our study's normality condition is unsatisfactory, as the sample size is only 137. Therefore, we need to use caution when interpreting the results and make necessary adjustments to the model.

Furthermore, Park & Gupta (2012) offer extensive guidelines on this front, especially on how to deal with endogeneity issues that are not well tackled in most empirical studies involving non-experimental data. To ensure the accuracy of our findings, we followed their recommendations and guidelines and utilised the latest version of SmartPLS, version 4.0, as described in Ringle et al. (2022). Specifically, we thoroughly analysed the GC on each path (SCV→DT; DT→HSCR) to assess any potential critical endogeneity. Our analysis revealed that no critical endogeneity is present. To further examine the causality of our model, we conducted a causality assessment using a Nonlinear bivariate causality direction ratio (NLBCDR), as suggested by Kock (2022), which is considered a reliable method for assessing causality in nonexperimental data. The NLBCDR for our model was 0.8, which is greater than the recommended threshold of 0.7, indicating a robust causal relationship. We then examined each path and found a possible reverse link, though the support for this possibility is weak. On the basis of these tests, we infer that while endogeneity is not a critical issue, it cannot be eliminated in the case of non-experimental data. Overall, our analysis provides valuable insights into the causal relationships within our model.

4.3.2 Model Estimation and Analysis

The visual representation of estimates calculated through PLS analysis using the WarpPLS 7.0 commercial software for the PLS-SEM analysis is shown in Figure 2. Additionally, we used SmartPLS 4.0 to perform the GC test, which was discussed in the previous section. Our primary objective is not to compare these two commercial software solutions, as both offer unique advantages and are user-friendly, providing rich insights, especially for PLS-SEM analysis. We tested our hypothesised relationships with the WarpPLS 7.0. We tested for multi-collinearity by calculating each coefficient's variance inflation factor (VIF). Our model's VIF ranges between 1.001 and 2.043, significantly below the threshold limit of 10 (Hair et al., 2010). We discovered that the control variables of NO (nature of ownership) and HS (hospital size) have no significant effect on the model. Our interpretation on this observation is that the adoption of DT in both government-owned and privately-owned hospitals is still in its early stages, and any differences between the two may only be evident after a few years. Furthermore, hospital size does not influence the results.

The R^2 value of 0.76 suggests that our model explains significant variation in HSCR. The results (see Table 5) provide empirical evidence supporting the hypothesised mediating role of DT between SCV and HSC . Figure 2 depicts the importance of both the SCV-DT ($\beta=0.89$, $p<0.01$) and DT-HSCR ($\beta=0.85$, $p<0.01$) links, which serve as compelling evidence in support of research hypotheses H1 and H2. These findings suggest that the connections between SCV-DT and DT-HSCR are crucial and require further investigation.

Our research investigates the relationship between adopting DT and the HSCR through the path influenced by ED. To accomplish this, we conducted an analysis to test for the interaction effect of ED on the path joining DT and HSCR. Our findings revealed a statistically significant and positive relationship between DT and HSCR ($\beta=0.3$, $p<0.01$), which supports hypothesis H3. Moreover, the interaction plot presented in Figure 3 suggests that the occurrence of HSCR is likely to increase with the adoption of DT. However, the effects of high ED are quite distinct from those of low ED. In other words, the relationship between DT and HSCR changes depending on the level of ED. Therefore, it is necessary to examine the interaction effect of ED more thoroughly to gain better clarity on this relationship. Further research should be conducted to understand better the complex relationship between DT, ED, and HSCR.

As per Kock's (2014) recommendation, we used a mediation test to test H4. However, it has been observed that even though mediation tests are becoming more popular, scholars using PLS-SEM tools often fail to consider and analyse the mediation effects in their path models, as pointed out by Hair et al. (2010). To address this issue, scholars who advocate for the use of PLS-SEM suggest that it can not only simplify dealing with mediation tests in complex models but also eliminate the need for additional PROCESS macro to deal with complex mediation, as recommended by Hayes (2013) or the conventional method recommended by Baron & Kenny (1986) (see Kock, 2014; Sarstedt et al., 2020b). Kock (2014) recommended testing the mediation effect based on the arguments presented by Preacher & Hayes (2004) and Hayes & Preacher (2010). They pointed out that the Baron & Kenny (1986) test does not consider standard errors, which can introduce biases in the findings. Hence, Kock (2014) suggests a mediation test based on estimating indirect effects, which is incorporated into the WarpPLS package. Based on Appendix 3, we can conclude that the DT partially mediates the relationship between SCV and HSCR.

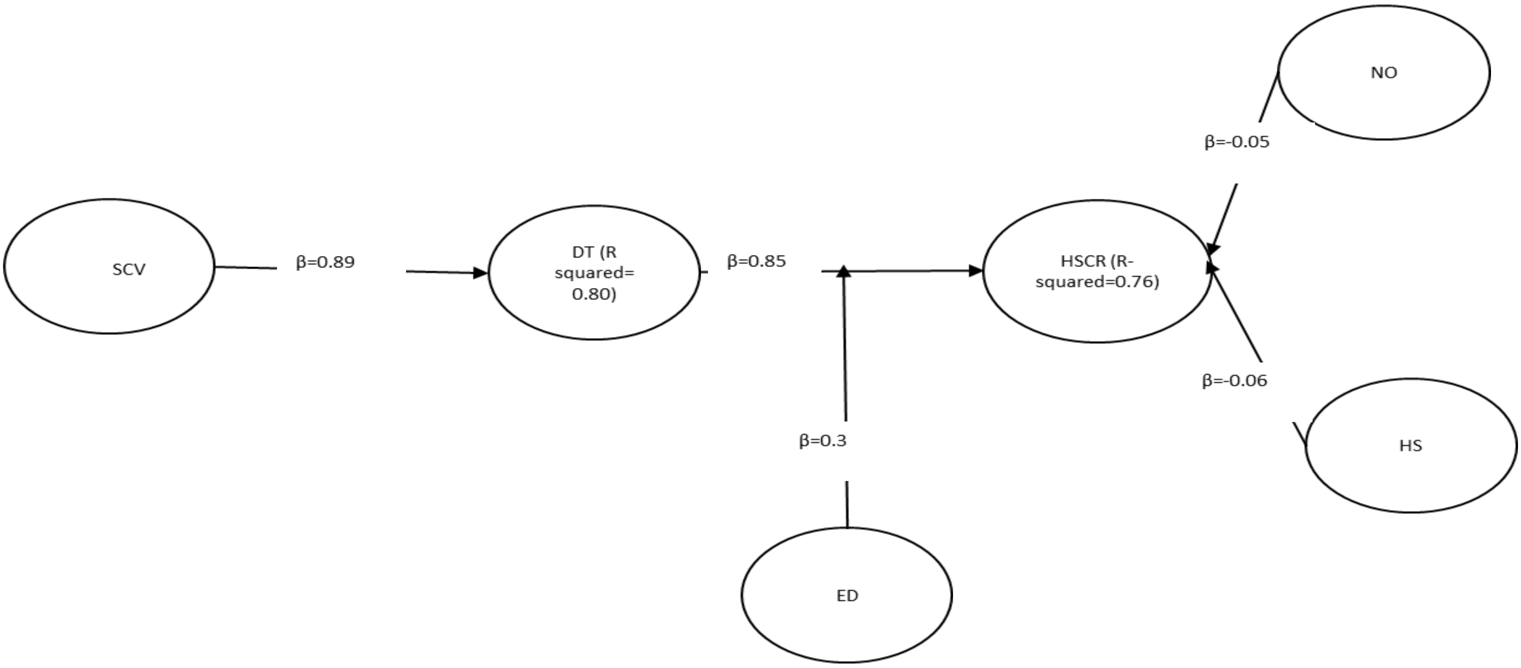

Figure 2: Final Model (PLS Analysis of Results)

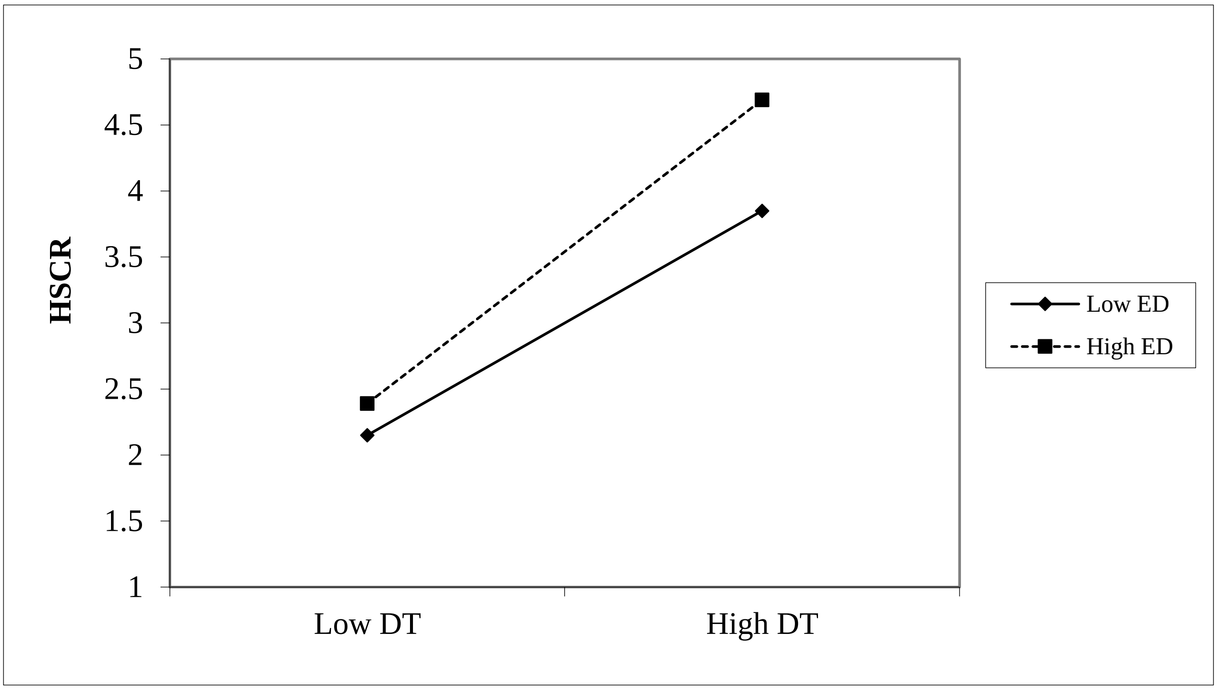

Figure 3: Interaction Plot

Table 5: Hypotheses Testing

Hypothesis	Driving variable	Outcome Variable	β	Results
Hypothesis 1	SCV	DT	0.89**	S
Hypothesis 2	DT	HSCR	0.85**	S
Hypothesis 3	SCV*DT	HSCR	0.3**	S

** $p<0.01$, S-supported, NS-not-supported

To provide a more precise explanation of the theoretical model's explanatory power, we calculated the R^2 of the endogenous constructs. DT has an R^2 of 0.80, while HSCR has an R^2 of 0.76, both considered vital according to Chin (1998). Additionally, we used the Cohen f^2 formula to analyse the effect size of each predictor variable. Our analysis involved determining the predictive power of our model, and we did this by calculating the f^2 values of SCV on DT (0.8) and DT on HSCR (0.76). In addition to this, we evaluated the model's ability to predict outcomes, which we did by assessing Stone-Geisser's Q^2. The Q^2 values for endogenous constructs were 0.8 for DT and 0.79 for HSCR. These results demonstrate that our model explains the relationships between the endogenous and exogenous constructs. The high Q^2 values indicate that the model can predict the endogenous constructs accurately. Our findings suggest that our model is reliable and is potentially helpful in predicting outcomes in similar scenarios.

4.3.3 Robustness Test

We conducted additional tests to ensure the accuracy and reliability of our results. Firstly, we checked for the presence of heteroscedasticity in our model. This means looking for any difference in residual variance within our model, which could invalidate any statistical significance tests, assuming the modelling errors have the same variance. To test this, we used the Breusch & Pagan (1979) and White (1980) recommended tests, which we performed using the R package with the "ncvTest" and "white" functions. Secondly, we introduced dummy variables for the nature of ownership (NO) without changing the results. Thirdly, we used seemingly unrelated regressions (SUR) to estimate the model equations and check for any error correlations. We found that the parameter estimates did not change, and the results remained almost the same, with no significant change. Fourthly, using Kock's (2014) recommendations, we performed an indirect effect test with the WarPLS 7.0 package. We also performed an additional moderated-mediation test, recommended by Preacher et al. (2007), where we estimated the indirect effects of the SCV on HSCR for -3σ to +3σ standard deviations of ED. We performed the bootstrap analysis with 5000 iterations to determine whether the bias-corrected intervals of the indirect effect of SCV are significant at high levels of ED. Finally, we performed a non-linear test of the moderation effect using WarpPLS 7.0, which is the main feature of this package. By doing all these tests, we ensured that our results are consistent and reliable.

5. Discussion

Our findings reveal that DT significantly impacts HSCR and ED. They also highlight the importance of SCV in ensuring efficient and effective healthcare services. Furthermore, our study indicates that healthcare organisations, whether private or public, need to adopt DT to remain competitive and responsive to the changing healthcare landscape. The insights from our research can help healthcare leaders make informed decisions about implementing DT to improve SCV and enhance resilience in the face of environmental changes. These findings offer exciting implications for theory and practice and provide food for thought for future research.

5.1 Implications for Theory

The literature has extensively discussed the importance of digital technologies (DT) in the healthcare system. However, despite a growing body of evidence, there is still a gap in understanding the essential enabling factors that facilitate the effective use of these technologies in the healthcare system (Tortorella et al., 2022; Fursteanau et al., 2022; Massaro, 2023). Most of the studies have focused on digital capabilities as a dynamic capability. In this study, we attempted to advance the definition of digital capabilities in the healthcare sector by recognising that investing in technologies alone does not help understand the complexity associated with the organisational elements. OIPT allows us to expand the scope of digital capabilities, further helping to expand the theoretical understanding of digital capabilities as perceived earlier by various scholars (see Warner & Wager, 2019; Sousa-Zomer et al., 2020).

SCV is a critical aspect of modern business operations. It enables organisations to track the movement of goods and services from one point to another, ensuring they are delivered to the right place at the right time (Barratt & Oke, 2007). By providing real-time information on inventory levels, shipment status, and delivery timelines, SCV helps businesses streamline their operations, minimise costs, and improve customer satisfaction (Caridi et al., 2010). Our research findings lend weight to the views expressed by Barratt & Oke (2007) and those of Srinivasan & Swink (2018) regarding the inherent value of healthcare technologies. Our analysis indicates that the true potential of these technologies lies not in the technologies themselves but in how they are leveraged. Therefore, to fully realise these technologies' benefits, all healthcare supply chain stakeholders must collaborate effectively and share information seamlessly to ensure that the technologies are being used to provide accurate results. Doing so can transform the entire healthcare ecosystem, improving patient outcomes and healthcare system efficiencies. Our study contributes to the literature by demonstrating that SCV is a crucial enabler that enhances the effectiveness of DT (Srinivasan & Swink, 2018).

Further, our study investigates how DT can enhance the resilience of healthcare supply chains in dynamic environments, adding to the findings of Ivanov (2021) and Tortorella et al. (2022). These findings highlight specific technologies and strategies proven effective in managing healthcare supply chains, especially during times of crisis and uncertainty. They emphasise the importance of using digital tools to ensure the uninterrupted flow of medical supplies and equipment, crucial for delivering quality healthcare services to patients. Our research explores the intricate relationship between DT and HSCR in the face of ED, deepening our understanding of how healthcare supply chains can effectively adapt and withstand the challenges posed by unpredictable and rapidly changing environments.

Finally, our study adds to the contingent view of organisational information processing theory (OIPT) by providing in-depth insights into how organisations can adapt their processing approach in different situations and contexts. The study highlights the importance of adapting practices to internal and external environments to manage and tackle crises effectively. It also sheds light on the complexities of organisational processing and presents a comprehensive framework for future research and practical applications.

Moreover, the research expands the theoretical scope of organisational processing theory by aligning with Tushman and Nadler's (1978) argument that uncertainties play a critical role in the information processing capabilities of organisations. By investing in information processing capabilities, healthcare organisations can better handle crises resulting from high levels of dynamism. Our study also contributes to the existing literature on organisational information processing theory by emphasising the importance of context-specific practices in processing. It suggests that organisations need to be aware of the unique characteristics of their environment and adapt their processing practices accordingly. This approach can lead to more effective decision-making, improved organisational performance, and a stronger competitive advantage. Overall, the study provides a detailed understanding of the contingent view of organisational processing theory and its practical implications. It significantly contributes to the existing literature and provides a strong foundation for future research.

5.2 Implications for the Policymakers and Managers

The COVID-19 pandemic has had a major impact on the healthcare sector worldwide, exposing numerous weaknesses in the robustness of healthcare supply chains. This has led to concerns among various stakeholders and governments about the sector's preparedness to deal with such crises in the future. Our study highlights some of the critical issues that policymakers need to address to improve the resilience of the healthcare sector. One of the critical findings is the importance of DT. The pandemic highlighted the need for digital tools that enable remote consultations, telemedicine, and remote monitoring of patients. These technologies can also help improve healthcare delivery efficiency and reduce the burden on healthcare workers.

Our study suggests that investing in DT alone is insufficient. Organisations must also focus on developing a culture of transparency and information sharing. This includes sharing data among healthcare providers, government agencies and other stakeholders to facilitate effective decision-making and improve healthcare supply chain resilience. Our study highlights the importance of both DT and a culture of transparency and information sharing to improve the resilience of the healthcare sector. Policymakers must address these critical issues to ensure the healthcare sector is better equipped to deal with future crises like the COVID-19 pandemic.

Effective technology implementation in the healthcare industry requires healthcare staff to be proficient in utilising complex digital systems. Adequate training and support for healthcare staff utilising these DT is critical for effective implementation. By ensuring that healthcare staff are well-trained in digital systems, healthcare organisations can achieve optimal outcomes, including improved patient care and streamlined supply chain management. Therefore, healthcare organisations must invest in training programs that equip staff with the skills and knowledge necessary to utilise DT effectively. In digital technology, trust, effective collaboration, and information sharing are vital pillars in successfully functioning. Trust is an essential factor that enables different entities to rely on each other and work towards common goals. Effective collaboration is necessary to ensure that all parties involved in the project work together seamlessly and efficiently. Information sharing is critical as it helps disseminate knowledge and ensures all stakeholders know the latest developments. Combining these three factors forms the bedrock of a thriving digital technology ecosystem.

5.3 Limitations of the Study and Future Research Directions

In our study, we adopted a deductive approach that enabled us to address the research questions systematically. However, we recognise that despite our rigorous efforts, we may have missed out on some valuable insights related to the enablers of SCV and the challenges healthcare managers face in effectively utilising DT. These critical issues require further exploration and in-depth analysis to understand better the underlying factors that drive success or failure in this domain. Therefore, we believe that more research is needed to fully address these issues and provide a comprehensive understanding of the complex dynamics involved in healthcare supply chain management. By leveraging an inductive study approach involving semi-structured interviews with stakeholders, it is possible to gain a deeper understanding of various unanswered questions. Such an approach allows one to explore uncharted territories and uncover valuable insights that may not be immediately apparent through other research methods. By engaging with stakeholders, researchers can obtain firsthand knowledge and perspectives from individuals directly involved in the issue. This can help to shed light on complex issues and provide a more nuanced understanding of the topic under investigation. Overall, the inductive study approach via semi-structured interviews is a powerful tool for gaining rich insights into a wide range of questions (see Gioia et al., 2013; Bansal et al., 2018).

Our research was based on the insights of consultants implementing DT across different healthcare sectors. We recognise that relying on data from only one source may result in biases. Therefore, we acknowledge the need to gather data from multiple informants in future studies, as Ketokivi and Schroeder (2004) recommended.

It is imperative to acknowledge that the findings of our study may not apply to developed economies, where the level of technology adoption may differ significantly from the one observed in our data. This could be due to various factors, such as differences in cultural attitudes towards technology, infrastructure availability, and economic development (Gupta & Gupta, 2019; Gupta et al., 2022). As a result, it is essential to exercise caution when interpreting our study's results and consider the context in which the data was collected. We must conduct more collaborative studies to gather comprehensive data for future research. These studies should involve experts from various fields, communities, and organisations to ensure a wide range of perspectives. Additionally, the studies should be conducted using rigorous methods and transparent protocols to ensure the accuracy and reproducibility of the findings. By doing so, we can obtain a more in-depth understanding of the subject matter and make informed decisions based on reliable data.

6. Conclusions

Our study aimed to investigate the relationships between SCV, DT, environmental changes, and the ability of healthcare supply chains to withstand disruptions. Previous research has not comprehensively understood the critical factors required to implement DT in highly dynamic environments. Therefore, we sought to shed light on the factors that enable the implementation of DT in healthcare supply chains to build resilience. To answer the first research question, "*What factors enable the implementation of DT in resilient healthcare systems?*", our study used organisational information processing theory to explain how SCV can increase the effectiveness of DT. To address the second research question, "*How do environmental uncertainties affect the connection between DT and healthcare supply chain resilience?*", we used a deductive approach to test the theoretical model. The results of our study contribute significantly to the organisational information processing theory by explaining how uncertainties shape an organisation's information processing capability to address challenges in the healthcare sector. Our study provides valuable insights and avenues for further research to understand better the complex associations between visibility, technology, and resilience in the healthcare sector.

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Appendix 1: Measurement Items

Construct	Items
Supply Chain Visibility *(adapted from Williams et al. 2013)*	**Demand Visibility**
	The information we receive from the health centres regarding the demand for medicines is timely, accurate and complete.
	The information we receive from the health centres regarding the PPE kits or necessary items is timely, accurate and complete.
	The forecast information we receive from the health centres is timely, accurate and complete.
	The inventory details of medicine, PPEs, and other necessary items each healthcare centre provides are accurate.
	The information we gather from external sources regarding the demand for critical items of healthcare centres, including medicines, PPEs, and other accessories, is accurate.
	Supply Visibility
	The supplier's inventory information is accurate and complete.
	We have accurate information about the supplier's capability to meet future needs.
	The advance shipment notice we receive from the suppliers is accurate and timely.
	The information regarding the inventory of the items in the distribution centres is accurate and complete.
	The suppliers provide accurate information at the time of quotations.
Digital Technologies *(adapted from Alvarenga et al. 2023)*	*Healthcare centres use machine learning algorithms to forecast the demand for healthcare items.*
	Healthcare centres use social media analytics tools to understand the demand for healthcare support services.
	Healthcare centres use artificial intelligence-driven data analytics capability to predict the demand for critical healthcare items during and after the COVID-19 crisis.
	Healthcare centres use RFID technology for asset tracking to have accurate information on the inventory.
	Healthcare centres have adopted distributed ledger technologies to share information or important details among stakeholders.

Healthcare Supply Chain Resilience *(adapted from Mandal, 2017b)*	*Healthcare centres can quickly restore their healthcare operations during disruptions caused by unpredictable events.*
	Healthcare centres can provide uninterrupted services to their patients during the disruptions.
	Healthcare centres are adept financially at dealing with emergencies proactively.
	Healthcare centres possess the desired capabilities to deal with any disruptions positively.
	Healthcare centres can source suppliers alternately during the disruptions.
Environmental Dynamism *(adapted from Schilke, 2014)*	*Healthcare centres face a high degree of demand fluctuation for critical healthcare items.*
	Healthcare centres face a high degree of supply uncertainties for critical healthcare items.
	Healthcare centres often struggle to adapt to new technologies.
	Healthcare centres are experiencing a significant shortage of healthcare support staff.
	Healthcare centres face a high degree of disruption due to global trade barriers affecting the import and export of critical items.

Appendix 2: Item Loadings and Cross Loadings

	SCV	DT	HSCR	ED	NO	HS	ED*DT	Type	SE	P value
SCV1	**0.86**	-0.21	-0.16	0.19	0.02	0.04	-0.03	Reflect	0.07	<0.001
SCV2	**0.86**	-0.23	-0.07	0.31	-0.08	0.02	0.00	Reflect	0.07	<0.001
SCV3	**0.91**	-0.38	0.17	-0.01	-0.03	0.02	-0.06	Reflect	0.07	<0.001
SCV4	**0.84**	0.09	-0.03	-0.35	0.13	0.07	-0.13	Reflect	0.07	<0.001
SCV5	**0.85**	0.22	0.03	-0.29	0.07	-0.05	0.08	Reflect	0.07	<0.001
SCV6	**0.82**	0.32	0.09	-0.25	-0.10	0.00	0.08	Reflect	0.07	<0.001
SCV7	**0.86**	0.37	-0.10	-0.29	-0.06	0.05	0.09	Reflect	0.07	<0.001
SCV8	**0.86**	-0.43	-0.25	0.22	0.08	0.00	-0.07	Reflect	0.07	<0.001
SCV9	**0.87**	0.02	0.13	-0.37	0.00	-0.10	0.11	Reflect	0.07	<0.001
SCV10	**0.89**	-0.30	0.18	0.11	-0.03	-0.05	-0.08	Reflect	0.07	<0.001
DT1	0.46	**0.85**	0.03	-0.47	0.08	-0.02	0.10	Reflect	0.07	<0.001
DT2	-0.23	**0.91**	0.31	0.07	0.06	0.03	-0.08	Reflect	0.07	<0.001
DT3	0.08	**0.88**	0.12	-0.17	-0.02	0.06	-0.12	Reflect	0.07	<0.001
DT4	-0.45	**0.84**	-0.35	0.31	-0.10	-0.07	-0.02	Reflect	0.07	<0.001
DT5	-0.11	**0.88**	-0.13	-0.02	-0.03	-0.01	0.12	Reflect	0.07	<0.001
HSCR1	0.36	-0.25	**0.83**	0.21	0.03	0.06	0.08	Reflect	0.07	<0.001
HSCR2	-0.19	-0.05	**0.90**	0.11	0.00	-0.01	-0.08	Reflect	0.07	<0.001
HSCR3	-0.17	-0.11	**0.91**	0.01	0.03	-0.09	0.00	Reflect	0.07	<0.001
HSCR4	-0.04	-0.01	**0.88**	-0.20	-0.03	0.04	0.00	Reflect	0.07	<0.001
HSCR5	-0.16	0.39	**0.91**	-0.11	-0.03	0.01	0.01	Reflect	0.07	<0.001
ED1	0.08	0.25	-0.04	**0.88**	-0.01	-0.09	-0.18	Reflect	0.07	<0.001
ED2	-0.19	-0.07	0.03	**0.86**	-0.05	0.09	-0.04	Reflect	0.07	<0.001
ED3	-0.11	0.13	-0.35	**0.80**	-0.03	0.00	0.07	Reflect	0.07	<0.001
ED4	-0.15	-0.01	0.37	**0.86**	-0.04	0.05	-0.08	Reflect	0.07	<0.001
ED5	0.36	-0.30	0.25	**0.84**	0.12	-0.05	0.25	Reflect	0.07	<0.001

Appendix 3: Sum of indirect effect coefficients and number of paths for indirect effects

Indirect effects for paths with 2 segments

	SCV	DT	ED	HSCR	NO	HS	ED*DT
SCV							
DT							
ED							
HSCR	0.763						
NO							
HSCR							
ED*DT							

Number of paths with 2 segments

	SCV	DT	ED	HSCR	NO	HS	ED*DT
SCV							
DT							
ED							
HSCR	1						
NO							
HSCR							
ED*DT							