The Influence of Artificial Intelligence Techniques on Disruption Management: Does Supply Chain Dynamism Matter?

Abstract

Healthcare supply chains (HSCs) have been hard hit by disruptions such as COVID-19. Keeping pace during this interruption has been a significant challenge. HSCs' adaptability and collaboration using artificial intelligence techniques (AITs) have been recognized as key components of supply chain resilience for managing disruption. The current study aims to investigate how AITs might help improve HSC resilience (HSCR) by facilitating improved adoption and collaboration throughout its operation. Data was collected from the Indian healthcare sector and analyzed using the partial least squares structural equation modeling (PLS-SEM) technique. Additionally, an examination was conducted to determine the potential moderating role of supply chain dynamism (SCD) on the adoption and cooperation of HSCs with HSCR. The research shows that AITs encourage HSC adaptability and collaboration in their operations and that HSCR results from both factors. Moreover, SCD does not moderate the link between HSC adoption and HSCR but does moderate the link between HSC cooperation and HSCR. By enhancing HSC adaptability and effective collaboration with AI-enabled systems, AITs may help HSC stakeholders deal with disruptions in healthcare sector operations.

Keywords: Artificial intelligence; Healthcare supply chain; Supply chain dynamism; Resilience; Adaptability; Collaboration

1. Introduction

Epidemic breakouts are a unique disruption to supply chain (SC) operations. They may swiftly spread throughout various locations, making them exceedingly hazardous (Kähkönen et al., 2021). Risks of breakdown and disruptions in global SCs have grown concurrently with the anticipated cost and efficiency gains (Choi et al., 2020). Therefore, the operations of businesses were completely unequipped due to the swiftly disruptive consequences of COVID-19 on international SCs (Choi et al., 2020). Complexity in a supply network is directly correlated with increased risk, making the SC more susceptible to attack (Blackhurst et al. 2018). These vulnerabilities in SC operations were exposed during the global COVID-19 pandemic, which created significant difficulties for healthcare supply chain (HSCs) operations everywhere (Spieske

et al., 2022). Resilience is defined as the ability of an organization or supply chain to respond to disruption and restore its original state with minimum delay.

Furthermore, resilience in HSC operations is an emergent attribute of sophisticated sociotechnical structures necessary for their longevity and satisfactory performance under predictable and unforeseen events (Senna et al., 2021). Therefore, resilience is an important factor in restoring HSC operations in disruptions. Additionally, improvements in a company's capabilities are vital to bouncing back from SC operations disruptions and establishing resilience (Chowdhury and Quaddus 2016). Organizations may build resilience and overcome the difficulties of inefficient supply networks by integrating and collaborating throughout the supply chain (Khuntia et al., 2021). Developing dynamic capabilities is essential for businesses to mitigate risks successfully over the long term (Chowdhury and Quaddus 2017). The capability to respond to operations disruption and recover quickly once it has occurred is essential for mitigating its effects (Chowdhury and Quaddus 2016). For instance, the Shanghai-GM-Wuling automobile plant created face masks during the COVID-19 pandemic by swiftly switching between the operations of their product lines (Betti and Ni 2020). Therefore, developing and adapting dynamic capabilities in HSC operations helps to build HSC resilience (HSCR) or manage disruptions. HSC adaptive capabilities (HSCAC) (referred to as the internal efficiency of HSC in this article) and HSC collaboration (HSCC) (referred to as the external efficiency of HSC in this article) are important factors of HSC operations for a firm. Ponomarov and Holcomb (2009) defined HSCR as the "adaptive capability of the SC to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function". Therefore, HSCAC is needed to deliver HSCR.

For instance, 81% of executives have enhanced their supply effectiveness by using digital transformation as an adaptable technique (Smedberg 2021). Furthermore, HSCC is also important to achieve HSCR. For instance, some HSC stakeholders reacted to stock outs of health commodities by hoarding the items in anticipation of a future need (Friday et al., 2021). This was exacerbated by a shortage of collaborative strategies among HSC stakeholders (Friday et al., 2021). Arya et al. (2015) argue that enhanced technological cooperation has significant implications on the resilience of SC operations, particularly when considering the influence of SCC. The primary purpose of data sharing within a SC is to enhance its resilience. By engaging in

collaborative efforts, stakeholders may enhance their comprehension of operational disruptions, as highlighted by Papadopoulos et al. (2017). Prior research has shown that a deficiency in collaboration among existing participants in the SC might lead to worse outcomes with increased expenses for the system, as well as an inability to build standardized healthcare protocols (Kwon et al., 2016). In addition, the complexity of the operations of SC management in the healthcare industry makes it difficult to restructure SC (Bhakoo et al., 2012). However, integrating or restructuring the SC is critical for any healthcare system since supply-related expenditures account for 30%-50% of a hospital's operational expenses (Francis, 2020). Therefore, the adaptation and collaboration of HSC to attain HSCR will be an emergent discussion, which has not been discussed much in the past literature. In recent years, there has been a notable increase in investment, research endeavours, educational initiatives, training programmes, and academic publications on artificial intelligence (AI) and machine learning (Bratanova et al., 2022). The advancement of AI has brought about significant transformations in all domains of human existence, notably healthcare (Uzir et al., 2021). Moreover, AI innovation in healthcare has grown as a progressively important domain of scholarly investigation (Zahlan et al., 2023). In addition, past scholars have examined the possibility of using innovative technologies such as AI to address the COVID-19 pandemic (Reddy et al., 2019). For instance, robots can manage medical records and vital signs automatically, making it easier for doctors to keep tabs on a patient's health and recovery (Sharma et al., 2022).

Conversely, AI technologies such as deep learning and machine learning have been employed as potent instruments to improve COVID-19 identification, treatment, immunization development, and comprehensive data assessment (Vaishya et al., 2020). Acquiring a comprehensive understanding of the patterns of AI implementation would aid scholars in forecasting the prospective advancements of this adaptable technology and making well-informed investments to augment its capabilities. (Hajkowicz et al., 2023). AI improves the adaptation capability of firms (internal efficiency) to improve the operations of HSC. For instance, Dehghani et al. (2021) used an integrated "two-stage stochastic programming model and a Quasi-Monte Carlo sampling" technique to handle the operations management of perishable blood supply in climates with unpredictable demand, and they evaluated the efficacy of their proposed model through proactive transhipment among Australian hospitals. Additionally, AI-based solutions are rapidly evolving in the HSC. AI-based solutions in the field of healthcare include the

implementation of care robots designed to aid those with physical disabilities or the old population, the use of chatbots to provide anonymous online mental health consultations, and the development of diagnostic software that incorporates machine learning techniques (Ho et al., 2022). Furthermore, Fan et al. (2018) looked into the level of confidence doctors in Chinese hospitals have in "AI-based medical diagnosis decision support systems" for curing disease-oriented operations. AI also improves collaboration in HSC (firm's external efficiency) to improve resilience. For instance, to assess and choose between the potential vendors of SC operations, Özkan and İnal (2014) suggested using the "Adaptive Neuro Fuzzy Inference System". Therefore, AI could be seen as an important facilitator of the internal and external efficiency of HSC operations. Nevertheless, the empirical evidence to validate this association is not available in the past literature, which motivates us to formulate the research questions of the present research as follows:

RQ1: What role does AI play in affecting the internal and external efficiencies of HSCs?

RQ2: Can adaptation capability (internal efficiency of the firm) and collaboration (external efficiency of the firm) lead to the resilience of HSCs?

In light of the ever-evolving nature of the corporate world, adopting a flexible and dynamic point of view is essential (Samsudin et al., 2019). However, the notion of dynamic capabilities has redeemed the situation by articulating the firm's competitive edge in the dynamic context (Samsudin et al. 2019). Since retaining competitive advantage is a never-ending, dynamic process (Hung et al. 2010), researchers have suggested that, for a business to survive and thrive in a constantly shifting market (Jashapara 1993; Senge 1990), it must cultivate a set of dynamic capabilities and engage in a culture of constant learning (Wilden 2013). If the company cannot adapt to its dynamic world, it will not be able to stay ahead of the competition (Easterby-Smith 2009). Therefore, dynamic capability theory (DCT) is selected in this study as a theoretical lens to examine the relationship between AI, HSCAC, HSCC, and HCSCR.

2. Theoretical underpinning and hypotheses formulation

2.1. Dynamic Capability Theory

In recent years, the field of operations research has increasingly included the concept of dynamic capabilities (DCs) as a key theoretical lens (Schilke et al., 2018; Tran et al., 2019). Teece

et al. 1997, who proposed the DC concept, defined DC as "the ability of the firm to combine, develop and reconfigure external and internal expertise to respond to speedily changing environment". DCs are seen as the process through which an organization's resource foundation is constructed and altered to achieve the needed organizational compatibility with the surrounding context from the standpoint of adaptive norms (Levinthal et al., 2015). DCs ensure prompt restructuring, which helps businesses maintain a competitive edge via high performance in a rapidly shifting, unpredictable setting (Eisenhardt and Martin 2000). There is widespread agreement that DCs are important for dealing with even mildly disruptive or highly predictable settings (Eisenhardt and Martin 2000). According to Teece (2007), the capabilities of sensing, seizing, and reconfiguring (transformation) are the foundation of dynamic capabilities. Dynamic capacities can be thought of as managerial and organizational procedures that assist businesses in sensing opportunities and risks and taking advantage (seize) of sensed opportunities and risks while rearranging (reconfiguring) their resources to better suit the changed environment (Kähkönen et al., 2021). Furthermore, we conducted a literature review on DCTs in the present study context. The findings of the literature survey are reported in Table 1. Table 1 offers insights into some of the pioneering research after 2020 (as COVID-19 impacted that timeline, significant research could happen only after 2020), relevant to disruption management in HSC operations from various theoretical lenses.

Table 1: Past literature on SC resilience from various theoretical lenses

Studies	Context	Base theory for research
Munir et al. (2022)	Identify important competences to cope with unanticipated and unusual disruptions, such as those driven on by COVID-19, and study how these skills act as crucial facilitators of supply chain resilience (SCR) and flexibility, eventually leading to increased performance.	Dynamic capability view (DCV); Information processing view (IPV)
Dubey et al. (2022)	This research aims to clarify how artificial intelligence-driven big data analytics capabilities contribute to disaster relief efforts.	DCV
Münch and Hartmann (2022)	This research utilizes a multicase study approach across three related businesses to shed light on the effects of the Covid-19 epidemic on supply chain resilience.	DCV; Relational capability view (RCV)

Kähkönen et al. (2021)	Find out whether the COVID-19 epidemic has weakened a company's SCR and how its dynamic capabilities have changed as a result.	DCV
Mohammed et al. (2021)	This research creates a unified approach to assessing SCR from the perspectives of an organization's dynamic capabilities and its suppliers' resilience.	DCV
Ruel and El Baz (2021)	Using the backdrop of the recent COVID-19 epidemic, this research examines how supply chain (SC) catastrophe preparedness affects SC resilience and durability, and how that in turn affects enterprises' monetary performance.	DCV; Organizational readiness for change (ORC)
Meriton et al. (2021)	Using a two-pronged strategy, this research investigates the factors that generate value in such a supply chain.	DCV

The findings of Table 1 indicate that DCT is the most appropriate theoretical lens for our study, as most past studies have used DCT as the theoretical base to investigate the resilience of HSC operations. Therefore, the selection of DCT in the current setting is very relevant.

2.2. Artificial intelligence techniques and HSC internal efficiency

The adaptive capabilities (AC) of a corporation refer to its inclination to accept and accommodate change, as well as its commitment to invest the necessary resources and exert the requisite effort to adjust to novel situations and demands (Dovers and Handmer 1992). AI has been shown to be an excellent method for simulating adaptability in complex systems, hence enhancing their structure, reconfigurability, and adaptability. This is exemplified by research conducted by Leitao (2009). In addition, research done by Macas-Escrivá et al. (2013) yielded findings that support the notion that AITs have a significant impact on the advancement of novel iterations of adaptable structures. Baryannis et al. (2019) and Rodrguez-Espndola et al. (2020) have emphasised the ability of AITs to provide accurate and up-to-date estimates, together with near-actual-time monitoring of stocks. Also, the advent of AI has brought about a significant and impactful period for the AC of the HSC. This has resulted in concrete advantages via the implementation of novel applications. An illustrative instance is predictive analytics, which uses

AI algorithms to anticipate demand by analyzing historical data, seasonal patterns, and external variables such as disease outbreaks (Furstenau et al., 2022). Healthcare facilities may use these predictions to optimize their inventory levels, guaranteeing a continuous availability of crucial medical resources such as personal protective equipment and drugs while avoiding excessive stockpiling. AI-powered SC management solutions, such as IBM Watson SC, have shown notable achievements in augmenting the flexibility of supply chains via the automation of many operations, including order processing and shipment tracking[1]. Moreover, the expeditious advancement of robotics and AITs aids in the adaptation to the obstacles encountered within the healthcare domain. Intelligent speech technology has been used to enhance medical practices and lessen the stress on healthcare professionals and patients, resulting in improved efficiency in medical care (Zhang et al., 2023). This capability effectively addresses the challenges of cooperation among stakeholders arising from variations in demand and supply. According to Helfat and Peteraf (2003), the DCT is the process of developing, integrating, or reorganizing tactical capabilities and resources to achieve a competitive advantage. They argue that this process requires both adaptation and transformation. Furthermore, the use of AI has the potential to provide support for DCs, thus mitigating the probability of operational disruptions and ideally preempting any prospective issues from arising (Grover et al., 2020). Ivanov et al. (2019) suggest that it is crucial for SC to rely on technology to develop strategies that can effectively adapt to the dynamic nature of changing conditions. Hence, it is expected that the use of AITs will facilitate the development of those competences (Grover et al., 2020). Therefore, the integration of AI can adjust and cooperate in the digitization of HSC activities, therefore enhancing their efficiency even in a constantly changing context and enabling them to sustain their competitive edge. Thus, we hypothesize the following:

H1: AI techniques positively affect the internal efficiency (adaptive capabilities) of HSC operations.

2.3. Artificial intelligence techniques and HSC external efficiency

To thrive, businesses must establish a foundation of robust coordination and cooperation across SC participants (Luthra et al., 2019). The use of AI in facilitating actual-time data

[1] https://www.ibm.com/downloads/cas/YLEKOE53 (Accessed on 4/10/2023).

transmission has the capability to enhance cognitive processes, namely, in the areas of SC cooperation (SCC), SC integration, and stakeholder cooperation (Helo and Hao, 2021). Jain et al. (2017) define SCC as the collaborative coordination and operation of several enterprises or partners to plan and execute different activities within the supply chain. The achievement of successful integration of AI inside the SC will require the establishment of efficient collaborative efforts with partnering enterprises, rivals, government entities, and domain experts (Ashaye and Irani, 2019). AITs play a crucial role in enhancing cooperation across HSC operations. AITs facilitate the implementation of sustainable practices inside organizations, including the adoption of environmentally friendly operations and the establishment of collaborative relationships with suppliers (Singh et al., 2018). These initiatives contribute to the reduction of waste generation, carbon emissions, and mitigation of environmental concerns (Singh et al., 2018). Through the analysis of extensive data, AI can forecast changes in demand. This enables organizations to take proactive measures in managing their inventory levels, thus mitigating the risk of shortages or excessive stock (Nilashi et al., 2016). Furthermore, the use of AI in predictive analytics enables the identification of prospective disruptions within the SC. This capability empowers stakeholders to engage in collaborative efforts and proactively establish contingency plans. During the COVID-19 pandemic, the use of AI-driven models played a crucial role in enabling healthcare systems to proactively forecast increases in the need for certain medical resources. Furthermore, these models permitted collaborative endeavours aimed at reallocating resources to the areas that need them the most (Nilashi et al., 2016). The use of AITs facilitates the enhancement of transparency, agility, and responsiveness within the context of the HSC, eventually reinforcing its collaborative capacities. An illustrative instance within the industry is the collaboration between Pfizer, a prominent pharmaceutical corporation, and IBM. Pfizer has implemented IBM's Watson SC platform, which utilizes AI and blockchain technology to enhance cooperation and transparency across its SC (Pfizer, 2016). By using AI-powered predictive analytics, Pfizer is able to enhance its demand forecasting capabilities, facilitating improved collaboration with suppliers and distributors to guarantee the timely supply of drugs (Pfizer, 2016). This collaborative effort exemplifies the potential impact of AI approaches on enhancing external efficiency within the pharmaceutical industry. By facilitating smooth communication between pharmaceutical businesses, suppliers, and distributors, these techniques contribute to the

establishment of a more dependable and agile SC, therefore effectively addressing the crucial healthcare requirements of patients. Therefore, we hypothesize:

H2: AI techniques positively affect the external efficiency (collaboration) of HSC operations.

2.4. Internal efficiency and disruption management

The increasing intricacy and uncertainty of supply chain operations in recent years have necessitated the consideration of disruption risk in their design and planning (Ivanov and Dolgui, 2018). The COVID-19 pandemic, caused by the novel coronavirus, has brought attention to the critical need to advance SCR research and practices (Ivanov and Dolgui, 2020). Jain et al. (2017) emphasized the use of resilience training as a risk management approach to enhance the adaptability of firms when confronted with SC interruptions and other types of uncertainty. There is frequently a perceived direct relationship between disruptive occurrences and the incidence of SCC. However, there is a dearth of information in the current academic literature on how SCR and adaptation operate that might shed light on the disruptions brought on by the COVID-19 pandemic (Chowdhury et al., 2021). Hence, additional research is needed to enhance our understanding of strategies to maintain the adaptability and resilience of SCs in the presence of unforeseen disruptions such as the COVID-19 pandemic (Schleper et al., 2021). The COVID-19 pandemic has generated a fresh focus on enhancing SCR because of its ability to expose the vulnerability of HCSCs on a global scale (Craighead et al., 2020). The integration of SC enables enhanced operational efficiency via the facilitation of seamless information and commodity flow. Businesses often modify their operational strategy to align with consumer demand more effectively (Khuntia et al., 2021). Jain et al. (2017) suggest that AC plays a critical role in SCR, as it enables the recovery and potential enhancement of SC operations in the aftermath of disruptive events, mitigating their adverse impacts. Li et al. (2020) underscores the importance of adaptive planning and response in the development of surveillance and control measures for identifying and mitigating epidemics in urban environments. Furthermore, research conducted by Kochan and Nowicki (2018) supports the notion that the deployment of AC may have a positive influence on the development of SCR. This is achieved via the reduction of the likelihood of meeting unusual occurrences, the prevention of shock propagation by effectively managing the infrastructure of the SCs, and the prompt recovery from disruptions produced by such shocks. Thus, we *hypothesize the following:*

H3: The internal efficiency (adaptive capabilities) of HSC operations positively affects disruption management (HSC resilience).

2.5. External efficiency and disruption management

Jain et al. (2017) argue that collaborative alliances are crucial in facilitating efficient operations for mitigating SC risks in the presence of disruptions. This assertion is substantiated by the results of a study conducted by Dubey et al. (2020), which posit that when confronted with intricacy, it is imperative for SC stakeholders to collaborate to establish SCR. This collaborative effort serves to diminish the probability of operational disruptions by fostering a collective dedication to transparency throughout the entirety of the sourcing process. As a result, there has been an improvement in response times and the emergence of new commercial opportunities. Furthermore, Chowdhury et al. (2019) have shown that insufficient coordination among SC partners might potentially affect the vulnerability of both the SC and the SCR, hence adversely affecting the integration of overall SC operations. Hence, it is essential for SC experts to cultivate an environment that promotes open communication, effective collaboration, synchronized endeavours, and mutual confidence among all stakeholders engaged in the SC. This will ultimately enhance SCR and consequently optimize overall SC performance. The DCT offers a robust framework for assessing the capabilities of companies to adapt to the modifications and challenges posed by the COVID-19 pandemic (Kähkönen et al., 2021). In a more modern context, Ruel and ElBaz (2021) used the theoretical framework of DCT to examine the concepts of preparation and resilience in the context of the COVID-19 pandemic. The previously discussed part has shown its use as a theoretical framework for investigating strategies to enhance resilience in the context of the epidemic. According to Khuntia et al. (2021), organizations have the potential to enhance their ability to withstand and overcome challenges arising from insufficient supply networks by using integration and collaboration strategies across the whole supply chain. For example, the implementation of automated systems for managing patients' medical records and monitoring their vital signs may support healthcare professionals in monitoring their patients' well-being and tracking any advancements in diagnosis or recovery (Sharma et al., 2022). The facilitation of partner synergies, collaborative planning, and effective information sharing is enabled by SC collaboration. This cooperation plays an important role in the prevention, mitigation, and recovery from disruptions in SC operations, as highlighted by Scholten and Schilder (2015). The importance

of data sharing and collaboration in enhancing the resilience of SCs is shown by the research conducted by Scholten and Schilder (2015). Their results indicate that these practices contribute to improved visibility and agility within SCs. Thus, we *hypothesize the following:*

H4: The external efficiency (collaboration) of HSC operations positively affects disruption management (HSC resilience).

2.6. Moderating effect of supply chain dynamism

The notion of supply chain dynamism (SCD), as articulated by Zhou and Benton (2007) as the rapidity of transformation in goods and processes, is progressively acknowledged as a pivotal factor for enterprises to adeptly manage (Lee et al., 2016). This recognition stems from its capacity to foster agility among SC stakeholders (Zhou and Benton, 2007). To cultivate the essential dynamic skills for flexibility, longevity, and ongoing competitive advantage, organizations must continuously reorganize and refresh their SC's internal and external resources (Agwunobi and Osborne, 2016). The mobility and adaptability of SCs have been studied before (Chiang et al., 2012; Eckstein et al., 2015). Dynamic capabilities, as defined by Mandal and Sarathy (2018), are the company's distinct sensing, learning, and coordinating capacities. With accurate sensing, businesses can plan for the future rather than react to it (Aslam et al., 2018). The concept of sensing involves the use of new technologies to explore, comprehend, and scan client wants in both worldwide and local marketplaces (Agwunobi and Osborne, 2016). The ability to sense, learn, and coordinate gives businesses a leg up in making the most of their current resources, allowing them to spot and investigate environmental problems early on. Similarly, SCD boosts productivity by enabling real-time data exchange. Healthcare organizations can adapt effectively to external and internal environmental changes with the use of sensing capabilities (Bari et al., 2022). Companies may better anticipate their customers' wants and create innovative goods and services with the use of sensing. Using their sensing and learning skills, businesses develop unique products and services that set them apart from rivals and provide them with a competitiveness in the market (Hong et al., 2018). In addition, SCDs aid businesses in managing SC risk and uncertainty by incorporating redundancy and resilience into their operations. This allows businesses to continue supplying customers in the face of shocks such as political unrest, natural disasters, or global pandemics (Gupta et al., 2020). Thus, we hypothesize the following:

H5a: HSC dynamism has a significant moderating effect on the relationship between internal efficiency (adaptive capabilities) and disruption management (HSC resilience).

The design of SCR should aim to limit the risks arising from SCD and safeguard the overall performance of the SC from being compromised by the many uncertainties and disturbances that may be caused by SCD (Grover et al., 2020). Moreover, the research conducted by Wang and Pan (2022) suggests that the use of corporate AITs, fostering SCC, and adapting to external unpredictability might potentially enhance SCR and SC performance. Moreover, Dubey et al. (2020) and Jain et al. (2017) concur that having a comprehensive acknowledgment of SCD is crucial for organizations to enhance SCR and overall performance. According to Saqib and Zhang (2021), SCD facilitates the development of sensing, learning, and coordinating capabilities inside enterprises. This, in turn, allows for the integration of SC partners, hence assuring SC integration. According to Mandal (2017), organizations may achieve a sustained competitive edge by improving their skills in detecting, learning, and coordinating. Hence, it is essential for organizations to enhance their SCD and develop robust SCR to effectively mitigate the impact of disruptive events such as the COVID-19 pandemic (Hayat et al., 2021). Therefore, SCD plays a major role in improving SC integration, allowing enterprises to improve coordination with their upstream and downstream SC partners. Qader et al. (2022) claim that SCD serves as a catalyst for enhanced SC integration and contributes to the increased resilience of organizations in the face of SC disruptions. Thus, we hypothesize the following:

H5b: HSC dynamism has a significant moderating effect on the relationship between external efficiency (collaboration) and disruption management (HSC resilience).

Finally, based on the developed hypotheses, we have proposed a conceptual framework for this study (see Figure 1).

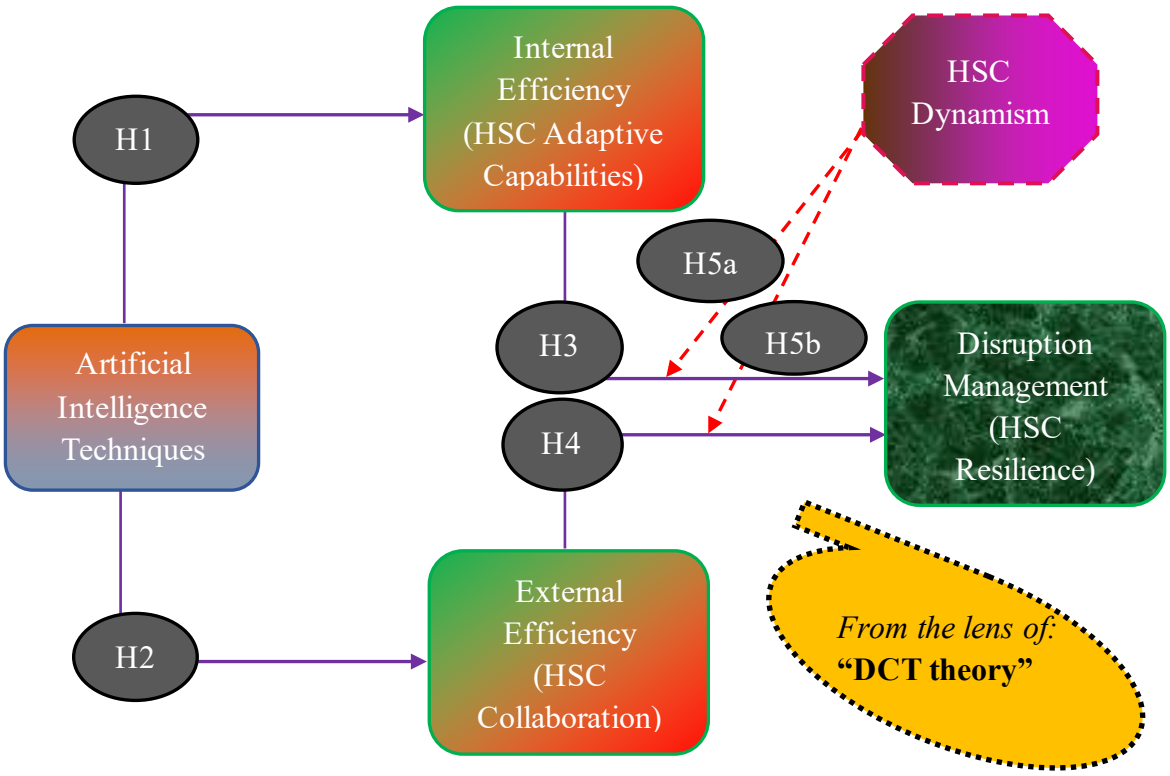

Figure 1: Conceptual framework proposed

3. Research methodology

3.1. Sample, data collection, and measures

Figure 2 illustrates the methodological flow throughout the present research. The authors first proposed a conceptual framework based on a comprehensive review of the existing literature and collaborative brainstorming among the members of the research team. Following this, the conceptual framework was used as a steering instrument for the study's contextual structure. The study uses these factors to guide the selection of constructs that the authors decide to examine. We took two approaches to pre-test our questionnaire survey to ensure that respondents would have no trouble with the questions. Prior to conducting the survey, the survey items were produced in a collaborative process involving the authors, which included a review of relevant literature and a brainstorming session. This process aided us in improving the arrangement and wording of the questions, as well as ensuring the inclusion of all essential elements.

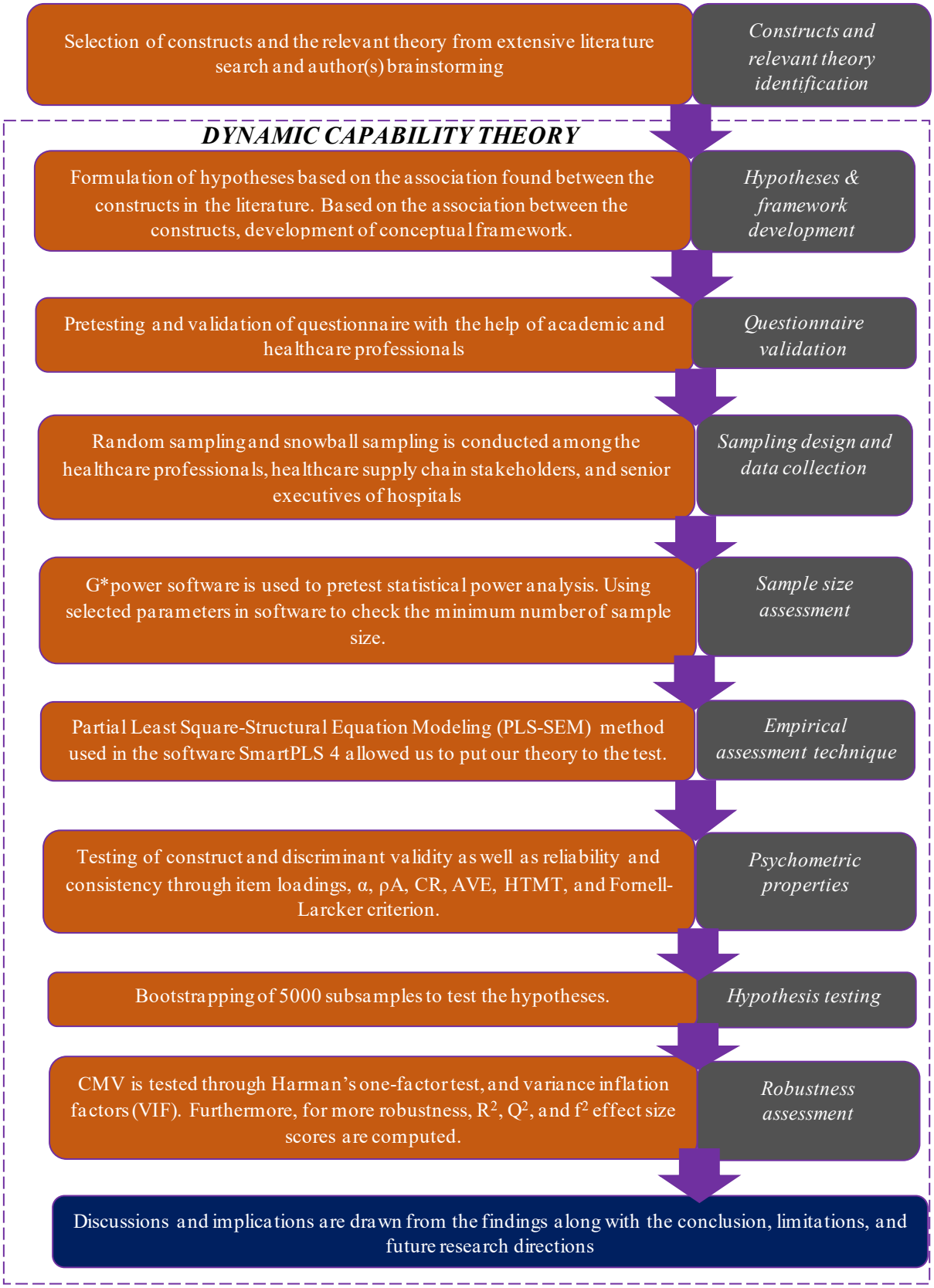

Figure 2: Methodological flow chart of research

The main objective of this study was to assess the superficial validity of the survey and determine the projected time required for responders to complete it. Upon thorough examination of the comments received, we have taken the necessary steps to modify the design, language, applicability to sample sectors, and comprehensiveness of the questionnaire. Additionally, any questions that were deemed irrelevant to the given situation have been eliminated. During the subsequent phase, we initiated communication with a select cohort of industry professionals that had a track record of investing in HSC and/or AI during the preceding period. Given that industry experts and top-level management possess the most comprehensive understanding of SC disruptions and the influence of AI on HSC, we sought their valuable insights via our questionnaire survey. A number of recommendations and comments were identified as very beneficial, particularly in relation to the activities that the authors were required to repeat. The comments provided by the experts were thoroughly examined, and subsequently, our survey questionnaire (Appendix 1) was finalized. A content and face-validated version of our study questionnaire was successfully generated.

The healthcare business in India was selected as a representative sample for our study. India, a burgeoning economy, is diligently striving to enhance its healthcare infrastructure. India is confronted with a challenging task since it is required to accomplish this purpose while simultaneously avoiding any hindrance to its economic progress. The data was collected over the period spanning from October 2022 to March 2023, with a specific emphasis on healthcare enterprises. The healthcare business exhibits a high degree of sensitivity and prioritizes data privacy, resulting in challenges associated with data acquisition. Obtaining data from firms in India may pose challenges, particularly due to the absence of well-established professional networks within the industry. Consequently, in order to get responses from the participants, the authors used many sources, including social networking and personal connections. The research focus of this study pertains to the contemporary and emerging field. Consequently, using the chain referral technique, specifically snowball sampling, we contacted organizations that demonstrate a strong interest and competence in comprehending the importance of AI in their healthcare systems. The use of the chain referral approach serves the purpose of capturing the network structure while simultaneously maintaining the pertinent information (Kolaczyk, 2009). The procedure entails the iterative collection of information from vertices that are related to the vertices obtained in the previous iteration (Chan, 2020). Moreover, this method offers a cost-effective solution for the

collecting of samples. According to Chan (2020), academic researchers have the capacity to efficiently acquire substantial volumes of data by gathering information from the vertices connected to the samples in the preceding iteration.

Upon arrival at the businesses, we established contact with the individuals and provided them with a comprehensive explanation of the study's aims. This approach aimed to facilitate their comprehension and encourage their active participation. Through the use of random sampling, an equitable opportunity was provided to all individuals to get involved in the survey. The objective of this strategy is to generate a sample that is typical of the whole population, with the intention of correctly reflecting its features. By using this approach, we successfully established a connection with the participants, hence facilitating the acquisition of unbiased responses. In light of the significance of the dataset pertaining to the resilience of HSC, we have opted to engage in direct, in-person interactions with the participants. This factor contributes to the extended duration required for gathering responses for this survey. Moreover, the participants played a crucial role in spearheading the AI efforts inside their respective businesses across different levels of hierarchy. Based on the factors mentioned earlier, it is evident that the individuals in question will provide a precise and relevant evaluation of the objectives of the present investigation. In the present research, responses are excluded and eliminated from the dataset if they exhibit indications of dishonesty, such as random or haphazard completion of the questionnaire. Furthermore, questionnaires that were incomplete or had brief responses were deemed invalid and therefore excluded from the analysis. This resulted in a final sample size of 335 respondents, after removing the 11 ineligible responses. Table 2 provides an overview of the attributes of the participants.

Table 2: Demographic profile of the respondents

Sample characteristics		Frequency	Percentage (%)
Age	20-25 years	68	20.30
	26-35 years	107	31.94
	36-50 years	113	33.73
	Above 50 years	47	14.03
Gender	Male	279	83.28
	Female	56	16.72

	High school	78	23.28
Education	Graduation	120	35.82
	Post-Graduation	137	40.90
	North	187	55.82
Region	West	79	23.58
	South	40	11.94
	East	29	8.66
	Less than 5 years	32	9.55
Experience in the healthcare sector	6-10 years	38	11.34
	11-25 years	207	61.79
	More than 25 years	90	26.87
Total		**335**	**100%**

Determining the appropriate sample size and carrying out a power analysis are now essential elements in the process of both performing research and reporting the findings of that research (Kang, 2021). Calculating sample size and power is an exceedingly challenging and time-consuming endeavour that necessitates an in-depth understanding of several statistical principles (Kang, 2021). In addition, there is a severe lack of trained programmers, and the price of most commercial software is prohibitively high for any practical application (Kang, 2021). To guarantee the accuracy of the sample, we performed a series of examinations to rule out any potential flaws. To commence, we used a "pretest statistical power analysis" (Cohen, 1988) using G*power software with the following parameters: "a medium effect size (0.15), a statistical power level of 0.95, four predictors, and a confidence level of 0.01%". According to the power study findings, we know that a representative sample of at least 129 businesses is needed for the framework we have presented. Because we have 335 responses, we can claim with absolute certainty that our sample is valid and contains sufficient statistical power to identify differences that are important (Cohen, 1988).

4. Analysis and findings

The “partial least squares-structural equation modeling” (PLS-SEM) method used in the software Smart PLS 4 allowed us to test our theory. Many studies now use PLS-SEM, which has gained popularity (Agarwal et al., 2018; Delic and Eyers 2020). PLS-SEM is considered suitable for analysis based on two key features. In this work, the attention lies on the preference of PLS-SEM over "covariance-based structural equation modeling" (CB-SEM) for the projection of intricate models and the development of theories, as highlighted by Leong et al. (2020). Furthermore, it should be noted that PLS-SEM exhibits less constraints in terms of sample size and the assumption of normal distribution, as highlighted by Leong et al. (2013) and Memon et al. (2017). Hence, the selection of PLS-SEM over CB-SEM was based on the novelty of the correlations under investigation in this research (Henseler et al., 2014).

4.1 Common method variance

Various strategies were used to mitigate and assess the possible influence of common method variance (CMV). Initially, scholars have been implementing the recommendations put forward by Podsakoff et al. (2003) in order to mitigate the impact of CMV on the data gathering procedure. Various procedural remedies may be used to enhance the quality and reliability of research data. These remedies include acquiring explanatory and outcome variables from diverse sources, removing shared scale features, rephrasing questions to minimize ambiguity and social desirability bias, and employing varied phrased questions (MacKenzie and Podsakoff, 2012). It was also made clear to participants that their responses would be kept anonymous and private and that they should react as truthfully as feasible. We also conducted various statistical tests to determine how severe CMV is. First, we used the standard Harman's one-factor test, as recommended by Podsakoff et al. (2003). The outcomes of this experiment indicated that the single factor accounts for just 37.675% (approximately) of the overall variance, which is well below the minimum acceptable level of 50%. Nevertheless, as suggested by Ketokivi and Schroeder (2004), we recognize that a lone Harman test may not provide a reliable evaluation of CMV. As a result, we used a comprehensive method for assessing collinearity to determine variance inflation factors (VIFs). A full collinearity test was also performed to lessen the impact of CMV. The procedure followed by Kock (2017) was followed, which included calculating a VIF for every model component. According to the PLS fit assessment results, there are no VIF values over the cutoff

score of 3.3 (see Table 3) (Kock, 2017), suggesting that CMV did not represent a serious challenge to the researchers.

4.2. Psychometric properties

Following the recommendations of the reflective measurement framework (Hair et al. 2011), we conducted reliability and validity tests on the IE and EE of the firm along with the DM and AI latent constructs shown in Table 2. The data were subjected to tests of "convergent and discriminant validity" for the various constructs. Composite reliability (CR) and Cronbach's alpha (α) scores were calculated to assess the consistency of the measures used to evaluate the constructs, and then the constructs' validity was assessed. Furthermore, "bootstrap confidence intervals" were used to assess if the construct reliability exceeded the prescribed minimal level in a statistically meaningful manner. It is recommended that the "lower limit of the 95% confidence interval (CI)" for construct reliability should exceed 0.70 (Hair et al., 2019). Likewise, it is essential that the construct reliability be notably below the recommended upper level. According to Hair et al. (2019), it is suggested that the "top limit of the 95% CI" for the construct dependability should not exceed 0.95. The findings from Table 3 indicate that the values of construct reliability are between 0.70 and 0.95, which leads to the validity of the constructs used in this research. Furthermore, the reliability of convergent validity was determined using "average variance extracted" (AVE) (Hair et al. 2019). Table 3 shows that across the board, AVE was higher than the threshold of 0.50 indicated for all constructs (Hair et al. 2019). The HTMT measure was used to assess the discriminant validity of concepts, as described by Henseler et al. (2015). Henseler et al. (2015) introduced the HTMT as an alternative method for evaluating discriminant validity in the context of PLS-SEM, offering a more thorough and less restrictive approach for researchers. This approach has a broad scope of applicability across many latent variable methodologies, since its computational process is independent of the specific model estimates (Franke and Sarstedt, 2019). The coefficient scores for the HTMT constructs in Table 4 are all statistically significant and are found to be lower than the maximum threshold of 0.85. According to Henseler et al. (2015), Furthermore, we conducted a comparison between the square roots of the AVE and the correlation coefficients among the latent variables, as suggested by Fornell and Larcker (1981). Each construct has high discriminant validity, as seen in Table 4 (all AVE square root values are above the corresponding correlations with other constructs).

Table 3: Construct reliability and validity measures

Constructs	Item code	Loadings	VIF	α	ρA	CR	AVE
Artificial Intelligence Techniques (AITs)	AIT1	0.804	2.048	0.904	0.906	0.926	0.675
	AIT2	0.830	2.306				
	AIT3	0.802	2.228				
	AIT4	0.801	2.093				
	AIT5	0.841	2.434				
	AIT6	0.849	2.468				
Internal Efficiency (IE)	IE1	0.834	1.864	0.834	0.839	0.889	0.668
	IE2	0.835	1.892				
	IE3	0.801	1.780				
	IE4	0.798	1.766				
External Efficiency (EE)	EE1	0.828	2.019	0.871	0.874	0.906	0.658
	EE2	0.810	1.987				
	EE3	0.791	1.879				
	EE4	0.810	1.996				
	EE5	0.818	1.913				
Disruption Management (DM)	DM1	0.879	2.461	0.885	0.891	0.921	0.744
	DM2	0.813	1.929				
	DM3	0.887	2.596				
	DM4	0.870	2.381				
HSC Dynamism (HSCD)	HSCD1	0.822	1.553	0.815	0.825	0.890	0.730
	HSCD2	0.895	2.187				
	HSCD3	0.845	2.012				

Table 4: Discriminant validity (HTMT and Fornell-Larcker criterion)

	Heterotrait-monotrait ratio (HTMT) criterion				
	AIT	**DM**	**EE**	**HSCD**	**IE**
AIT	-				
DM	0.544				

EE	0.605	0.561			
HSCD	0.339	0.478	0.309		
IE	0.684	0.567	0.666	0.374	-

Fornell-Larcker criterion

	AIT	**DM**	**EE**	**HSCD**	**IE**
AIT	**0.821**				
DM	0.488	**0.863**			
EE	0.542	0.498	**0.811**		
HSCD	0.298	0.411	0.262	**0.854**	
IE	0.597	0.493	0.567	0.311	**0.817**

Moreover, the convergent threshold (Hair et al., 2019) is met for all latent variables, meaning that all factor loadings are more than 0.4, which is the least threshold for exploratory research (Delic and Eyers 2020). In conclusion, the results from our construct measurement tests indicate that all constructs we used to create our measurement model are reliable and discriminantly valid.

4.3. Synergies between AI techniques, IE, EE, DM, and HSCD (hypothesis testing)

The primary focus of our investigation is to determine the impact of AI, IE, and EE on the operations of HSC and to test the hypothesis that these factors have a multiplicative influence on the DM of HSC operations. We examined each response thoroughly, whittling the final sample down to 335 after discarding the ones that did not fit our selection criteria. Hypothesis testing within the framework of PLS-SEM often involves the computation of a p value for each path coefficient (Kock, 2015). To test the hypothesis that the estimated coefficient β is greater than zero, we perform a statistical analysis at a significance level of 0.05 (or a CI of 95%). This involves calculating the two-tailed p value related to path coefficient. The hypothesis is accepted if the p value is ≤ 0.05; otherwise, it is rejected (Kock, 2016). To perform the same examination using a 95% CI, it is necessary to compute the lower and upper boundaries of such a CI. The supplied values are represented as β −1.96*standard deviation (*STDEV*) and β +1.96* standard deviation (*STDEV*), respectively. If the value of zero does not lie inside this interval, denoted as "$0 \notin$ CI", then the hypothesis is accepted (Kock, 2016). Conversely, if zero is within the interval, denoted as "$0 \in$ CI", the hypothesis is rejected (Kock, 2016). Therefore, we have taken two criteria to accept or reject the hypothesis. First, the p value should be ≤ 0.05 for hypothesis acceptance. In the second parameter, zero should not lie between the values of β −1.96**STDEV* and β +1.96**STDEV* for

accepting the hypotheses. If either of the criteria was not met during the analysis, we rejected the hypotheses.

H1: AI techniques positively influence the internal efficiency (adaptive capabilities) of HSC operations.

Path model H1 evaluation is shown in Figure 3. The R^2 value (0.356) was more than the arbitrary threshold of 0.10 (Hair et al. 2016). The f^2 effect size of 0.553 was found, which indicates that the widespread use of AI techniques has a substantial impact on the IE of HSC operations (Hair et al., 2017). In addition, the results of the Stone-Geisser test ($Q^2 > 0$;0.231) showed a high level of cross-validated predictive relevance. Last but not least, a bootstrap process applied to the data confirmed the significant correlation between AI techniques and IE of HSC operations (β = 0.597; t = 11.103; p = 0.000; 0 ∉ CI).

H2: AI techniques positively influence the external efficiency (collaboration) of HSC operations.

Figure 3 illustrates the outcomes of our assessment of the H2 path model. The R^2 value (0.293) was higher than the threshold score of 0.10 (Hair et al. 2016). The f^2 effect size of 0.415 obtained suggests that the AI techniques' pervasive adoption has a major effect on the EE of HSC operations (Hair et al. 2017). Additionally, the Stone-Geisser test demonstrated a high level of cross-validated predictive relevance (Q^2> 0; 0.187). Finally, the bootstrap method suggests a validated relationship between AI methods and the EE of HSC operations (β = 0.542; t = 9.989; p = 0.000; 0 ∉ CI).

H3: The internal efficiency (adaptive capabilities) of HSC operations positively influences disruption management (HSC resilience).

H4: The external efficiency (collaboration) of HSC operations influences disruption management (HSC resilience).

In Figure 3, through a similar way of assessing H1 and H2, we have assessed the evaluation of H3 and H4. The R^2 value (0.387) was higher than the threshold score of 0.10 (Hair et al., 2016). The f^2 effect size of 0.051 for H3 and 0.082 for H4 is obtained from the analysis, which indicates the major influence of IE and EE of HSC operations on DM (Hair et al., 2017). Additionally, the Stone-Geisser test demonstrated a high level of cross-validated predictive relevance ($Q^2 > 0$;

0.275). Finally, the bootstrap method revealed a significant relationship between the IE of HSC operations and DM ($\beta = 0.226$; $t = 3.264$; $p = 0.001$; $0 \notin$ CI) and the EE of HSC operations and DM ($\beta = 0.278$; $t = 4.339$; $p = 0.000$; $0 \notin$ CI).

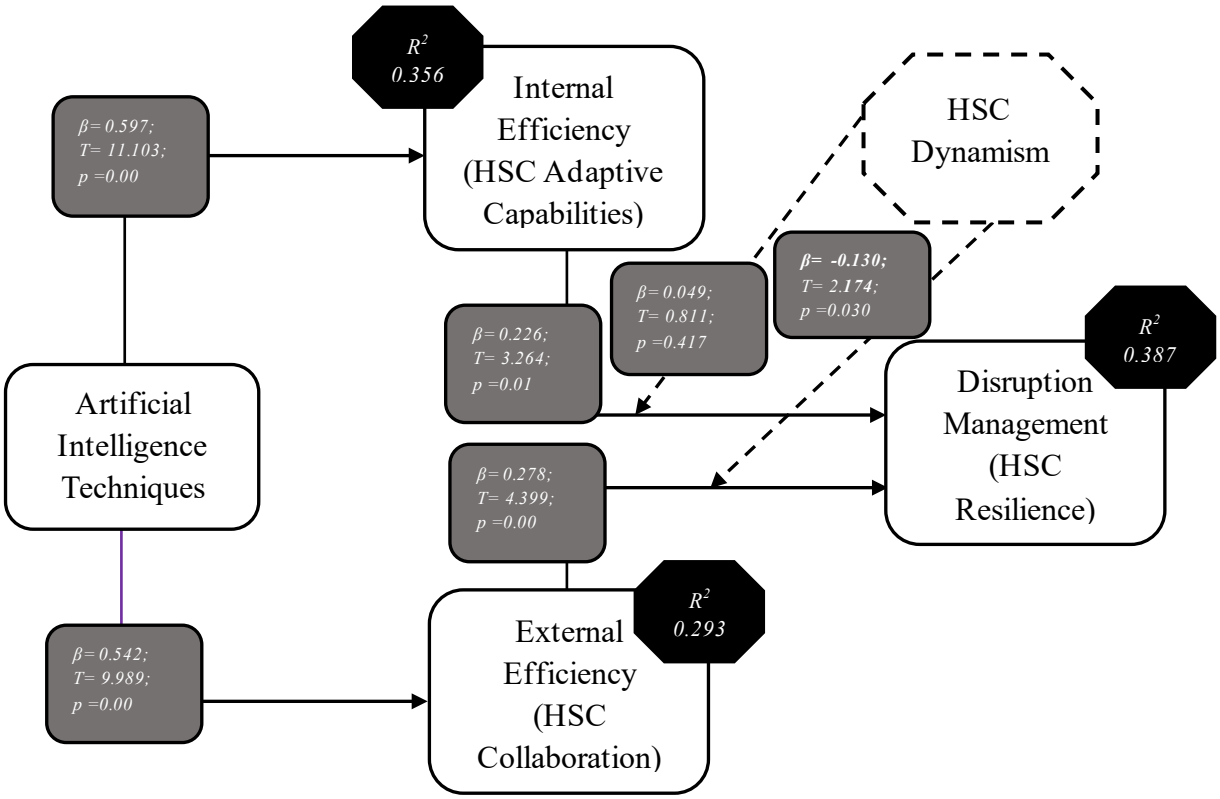

Figure 3: Empirical validation of the framework

H5a: HSC dynamism has a significant moderating effect on the relationship between internal efficiency (adaptive capabilities) and disruption management (HSC resilience).

H5b: HSC dynamism has a significant moderating effect on the relationship between external efficiency (collaboration) and disruption management (HSC resilience).

The framework (refer to Figures 1 and 3) included HSCD as a moderating variable. The interaction effect of HSCD and IE was observed for H5a. In Figure 3, the values indicate that the interaction of HSCD and IE (HSCD×IE) does not have a significant impact on DM. In other words, the values of $\beta = 0.049$, $t = 0.811$, $p = 0.471$, and $0 \in$ CI indicate that HSCD does not moderate the relationship between IE and DM. Therefore, hypothesis H5a is rejected. Furthermore, for H5b, in Figure 3, the

results suggest a negative effect of HSCD×EE on DM. A negative moderation effect of HSCD on the association between IE and DM is suggested by the values of β = -0.130, t = 2.174, p = 0.030, and 0 ∉ CI. Thus, the results suggest that HSCD negatively moderates the EE and DM relation. Therefore, hypothesis H5b is accepted. For hypotheses H5a and H5b, we did not follow the directional approach for moderation checking, which may be indicative of a positive or negative impact on the main (exo and endo variables) relationships due to inconsistent previous findings for hypothesis formulation. However, the path coefficient (β) clearly indicates the positive (strengthening) or negative (weakening) impact of the moderating effect on the main variables. Furthermore, the results of hypothesis testing are given in Table 5.

Table 5: Hypothesis testing results

Relationship	**Path coefficient (β)**	***β- 1.96* STDEV***	***β+ 1.96* STDEV***	**T value**	***p value***	**Hypothesis**	**Decision (Acceptance/ Rejection)**
Direct effect							
AIT→IE	0.597	0.491	0.702	11.103	0.000	H1	Acceptance
AIT→EE	0.542	0.435	0.648	9.989	0.000	H2	Acceptance
IE→DM	0.226	0.090	0.362	3.264	0.001	H3	Acceptance
EE→DM	0.278	0.154	0.402	4.399	0.000	H4	Acceptance
Moderation effect							
HSCD × IE→DM	0.049	**-0.070**	**0.168**	0.811	**0.471**	H5a	**Rejection**
HSCD × EE→DM	-0.130	-0.247	-0.013	2.174	0.030	H5b	Acceptance

Note: There is only a relationship (HSCD × IE→DM), for which zero lies between β- 1.96 STDEV and β+ 1.96* STDEV.*

4.4. Interaction effect analysis

In order to provide further insight into the moderation analysis, we have generated visual representations in the form of interaction graphs, which can be seen in Figures 4 and 5. Additionally, we have compiled the relevant statistical information in Tables 6 and 7. The process involves constructing a set of straightforward regression equations and afterwards computing the anticipated values of the reliant variable at both elevated and diminished levels of the variables

that are predicted (Aiken et al., 1991; Dawson 2014). According to the study conducted by Cohen et al. (2015), the high levels were defined as one standard deviation above the mean or average, whilst the low levels were defined as one standard deviation below the mean or average. Following the charting of the interactions, we conducted basic slope analyses to examine the statistical significance of the deviations from zero in the gradients of the simpler regression lines (Aiken et al., 1991). The analysis of the slopes shown in Figure 4 and Table 6 revealed a strong positive correlation between IE and DM when HSCD was at a low level (β = 0.471; p < 0.001). Nevertheless, in cases when the HSCD is high, there is no substantial correlation shown between IE and DM (β = 0.325; p = 0.007). In a similar vein, our analysis of the slopes shown in Figure 5 and Table 7 revealed a statistically significant positive correlation between EE and DM at lower levels of HSCD (β = 0.533; p < 0.001). There was no statistically significant association seen between EE and DM for high levels of HSCD (β = 0.274; p = 0.015). In summary, the findings suggest that the adaptive and collaborative capabilities of HSC have a notable and favorable influence on DM when the degree of HSCD is relatively low. However, when considering a high degree of HSCD, the influence of HSC adaptive and collaborative capacities on DM seems to be negligible.

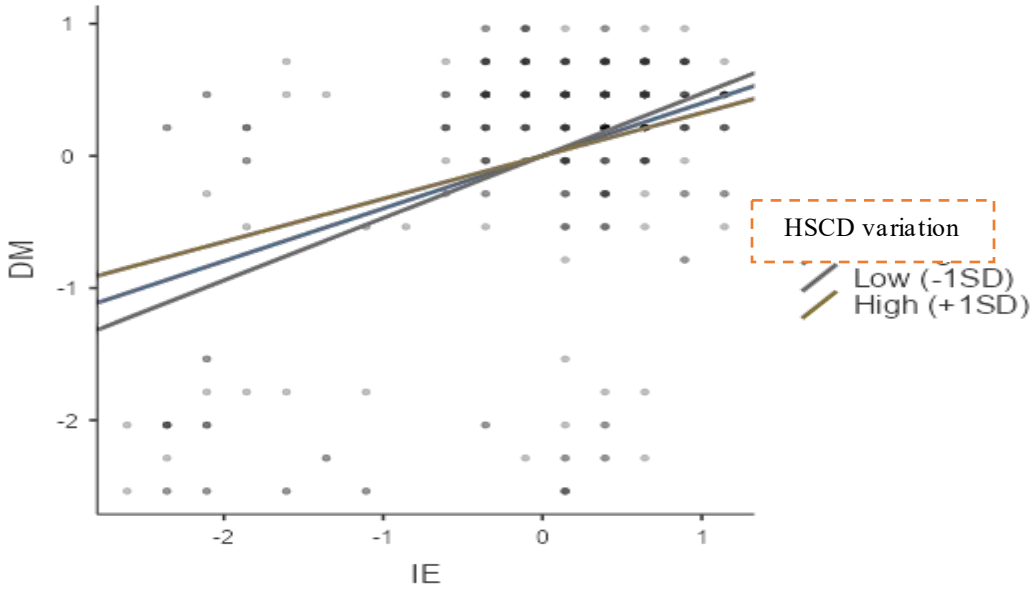

Figure 4: Illustration of the interaction effect between IE and DM with HSCD as the moderator

Table 6: Results of IE and DM interaction due to moderator variation

Moderator variation	Estimate (*β*)	Standard Error (SE)	95% Confidence Interval		Z - value	p- value
			Lower	Upper		
Average	0.398	0.0804	0.2373	0.550	4.95	< .001
Low (-1SD)	0.471	0.0703	0.3292	0.605	6.70	< .001
High (+1SD)	0.325	0.1196	0.0795	0.544	2.72	0.007

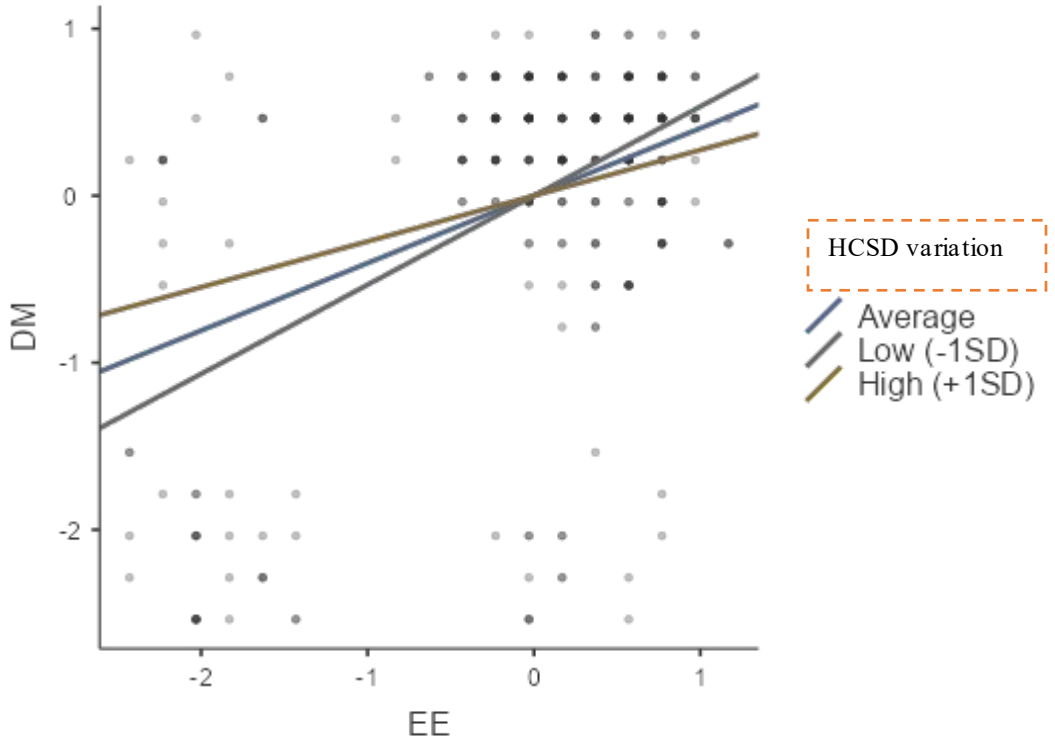

Figure 5: Illustration of the interaction effect between EE and DM with HSCD as the moderator

Table 7: Results of EE and DM interaction due to moderator variation

Moderator variation	Estimate (*β*)	Standard Error (SE)	95% Confidence Interval		Z - value	p- value
			Lower	Upper		
Average	0.404	0.0750	0.2579	0.544	5.39	< .001
Low (-1SD)	0.533	0.0673	0.3959	0.658	7.93	< .001
High (+1SD)	0.274	0.1131	0.0432	0.496	2.42	0.015

5. Discussion and implications

Our study primarily concentrated on the potential enhancements that AITs might bring to the IE and EE of HSC operations. Furthermore, we have examined the potential influence of these aspects on the DM involved in HSC operations. Additionally, we investigated the moderating influence of HSCD on the relationship between IE of HSC operations and DM, as well as the effect of EE of HSC operations on DM. Our first hypothesis, which examines the relationship between AITs and IE of HSC operations, is corroborated and consistent with the prior research conducted by Ivanov et al. (2019) and Grover et al. (2020). One potential rationale for endorsing this concept is the use of advanced technological tools to enhance strategies in the HSC, hence fostering resilience within the system. Moreover, the acceptance of the second hypothesis, which investigates the favorable impact of AITs on the EE of HSC operations, is corroborated by the existing scholarly literature (Helo & Hao, 2021). One potential explanation for the favorable impact of AITs on the EE of HSC operations is the ability of AI to facilitate collaboration among various stakeholders involved in HSC. Hypothesis three examines the correlation between the IE of HSC operations and DM. This concept is also widely acknowledged and aligns with the results of previous studies conducted by Jain et al. (2017) and Kochan and Nowicki (2018). The inclusion of AC is of significant importance in SCR as it facilitates the restoration and potential improvement of SC operations after disruptive events, hence lessening their negative effects. This might perhaps explain the acceptance of the third hypothesis. The fourth hypothesis, which

examines the correlation between the EE of HSC operations and DM, appears to be valid based on the substantial standard coefficient values. This finding is further reinforced by the prior research conducted by Jain et al. (2017) and Khuntia et al. (2021). The lack of coordination among SC partners has the potential to impact the vulnerability of both the SC and the SCR, hence negatively influencing the integration of overall SC operations. Therefore, it is essential for SC professionals to foster an atmosphere that encourages transparent communication, efficient cooperation, coordinated efforts, and mutual trust among all stakeholders involved in the SC. Two aspects of HSC operations piqued our curiosity in this area. Before anything else, there has been a dramatic increase in the number of HSC stakeholders that recognize the need for AITs in fostering adaptability and collaboration to provide HSCR (DM) in the operations of the healthcare sector. Most of these efforts during HSC DM operations, however, are documented in the management literature. Second, a DCT has been employed in previous research to clarify the HSCR for their operations. As the frequency and severity of natural and manmade disruptions have increased, AITs, HSCC, and HSCC have become standard procedures in the operations of most enterprises. The HSCR is designed to ensure business as usual, so the operations of SC may continue functioning normally even after experiencing disturbances. Using examples drawn from studies of commercial supply chains, we suggest that the DCT as a theoretical lens is especially applicable here.

Our conceptual paradigm was strengthened by our recognition of SCD's role in HSC operations. As a result, we believe that HSCD is a moderating factor. In most cases, SCR should be established to protect high levels of SC performance from the myriad of unexpected and disruptive consequences that SCD may have on SC operations (Grover et al., 2020). SCD's moderating effect sheds light on how HSC variation works. Of course, we could only get a good idea of how the organization deals with the SCD issue if we focused on a very small sample. This is a fantastic unexplored area of study. Interesting and potentially useful conclusions may be drawn from this research on the connections and interplay of AITs, IE, EE, and DM in the context of SC operations. Our findings have both practical and theoretical consequences and point to new directions for research in this area. Improvements in SCR and operational performance may result from a combination of corporate AITs, SCC, and external uncertainty (Wang and Pan 2022). Furthermore, our study provides empirical support for the hypotheses that AITs have a relationship to IE and EE and that IE and EE have a relationship to DM in the setting of HSC operations.

Improvements in SC engagements, SC integration, and stakeholder collaboration may result from genuine information exchange associated with AI (Helo and Hao 2021). In particular, Baryannis et al. (2019) emphasized how AITs may provide exact and up-to-date assessments and near-real exposure of inventories, hence resolving collaboration issues between stakeholders caused by demand and supply fluctuations in operations. An SCR's AC is crucial because it lessens the blow of shocks and allows SC operations to return to (and even exceed) where they were before a catastrophe struck, as stated by Jain et al. (2017). Dubey et al. (2020) argue that all stakeholders involved in the SC must work together to develop SCR, therefore decreasing the likelihood of disruption via a shared dedication to transparency across the board in the sourcing process. Additionally, we discovered divergent findings for the interaction impact of HSCD and IE on DM. The empirical findings show that the relationship between HSC operations' IE and DM is not moderated by HSCD. Given that prior research (Bari et al., 2022; Gupta et al., 2020) has shown a favorable influence of HSCD on the relationship between IE of HSC operations and DM, our study rejects hypothesis H5a. The second moderating impact of HSCD on the relationship between EE and DM in HSC operations is also negative. Since prior research (Hayat et al., 2021; Qader et al., 2022) suggests that HSCD has a beneficial influence on the relationship between the EE of HSC operations and DM, H5b is accepted but contradicts the literature, as the literature favors the positive effect of HSCD on the relationship between the EE of HSC operations and DM. Furthermore, to clarify the contradictory results, as per Tables 6 and 7, both H5a and H5b are accepted only at a low value of HSCD, i.e., -1 SD; however, both hypotheses are rejected at a high level of HSCD, i.e., +1 SD. Therefore, H5a has consistent results at high levels of HSCD, and H5b has consistent results at low levels of HSCD.

5.1. Theoretical implications

There has been much discussion about the importance of AITs in the field of HSC operations (Arnold and Wilson 2017). Concerning HSCA and HSCC, little is known about the impact of AITs from the operations perspective. Applying the theoretical lens of DCT, this research aids in expanding our knowledge in this field. There are two methods through which this is accomplished. First, we analyze the impact of AITs on IE and EE of HSC operations and how IE and EE of HSC operations, as unique but not particularly infrequent activities, have on DM. The degree to which a corporation can integrate new information and reorganize itself quickly in

response to internal and external changes is reflected in its DCs (Huo et al. 2016). DCs, as outlined by Brusset and Teller (2017), allow businesses to define their desired enhancements to existing functional capabilities throughout the operations of SCs. The DCT was developed from the idea that a firm's capabilities are its greatest competitive asset. We backed this approach and suggested that AITs can be utilized as a DC to help IE and EE of HSC operations improve so they can better provide the DM and gain a competitive edge within operations management. Consequently, it makes far more sense to use the DCT to clarify how AITs become the capacity, aid in enhancing IE and EE of HSC operations and advance DM.

The second argument is based on Bromiley and Rau's (2016) idea that organizations lack knowledge of the behaviors that may be beneficial to them owing to restricted rationality. This is why we believe that AITs, HSCA (IE), and HSCC (EE) all play a crucial role in determining the HSCR (DM) from the perspective of operations management. To fill a gap in the HSCR literature, we developed research questions (RQs): "How can the adaptation capability (IE) and collaboration (EE) of HSC operations contribute to the resilience of HSCs?" For this RQ, we conducted empirical research to examine possible connections between IE, EE, and HSCR. According to our results, IE and EE of HSC operations are both robust predictors of HSCR. These results provide credence to the DCT's central tenet that the corporate environment is in a constant state of flux, making it essential to maintain a dynamic and adaptable perspective for the operations of SC. Thus, the results of our research deepen the DCT proposed by Samsudin et al. (2019) to account for IE and EE of HSC operations as DCs of the company. This research builds upon previous efforts by Jain et al. (2017) and Dubey et al. (2020). For our following RQ, we asked, "What role does AI play in affecting the IE and EE of HSC operations?" to further investigate the DCT. To address this RQ, we conducted empirical tests of the link between AITs and IE/EE of HSC operations and found that it is substantial, lending credence to the findings of Grover et al. 2020 in their prior work on DCT. Our research also reveals how DCT helps to explain the ever-changing nature of the operations of SCs owing to the many internal and external constraints that continue to stifle their productivity and the moderating influence of HSCD on the IE/EE of HSC operations and the DM relationship. These results expand upon the previous work by Lee et al. (2016).

5.2. Managerial implications

This research provides helpful guidance for HSC operation managers who are responsible for DM activities. First, HSC operation managers need to understand the importance of both IE and EE in HSC operations to reap the advantages of DM. When analyzing the relationship between HSCAC (IE) and HSCC (EE) of HSC operations, we discovered that both are very advantageous features of the HSC that significantly affect HSCR (DM). For instance, according to the most recent study results from the "Agile Procurement Insights Research", which was undertaken by SAP in partnership with Oxford Economics, procurement operations that allow larger adoption of technology, such as AI and robotics, accomplish greater corporate advantages. These advantages include the enhanced performance of suppliers, higher process efficiency and cost benefits, greater conformance, and enhanced transaction precision (Smedberg 2021). Furthermore, Smedberg (2021) states that "A business' future ability to pivot will have a lot to do with maintaining the flow of information in the operations of supply network through digital channels and collaboration with a partner ecosystem".

As a second finding, we discovered that AITs significantly affect the HSCA (IE) and HSCC (EE) of operations. If HSC operation managers respond to DM by providing HSCA or HSCC based on an AIT's capabilities, then those operation managers are more likely to be adaptable. For example, an AI-focused tool organizes data from SC operations, enabling manufacturers, retailers, and pharmacies to forecast and evaluate procurement, delivery methods, and total costs more accurately (ETHealthworld 2022). Additionally, to retain a diversified collection of suppliers and fend against disruptions, HSC operations can use AITs to combine supplier data (Stewart 2022). Finally, HSCD acts as a negative moderator of the association between EE and DM. Consequently, HSC operation managers might be alert to HSCD while employing the EE of HSC operations to enhance the performance of the DM. Because the appearance of SCD will negate EE's beneficial impact on DM, EE will not function well when SCD is present. As a result of SCD, for instance, inadequate stock levels are the outcome of overordering in response to inaccurate projections. Having too much stock on hand may be pricey for businesses, and if sales do not go up, that is money that was squandered (Ohiouniversity 2022). However, if you do not have enough items, you could have to turn away customers since you cannot complete their purchases (Ohiouniversity 2022). Companies may incur high costs as a result of these errors in their operation (Ohiouniversity 2022).

6. Conclusion, limitations and future research

Our research aimed to understand the impact that AI methods, IE, and EE of HSC operations had on HSC DM by way of HSC inherent resilience. Our primary interest was in learning how AI helps to improve the operations of HSC for DM, which is how IE and EE help. Data from this study indicate that HSCD acts as a negative and substantial moderator of the associations between EE and DM. These results provide a novel and practical understanding of the expanding literature on DM, EE, and IE within the context of operations management. In addition, our research shows that the use of AI methods, IE, and EE of HSC operations are all favorably associated with HSC DM. Significant theoretical and managerial insights are provided, although there are still some gaps in the research. The sheer pace of various technologies in such fields may represent a barrier to our operationalization of AI approaches and HSC robustness. There is a steady influx of cutting-edge innovations in HSC, such as blockchain technology, big data analytics, and more interoperable digital systems. In addition, we used statistical tests to ensure that the sample was representative, analyzed the data using PLS and bootstrapping, and double-checked the accuracy of the replies from a random subset of respondents to thoroughly address any potential problems. Additionally, we were unable to obtain complete data from the businesses that fell outside the parameters of our survey. Thus, in the future, researchers might take on a comparative assessment of relative performance between AI methods with HSC-funded firms and those that invest in AI techniques without investing in HSC, with the appropriate controls in place.

Our survey respondents were senior executives and supply chain stakeholders who had limited familiarity with the difficulties of DM analysis and quantification. The study's variables might therefore include not only quantitative factors but also qualitative factors such as supply chain size, population, and hospital types. This research may help businesses comprehend the potential advantages of using AI approaches to strengthen their HSC operations by enhancing IE and EE. Although our research was conducted only in the Indian healthcare sector, its results may be of particular use to other developing countries. Future research may want to expand the suggested technique to other regions/industrial areas to compare and contrast the similarities and differences between these settings. The authors also recommend doing single and multicase studies on the uptake of AI approaches in HSC to better comprehend the adoption process and the factors

at play in the observed variations in acceptance and subsequent advantages across industries and geographic locations. Our conceptual and empirical models would benefit from being tested in other geographical, industrial, legal, and cultural settings; hence, we recommend future studies using larger, multiregional and national datasets to do so.

Data availability statement

Data related to this article are available upon request.

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