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Analysis of the adoption of emergent technologies for risk management in the era of digital manufacturing

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Analysis of the adoption of emergent technologies for risk management in the era of digital manufacturing

Abstract

The Industry 4.0 (I4.0) revolution has led to rapid digital transformation, automation of manufacturing processes and efficient decision-making in business operations. Despite the potential benefits of I4.0 technologies in operations management reported in the extant literature, there has been a paucity of empirical research examining the intention to adopt I4.0 technologies for managing risks. Risk management identifies, assesses, and introduces responses for risks to avert crises. This study combines institutional theory, the resource-based view and the technology acceptance model to develop a novel behavioural model examining the adoption of big data, artificial intelligence, cloud computing, and blockchain for risk management from the operations manager's perspective, which has never been examined in the literature. The model was tested for each I4.0 technology using data collected from 117 operations managers in the UK manufacturing industry which were analysed using structural equation modelling. We contribute to the theory on I4.0 in digital manufacturing by showing the impact of digital transformation maturity, market pressure, regulations, and resilience on the perceived usefulness and adoption of these technologies for managing risks in business operations. Based on the findings, we discuss implications for operations managers effectively and efficiently to adopt I4.0 technologies aiming to boost operational productivity.

Keywords: Risk management, emergent technologies, digital manufacturing, Industry 4.0, structural equation modelling

1. Introduction

The survival of organisations has been threatened by challenges ranging from internal disruptions to global catastrophes (Baghersad and Zobel, 2021; de Sousa Jabbour, Jabbour, Foropon and Godinho Filho, 2018; Rodríguez-Espíndola, Alem and Pelegrin Da Silva, 2020). The way companies handle those situations is currently in the spotlight due to the impact of the SARS-CoV-2 pandemic. Given the importance of understanding potential threats and alternatives to react and adapt to uncertain, chaotic, and changing conditions, risk management has gained increasing attention in global supply chains (MacCarthy, Blome, Olhager, Srai Jagjit and Zhao, 2016). It allows companies to identify, analyse, respond to, and control vulnerabilities to manage disruptions (Kodym, Kubáč and Kavka, 2020), which can have significant effects on resilience and business continuity.

Risk management, however, is a complex function facing multiple challenges. The increasing interconnectedness of stakeholders in supply chains has improved operations, but at the same time, it has created a dependency among firms, causing vulnerability to disturbances (Mwangi, Despoudi, Espindola, Spanaki and Papadopoulos, 2021). Currently, risk management faces a combination of massive amounts of information collected (Papadopoulos, Gunasekaran, Dubey, Altay, Childe and Fosso-Wamba, 2017) and the uncertainty about vulnerabilities and disruptions, which affects the efficiency and effectiveness of operations (Comes, Van de Walle and Van Wassenhove, 2020). Risk management requires consolidating and compiling multiple datasets in heterogenous formats, deriving strategic insights from voluminous and high-velocity data, undertaking complex financial monitoring, managing poor visibility and traceability in the supply chain, reducing discrepancies stemming from manual reporting, and managing conflicting information because of the absence of a central shared database. The effectiveness of these activities has a significant effect on risk planning, prediction and crisis management (Lee and Marc, 2003). For instance, the data breach in Fargo Wells showed the importance of risk management when looking at cybersecurity and the management of information. To reap the benefits of improved information management, automated decision support systems need to become a liaison between stakeholders and management stages (Ozdamar and Ertem, 2015), enabling managers to make sense of the information and use it to support decision-making (Comes, Van de Walle and Van Wassenhove, 2020). Indeed, in many cases, the problem has shifted from collecting and storing data to turning the information obtained from digital data streams into knowledge and actionable insights (Günther, Rezazade Mehrizi, Huysman and Feldberg, 2017). Emergent technologies coming from digital manufacturing have been suggested as suitable options to improve data-centric mechanisms to identify, analyse, and develop responses to risk and vulnerabilities.

Digital manufacturing involves the use of digital models and ontologies to digitalise the different stages of a networked company (Borangiu, Trentesaux, Thomas, Leitão and Barata, 2019). Digital manufacturing is seen as "the effect of digital transformation in manufacturing, driven by technology enablers such as the Internet of Things (IoT), cloud computing (CC), artificial intelligence, big data analytics, virtualisation and augmented reality" (Szalavetz, 2019). Therefore, digital manufacturing and information systems can allow integrated operations through the implementation of I4.0 (Szalavetz, 2019; Annarelli, Battistella, Nonino, Parida and Pessot, 2021; Lopes de Sousa Jabbour, Jabbour, Godinho Filho and Roubaud, 2018; Büchi, Cugno and Castagnoli, 2020), which will lead to connectedness and autonomous intelligence, where humans and technology have to collaborate to create strategic value for organisations (Reiman, Kaivo-oja, Parviainen, Takala and Lauraeus, 2021). I4.0 can be defined as a technological revolution redefining the manufacturing industry through the implementation of technologies that can improve the management of value supply chains and their related processes (Büchi, Cugno and Castagnoli, 2020; Reischauer, 2018). It allows the introduction of emergent technologies, allowing manufacturing companies to improve and innovate (Reischauer, 2018).

Following the debate about the way new digital technologies are changing manufacturing (Reischauer, 2018), I4.0 technologies (e.g. artificial intelligence, blockchain, CC and big data) have shown several potential benefits in supply chains to improve robustness, accuracy, transparency, accountability, and decision-making (Dubey, Gunasekaran, Bryde, Dwivedi and Papadopoulos, 2020; Fosso-Wamba and Queiroz, 2020; Dwivedi, Hughes, Ismagilova, Aarts, Coombs, Crick, Duan, Dwivedi, Edwards, Eirug, Galanos, Ilavarasan, Janssen, Jones, Kar, Kizgin, Kronemann, Lal, Lucini, Medaglia, Le Meunier-FitzHugh, Le Meunier-FitzHugh, Misra, Mogaji, Sharma, Singh, Raghavan, Raman, Rana, Samothrakis, Spencer, Tamilmani, Tubadji, Walton and Williams, 2019). For example, the Denver-based organisation Bext360 has integrated artificial intelligence (AI) systems and blockchain technology into a cloud platform that will help to enhance supply chain efficiency and transparency in the mineral, timber, coffee, and seafood sectors (Bext360, 2019). Common examples of advantages that can benefit risk management in supply chains include information sharing, consolidation and knowledge mining across the supply chain (Dev, Shankar and Swami, 2020), resource efficiency, asset utilisation and higher throughput due to accurate forecasting (Telukdarie, Buhulaiga, Bag, Gupta and Luo, 2018), data-driven management decision-making from sensor-based technologies (Dalenogare, Benitez, Ayala and Frank, 2018), operational flexibility, efficiency and performance (Frank, Dalenogare and Ayala, 2019), and aid digital transformation within organisations to help achieve sustainable business performance through business model innovation (Lopes de Sousa Jabbour, Jabbour, Godinho Filho and Roubaud, 2018; Bag, Gupta and Kumar, 2021). For instance, DHL worked with Accenture to improve information resilience by using blockchain to reduce tampering or counterfeiting drug issues in the pharma industry, thereby increasing transparency, traceability and trackability. Another example is the way production managers can gain a remote digital view of all machines in a factory by using a cloud monitoring software solution, which will enable them to view the performance and efficiency of each piece of equipment (IBM, 2019). Hence, managers are becoming increasingly aware of the value of I4.0 technologies for risk management. A survey of 3,000 C-suite executives found that a total of 29% and 56% of them in banking and insurance, respectively, identified AI as a function that could benefit their operations (Deloitte, 2021).

Another advantage of digital manufacturing technologies is that they can potentially enhance the resilience of stakeholders affected by damaged supply chains resulting from climate change and other shocks (James, 2017). This has resulted in calls for novel research looking to support the transformation of manufacturing through the improvement of adaptation to dynamic environments and enhanced risk management (Borangiu, Trentesaux, Thomas, Leitão and Barata, 2019). Harnessing I4.0 technologies' potential for risk management would allow companies to create more robust systems and become more resilient to disruptions (Rodríguez-Espíndola, Chowdhury, Beltagui and Albores, 2020) because of their capacity to mitigate risk at different stages (Khajavi, Partanen, Holmström and Tuomi, 2015). For instance, Cepham has introduced blockchain to assess the quality of the products before they are consumed by the customers to alleviate risks of product quality at the production and consumption stages.

Despite the potential benefits studied in the literature (Bag, Gupta and Kumar, 2021) and outlined in research reviews (Frank, Dalenogare and Ayala, 2019; Zheng, Ardolino, Bacchetti and Perona, 2021; Papadopoulos, Singh, Spanaki, Gunasekaran and Dubey, 2021), the adoption of emergent technologies in risk management is at an early stage (Baryannis, Validi, Dani and Antoniou, 2019). Leveraging I4.0 technologies is far from trivial. The challenges to adopting these new-age I4.0 technologies are myriad due to lack of skilled labour and technical know-how, financial constraints, operational complexities, lack of information management strategy, limited understanding of the return of investment, resistance to adopting and adapting their existing business models and practices, and lack of strategic alignment between business priorities and technological needs of the organisation (Bag, Telukdarie, Pretorius and Gupta, 2018; Raj, Dwivedi, Sharma, Lopes de Sousa Jabbour and Rajak, 2020). User acceptance is key to successfully implementing technology. For example, when Citigroup Inc. wired $900 million by mistake to Revlon's lenders in August 2020, the company claimed the issue was due to human error. Eventually, the problem was traced back to new software with a highly complex user interface (Alcántara, 2021), suggesting that user experience and acceptance was not properly considered for implementation. Therefore, it is important to look at the adoption of these technologies in the risk management context from the managerial perspective (Meindl, Ayala, Mendonça and Frank, 2021) to leverage their capabilities and enhance implementation (Fagundes, Teles, Vieira de Melo and Freires, 2020; Gillani, Chatha, Sadiq Jajja and Farooq, 2020).

This is a grey area where we need to examine and understand how the existing digital know-how within the organisation and the business competitiveness created by market pressure will affect the intention to adopt these technologies to build resilience through technology-driven risk management in business operations. To fill this void, the current study aspires to understand how the influence of internal organisational and external factors can help managers successfully plan the implementation of these technologies for managing risks in manufacturing companies by tackling the following research questions:

- RQ1: What is the impact of the level of digital transformation, awareness of requirements, market pressure, and regulations on the behavioural intention to adopt emergent I4.0 technologies for managing risks in the UK manufacturing industry?

- RQ2: What is the effect of organisational resilience on the behavioural intention to adopt emergent technologies for managing risks in the UK manufacturing industry?
- RQ3: What are the differences between the factors influencing big data, AI, CC, and blockchain adoption intention for managing risks in the UK manufacturing industry?

Answering these questions is important because I4.0 technologies will help companies to develop advanced manufacturing capabilities, providing scope and opportunity for cleaner, responsible production, minimising their environmental carbon footprint and leading to competitive advantage in the business environment (Telukdarie, Buhulaiga, Bag, Gupta and Luo, 2018; Bag, Gupta and Kumar, 2021). An important dimension to achieve sustainability and business competitiveness in the manufacturing sector is the ability of the organisations to identify, manage and mitigate risks using I4.0 technologies, which will ensure that critical business processes remain unaffected to achieve economic productivity (Giannakis and Papadopoulos, 2016). In the context of using I4.0 for risk management in the manufacturing sector, this paper aims to provide empirical evidence on the adoption of I4.0 technologies (big data, AI, CC and blockchain) for managing risks and building resilience within industrial operations. The contributions to knowledge in this article are as follows: This study develops and empirically tests a model for user acceptance of I4.0 technologies in risk management combining the resource-based view (RBV), the technology acceptance model (TAM), and institutional theory; it investigates the relationship of organisational resilience with technology user acceptance in risk management, and it provides insights into the differences between the user acceptance of four different emergent technologies in this context.

From a theoretical perspective, this article uses the lens of the RBV (Wernerfelt, 1984) and institutional theory (Meyer and Rowan, 1977; Meyer and Scott, 1983), along with TAM (Davis, 1989) to examine the intentions to use each of these I4.0 technologies from an operations manager's perspective. The intention to adopt I4.0 technologies in the context of risk management will depend on the perceived usefulness and easiness of using these technologies in business manufacturing operations. Therefore, it can be modelled using the TAM, which stems from information systems theory to examine the acceptance and use of technologies. The perceived usefulness and easiness of use will depend on both digital capabilities and readiness of the organisation and can be conceptually modelled using RBV, which posits digital culture and technology usage within organisations as strategic tangible resources to achieve both business productivity and competitiveness (Wernerfelt, 1984). Therefore, RBV helps to model the relationship between organisational resources (I4.0 technologies) and their impact on intention to adopt. Finally, institutional theory considers the impact of pressures created by the market and regulations, i.e., the external organismal environment (Meyer and Scott, 1983) on the intention to adopt I4.0 technologies. The purpose of integrating RBV, TAM and institutional theory is to account for the internal resources of the company and the external pressures affecting the implementation of I4.0 for risk management. Therefore, the theoretical relevance of the current study is the focus on four interesting and cross-disciplinary concepts within the OSCM literature: (1) information management (TAM and I4.0 technologies); (2) digital manufacturing (risk management); (3) strategic management (RBV); (4) organisational studies (institutional theory). The proposed novel behavioural adoption model is tested by capturing the insights of 117 operations managers in the UK manufacturing industry through a survey instrument; these insights are analysed using structural equation modelling (SEM). The analysis is used to validate the proposed novel behavioural adoption model for four I4.0 technologies; namely big data, AI, CC and blockchain, using the sample population. RBV, institutional theory and TAM are used theoretically to provide a deeper understanding of the adoption behaviour and influences to adopt these technologies for managing risks in the UK manufacturing sector, i.e., from a developed economy perspective, where I4.0 adoption and implementation is a priority agenda (BEIS, 2019). Therefore, the study reported in this article makes practical contributions for two stakeholders: (1) managers – effectively and efficiently to leverage, adopt and implement I4.0 for risk management and build organisational resilience; (2) government policy makers – to understand the influence of technology policies, regulations and financial incentives on the intention to adopt I4.0 technologies, especially managing risks stemming from advanced manufacturing capabilities to achieve sustainable business performance.

The article is organised into eight sections. Section 2 critically analyses contemporary knowledge on the topic and identifies the knowledge gaps. Section 3 introduces the model and its constructs, whilst Section 4 elaborates the methodology used and Section 5 presents the SEM analysis of the four models. Section 6 presents the discussion of the findings, Section 7 elaborates on the practical implications, and Section 8 delivers the conclusion and final remarks.

2. Literature review

I4.0 technologies can represent a significant opportunity for risk and crisis management in manufacturing firms. Ivanov (2019) argues that, as digital technologies are an aspect affecting supply chains and supply chains are affected by risks, digital technologies and risk management must be linked. The risk management field can make significant strides by embracing emergent technologies (Lohmer, Bugert and Lasch, 2020; Rane, Potdar and Rane, 2021), as these technologies can help in situations ranging from company-related risks to major general disruptions such as the COVID-19 pandemic (Spieske and Birkel, 2021). This section will present an overview of the existing literature regarding the four I4.0 technologies under study, their application in risk management, and current literature about their adoption in light of the research questions. That is followed by the theoretical lens employed to develop the conceptual model. Finally, the knowledge gaps stemming from this review are presented and linked to the contribution of this article.

2.1.Big data [DA]

Big data is characterised by its high volume, velocity, variability, variety and capability of being visualised, which will create value for consumers and business organisations

(Fosso-Wamba, Gunasekaran, Akter, Ren, Dubey and Childe, 2017; Gunasekaran, Papadopoulos, Dubey, Fosso-Wamba, Childe, Hazen and Akter, 2017; Sena, Bhaumik, Sengupta and Demirbag, 2019; Kava, Spanaki, Papadopoulos, Despoudi, Rodríguez-Espíndola and Fakhimi, 2021). For example, automobile manufacturing companies such as Ford and Mercedes generate real-time data from millions of vehicles on the road through onboard sensors. The data are used to facilitate regulatory compliance, keep the consumer informed (build trust), and provide automated diagnostics for roadside emergency assistance (Ford, 2020).

DA has opened new possibilities and avenues in the field of humanitarian logistics (Horita, de Albuquerque, Marchezini and Mendiondo, 2017), crisis and disaster management (Akter and Fosso-Wamba, 2019), organisational resilience (Rodger, Chaudhary and Bhatt, 2019), sustainability (Sivarajah, Irani, Gupta and Mahroof, 2020), and emergencies (Chen, Jyan, Chien, Jen, Hsu, Lee, Lee, Yang, Chen, Chen, Chen and Chan, 2020). DA introduces risk mitigation abilities whose forecasts can shape innovative solutions, enhance fraud detection (Maheshwari, Gautam and Jaggi, 2021), assess supply chain risks (Ivanov, Dolgui and Sokolov, 2019), and undertake real-time monitoring (Spieske and Birkel, 2021). The reason is that data captured from various digital streams, i.e., from the IoT (sensors) and experiences (social media and similar channels), are critical for identifying risks (Nateghi and Aven, 2021), prioritising them (Blekanov, Krylatov, Ivanov and Bubnova, 2019), simulating disruption scenarios (Zheng, Ardolino, Bacchetti and Perona, 2021), reducing uncertainty (Bechtsis, Tsolakis, Iakovou and Vlachos, 2021), and devising risk mitigation approaches (Ivanov, 2018).

Despite the significant potential to transform and enhance processes, Singh and El-Kassar (2019) mention that resource allocation to unlock value from DA to facilitate data-driven decision-making is still in its infancy, as managers are reluctant to engage more. Similarly, Chen, Preston and Swink (2015) mention that the majority of companies have not engaged with DA yet and are still learning about the risks and skills involved for its implementation. This implementation is a crucial step to reap the benefits from DA. Therefore, it is important to look at the factors affecting the successful adoption of this technology.

Chen, Preston and Swink (2015) use SEM to examine a model based on the technology-organisation-environment (TOE) framework by looking at the antecedents of DA implementation and its effect on value creation. Their results suggest that expected benefits, technological compatibility, top management support, organisation readiness, and competitive pressure affect DA implementation. Sun, Cegielski, Jia and Hall (2018) employ content analysis to produce a framework looking into the factors affecting the adoption of DA based on TOE and diffusion-of-innovation (DOI). They produced a list of 26 factors led by relative advantage, human resources, technology resources, management support, and cost of adoption in terms of frequency. Integrating RBV and institutional theory, Dubey, Gunasekaran, Childe, Blome and Papadopoulos (2019) aim to understand the relationship between institutional factors, internal resources of the company and business performance in the context of DA. The SEM analysis confirms the influence of human skills and tangible resources on the adoption of DA. Dubey, Gunasekaran, Childe, Bryde, Giannakis, Foropon, Roubaud and Hazen (2020) report the role of external pressure to select the tangible and intangible resources pertaining to developing DA powered AI capability and its relationship with the organisational culture and capability utilisation to enhance economic and operations performance in the organisations. Bag, Pretorius, Gupta and Dwivedi (2021) explore the antecedents of DA powered AI and its impact on sustainable manufacturing and circular economy capabilities. The SEM analysis shows that tangible resources and workforce skills influence DA adoption.

Considering the importance of adoption and implementation, the lack of impact of DA in the risk management area (Baryannis, Validi, Dani and Antoniou, 2019) can be linked to the absence of studies looking at the implementation of DA in this context. Hence, it is important to develop further research to facilitate the adoption of big data in risk management, looking to leverage its capacities (Fagundes, Teles, Vieira de Melo and Freires, 2020).

2.2.Artificial intelligence [AI]

AI refers to a set of techniques and algorithms that can automatically integrate, process and learn from data and apply those learnings to achieve specific objectives and tasks (Haenlein and Kaplan, 2019). From the risk management perspective, AI algorithms can provide analytical capability to organisations that will help them to understand the impact of the risks (Bechtsis, Tsolakis, Iakovou and Vlachos, 2021), introduce automated recommendations to mitigate and manage these risks (Larkin, Drummond Otten and Árvai, 2021), react quickly to the changing environment (Yang, Fu and Zhang, 2021), identify trends to inform policy (Johnson, Albizri, Harfouche and Tutun, 2021), and enhance firm resilience (Bechtsis, Tsolakis, Iakovou and Vlachos, 2021). This is achieved by systematically and efficiently managing risks and recovering from crises (Rodríguez-Espíndola, Chowdhury, Beltagui and Albores, 2020) and major disruptions (Naz, Kumar, Majumdar and Agrawal, 2021) through: (1) reducing aggregating latency, i.e. capturing and consolidating digital data streams automatically (Dubey, Gunasekaran, Childe, Bryde, Giannakis, Foropon, Roubaud and Hazen, 2020); (2) reducing processing latency, i.e. automatically processing and summarising huge streams of data, and visualising them using intuitive and aesthetically pleasing interfaces (Mariani and Fosso-Wamba, 2020); (3) reducing decision latency, i.e. augmenting human intelligence through automated recommendations (Borges, Laurindo, Spínola, Gonçalves and Mattos, 2020); and (4) increasing analytics agility, i.e. increasing the foresight of decision-makers by extracting and identifying interesting trends and patterns within digital assets and data streams (Bieda, 2020).

Despite these benefits, the adoption of AI systems in business organisations has been limited and slow (Barro and Davenport, 2019). In their literature review, Baryannis, Validi, Dani and Antoniou (2019) mention that the predictive and learning capabilities of AI for supply chain risk management are still in their infancy, as little attention has been given to the development of automated solutions for decision-making. That is reflected in the low number of implementations in practice (Bechtsis, Tsolakis, Iakovou and Vlachos, 2021). The reasons are linked to the preference of users to obtain risk management advice from humans rather than from AI, lack of skilled talent, limited budget and financial resources, poor access to technology, lack of leadership and commitment from senior management, absence of experience, limited knowledge and awareness of managers and teams, oversight, fear of the unknown, organisational culture and dynamism, poor digital environment readiness of the organisation, and the existence or lack of government regulatory guidance and incentives (Larkin, Drummond Otten and Árvai, 2021; Brock and von Wangenheim, 2019).

Adoption has to be carefully considered, as important risks of an AI crisis would involve the implementation of unprepared and underdeveloped solutions that could generate failures paralysing the production process (Popkova, Alekseev, Lobova and Sergi, 2020). In this context, Grover, Kar and Dwivedi (2020) have identified through a structured literary review that perceived ease of using the technology, performance expectancy, social influencers, and facilitating conditions significantly impact adoption behaviour. Kuberkar and Singhal (2020) use the unified theory of acceptance and use of technology (UTAUT) model to determine that performance expectancy, effort expectancy, social influence, facilitating conditions, anthropomorphism, and trust significantly and positively influence the intention to adopt AI for automating routine tasks. AlSheibani, Yen and Messom (2018) integrate the TOE framework and DOI to develop a model looking at the impact of digital readiness, organisational readiness and external constructs (market pressure and regulations) on readiness to implement AI and its adoption. Jöhnk, Weißert and Wyrtki (2020) propose a strategic alignment between business goals and understanding the capabilities of AI, organisational resources, knowledge, culture, and data management strategy as key dimensions that will facilitate the adoption of AI. Pillai and Sivathanu (2020) consider TOE and task-technology-fit frameworks to examine the AI adoption for human resource recruitment. The analysis showed that competitive advantage, organisational leadership, digital readiness, external market pressure and partnership with AI vendors significantly and positively influence the intent to adopt. Chatterjee, Rana, Dwivedi and Baabdullah (2021) combine the TAM and TOE models to examine AI adoption in manufacturing companies. They show how the intention to adopt AI is influenced by perceived usefulness and perceived ease of use, which are preceded by factors from the internal and external environment. Their results suggest internal (competency, complexity, readiness, compatibility) and external (competitive advantage, partner support) factors affect perceived usefulness, whereas only complexity (internal) and competitive advantage (external) affect perceived ease of use. These studies, however, are focused on a variety of contexts with little attention paid to risk management.

2.3.Blockchain technology [BC]

BC is a decentralised and distributed digital ledger accessible through a cloud platform, which can record immutable transactions in a secure, transparent, efficient, low-cost way (Schatsky and Muraskin, 2015). According to the International Chamber of Commerce, counterfeit goods are projected to cost the global economy US $4.2 trillion and are likely to put around five million jobs at risk by 2022, representing around 7% of global trade (ICC, 2017). Therefore, luxury brand manufacturing companies in the fashion industry such as Louis Vuitton and Givenchy and shipping companies such as Maersk and DHL are using BC platforms and collaborating with technology providers such as IBM and Microsoft (Mansour, 2020, Kramer, 2020) to validate the supply chain (a cryptographically secure and signed online certificate by all those involved in the supply chain - design, raw materials, manufacturing, distribution).

Current implementations of BC in the humanitarian and development sectors include the creation of digital identities for the distribution of aid and financial inclusion, support for tracing and vaccine passports after COVID-19 (Ricci, Maesa, Favenza and Ferro, 2021), the fight against fraud and corruption (Luciano, Magnagnagno, Souza and Wiedenhoft, 2020), the improvement of land tenure and property rights in developing nations (Kshetri and Voas, 2018), the support of gender equality, thus contributing to UN Sustainability Development Goals (Kamath, 2018), the protection of children and young women from being illegally trafficked (Zwitter and Boisse-Despiaux, 2018), the implementation of fully digitised and automated contract negotiation, and the support of procurement through the use of smart contracts (Rodríguez-Espíndola, Chowdhury, Beltagui and Albores, 2020).

BC has the potential to enable more proactive and connected risk management, which can identify intangible risks and provide multiple layers of protection (Min, 2019; Kouhizadeh, Zhu and Sarkis, 2020). Its enhanced visibility allows the inclusion of provenance knowledge and reduces consumer risk perception for purchasing decisions (Montecchi, Plangger and Etter, 2019), as well as adding transparency and ensuring security and privacy of donations for humanitarian operations (Khan, Imtiaz, Parvaiz, Hussain and Bae, 2021). It can enhance the risk management function by strengthening information security (Kodym, Kubáč and Kavka, 2020), reducing information uncertainty in credit decisions (Dashottar and Srivastava, 2021), and enhancing cyber threat intelligence sharing systems to manage risks (Riesco, Larriva-Novo and Villagra, 2020). On top of its value for security, it can increase connectivity between partners (Min, 2019). However, it is important to recognise that poor implementation can hinder the potential of BC and increase risks, endangering the impact of the investment (Kodym, Kubáč and Kavka, 2020).

The intention to adopt BC in Indian supply chains has been studied by Kamble, Gunasekaran and Arha (2018), using a model combining TAM, the technology readiness index (TRI) and the theory of planned behaviour. Kamble, Gunasekaran, Kumar, Belhadi and Foropon (2020) extend that study by combining TAM and TOE. Their findings suggest that TAM constructs significantly and positively influences behavioural intention. Queiroz and Fosso-Wamba (2019) combine TAM and UTAUT to study the adoption of BC in India and the US, and their empirical testing showed that performance expectancy influenced the intention to use in both countries, whereas social influence only affects the intention to adopt in India and facilitating conditions only affect the intention to adopt in the US. Queiroz, Fosso-Wamba, De Bourmont and Telles (2020) use UTAUT to examine BC adoption in Brazil and find that facilitating conditions, social influence, trust, and effort expectancy significantly influence BC adoption. Wong, Tan, Lee, Ooi and Sohal (2020) use UTAUT to examine BC adoption in Malaysian companies and find that relative advantage, complexity, and competitive pressure affect the behavioural intention to adopt BC, whereas Wong, Leong, Hew, Tan and Ooi (2020) adopt TOE to show that technology readiness, facilitating conditions, and technology affinity have a positive meaningful influence on the behavioural intention to adopt BC. However, users' perceptions of the implementation of emergent technologies such as BC in the area of risk management have been scantly investigated.

2.4.Cloud computing technology [CC]

CC provides on-demand access to data repositories and computing systems customised to the user's needs, with minimal intervention from the service provider, i.e. users can access the required services at their convenience from their personal machines (Khayer, Bao and Nguyen, 2020). It can be very useful to collect, appraise and evaluate data efficiently (Bhattacharya and Chatterjee, 2021). CC provides the technology infrastructure, resources on-demand, and service to host and execute the software, and enables collaboration between the various stakeholders involved. It can support identifying, assessing, managing and mitigating various risks in real-time, irrespective of the complexities, geographical barriers and uncertainties posed during crises (Gourley, 2021).

Agility, cost savings, flexibility, and better cooperation and efficacy for mobile and digital settings have been considered advantages of CC during emergencies (Brender and Markov, 2013). CC technology has been used in these instances to: (1) store business information on multiple data servers across the globe; (2) ensure data availability, back-up, and secure and safe storage; (3) provide failover capabilities; scalability and load balancing based on the traffic and usage, sharing data across multiple organisations; (4) host web-based social networks able to provide stakeholders (i.e. workers, first-responders, local disaster-related non-profit organisations, volunteers, and local residents) with access to information, communication, and collaboration; (5) make available storage in multiple, geographically dispersed data centres with extensive back-up and archives; (6) assure reliable service availability during emergencies; (7) lower data recovery costs that are protected far from disaster sites; (8) replicate data across multiple servers and assurance of the security of the data (Brender and Markov, 2013; Nezih, Graham, Gyöngyi, Karen, Peter and Alain, 2018; Velev and Zlateva, 2012).

Gillani, Chatha, Sadiq Jajja and Farooq (2020) argue that it is important to look at the implementation of technologies such as CC as it is a base technology that provides the infrastructure for front-end technologies such as smart manufacturing. Cloud technology adoption within business organisations has been examined in the literature deriving constructs from the TOE framework (Hsu, Ray and Li-Hsieh, 2014; Lin, Lee, Lau and Yang, 2018), institutional theory (Low, Chen and Wu, 2011), and TAM, UTAUT and use of technology (Gangwar, Date and Ramaswamy, 2015). Using information from companies in Portugal, Oliveira, Thomas and Espadanal (2014) combine the TOE and DOI frameworks to point out the determinants of CC. The SEM analysis suggests that relative advantage, complexity, technological readiness, top management support, and firm size influence the implementation of CC. Lian, Yen and Wang (2014) look at the hospital industry in Taiwan. Using an ANOVA with responses from 60 questionnaires, their analysis identifies data security, perceived technical competence, cost, top management support, and complexity as critical factors affecting the implementation of CC. Gutierrez, Boukrami and Lumsden (2015) use exploratory factor analysis and logistics regression to identify competitive pressure, complexity, technology readiness and trading partner pressure as factors influencing the adoption of CC in the UK. Through empirical evaluation, Jianwen and Wakil (2019) show that the key factors affecting cloud adoption in business organisations are innovation and knowledge within the organisations; limited resources and commitment from senior management; systems integration and cyberspace security; regulatory environment and competitive pressure. Khayer, Bao and Nguyen (2020) investigate the impact of CC on the business performance of organisations from the perspectives of users, technology and IT capability of the organisation, drawing upon constructs from technology acceptance models, RBV theory and expectation-conformation theory to identify end-user satisfaction, information quality, system quality, managerial information technology (IT) capability and technical IT capability as drivers affecting successful implementation of CC. Despite the value of CC to facilitate the cooperation between different stakeholders and support other front-end technologies, research in the area of risk management is largely absent.

2.5.Resilience

Supply chain resilience has received significant attention in the last two decades. It is considered a key element to help businesses plan, prepare, develop strategies for emergency operations, respond to unpredictable disruptions, and efficiently recover from such disruptions (Macdonald, Zobel, Melnyk and Griffis, 2018; Sheffi, 2007).

Existing research in this domain has acknowledged the role of people (i.e. individuals and teams, their knowledge and behaviour) as crucial elements in developing resilient business processes and models (Croson, Schultz, Siemsen and Yeo, 2013). Studies have highlighted the ways organisational leadership, strategy, resource capacity and human resource capability can facilitate restructuring supply chain operations to deal with unprecedented events (Ambulkar, Blackhurst and Grawe, 2015).

Organisational and supply chain resilience has been studied in the field of humanitarian logistics and disaster management, examining the impact of disasters on managing supply chain operations to deliver goods and services to the affected population (Kovács and Spens, 2007; Kunz, Wassenhove, Besiou, Hambye and Kovács, 2017). These studies have concluded the significance of information sharing, collaboration and coordination between the stakeholders and process optimisation using innovative technology to increase process, people, service, and product resilience. Additionally, they have emphasised the significance of risk management to avoid service disruption during humanitarian operations. Indeed, resilience can be supported by the use of emergent technologies such as blockchain to enhance collaboration between stakeholders (Lohmer, Bugert and Lasch, 2020). However, studies looking at the effect of organisational resilience on the successful adoption of emergent technologies are lacking.

2.6.Theoretical lens

We use an overarching theoretical lens based on *institutional theory* (Meyer and Rowan, 1977; Meyer and Scott, 1983), the *resource-based view* (RBV) (Wernerfelt, 1984) and the *technology acceptance model* (TAM) (Davis, 1989). This section elaborates on the perspectives underpinning the investigation of the impact of internal and external factors on the adoption of emergent technologies, and their impact on performance.

2.6.1. Technology acceptance model (TAM)

TAM has been used in the existing research studies dealing with behavioural intentions and usage of technology, for example, enterprise resource planning (Amoako-Gyampah and Salam, 2004), customer relationship management (Wu and Wu, 2005), CC (Gangwar, Date and Ramaswamy, 2015), software as a service (Wu, 2011), data warehousing (Wixom and Watson, 2001), big data analytics (Verma, Bhattacharyya and Kumar, 2018), and AI (Kuberkar and Singhal, 2020). It is adapted from the theory of reasoned action model (Fishbein and Ajzen, 1975) specifically for explaining the user acceptance and behavioural intention to adopt IT. The outcome variable (behavioural intention) is explained using perceived usefulness (impact on job performance, i.e., value creation), and ease of use (minimal effort to implement, i.e., resources and capability) (Huang, Quaddus, Rowe and Lai, 2011). TAM is used to model the behavioural intention to adopt I4.0 technologies, which is determined and influenced by an individual's (in a business environment, a manager's) attitude towards the technology and its usefulness.

2.6.2. The resource-based view (RBV)

RBV emphasises the role of internal resources in influencing organisation strategies and performance (Wernerfelt, 1984). We examine the use of I4.0 technologies to manage operational risks as a strategic resource, considering the RBV theory. Resources can be both tangible and intangible assets associated with the firm (Caves, 1992). In this context, I4.0 software technologies are tangible because they represent physical assets augmenting strategic human decision-making (Haibe-Kains, Adam, Hosny, Khodakarami, Shraddha, Kusko, Sansone, Tong, Wolfinger, Mason, Jones, Dopazo, Furlanello, Waldron, Wang, McIntosh, Goldenberg, Kundaje, Greene, Broderick, Hoffman, Leek, Korthauer, Huber, Brazma, Pineau, Tibshirani, Hastie, Ioannidis, Quackenbush, Aerts and Massive Analysis Quality Control Society Board of, 2020). From a firm's perspective, technology is often one of its core strategic resources and is essential to gain and sustain a competitive advantage (Alalie, Harada and Mdnoor, 2018). The effectiveness of a technological resource greatly depends on its adoption and context of use (Wernerfelt, 1984). Lack of understanding, purpose, usefulness and trust in technologies will negatively impact its adoption and subsequent use to generate value (Andriopoulos and Lewis, 2009). Regardless of how good the decision support tool or model is, its purpose will fail without managerial adoption and strategic alignment to the business goals and priorities. Therefore, from the RBV perspective, the digital readiness of organisations and awareness of technical requirements can be modelled as antecedents influencing the usefulness and ease of using I4.0 technologies, which will determine the intention to adopt (according to TAM).

2.6.3. Institutional theory

Based on the seminar work published by DiMaggio and Powell (1983), institutional theory introduces isomorphic processes resulting from formal and informal pressures exerted on organisations by government policies and regulations, other organisations in the dynamic business environment, and uncertainty in technology and market dynamics. This leads to decision-makers within an organisation adopting structures and practices like other organisations in their respective domains to remain competitive and relevant. Following the tenets of institutional theory, conformity to social norms such as market pressure and governmental policies will contribute to organisational productivity (Kauppi, 2013), especially in the context of adopting I4.0 technologies such as DA (Dubey, Gunasekaran, Childe, Blome and Papadopoulos, 2019). The theory considers dimensions external to the organisations within a social framework governed by economic and social practices, which will impact organisational practices, including the adoption of I4.0 technologies in varying contexts. The research constructs (market pressure and government policies) derived from this theory will help to shed light on the impact of these external factors on the intention to adopt I4.0 technologies.

In our study, TAM (information management literature) is used to model the outcome variable (intention to adopt), whereas RBV (strategic management literature) and institutional theory (organisational management literature) are used to derive the theoretical constructs pertaining to internal digital resources within the organisation and external business environment, respectively, acting as antecedents influencing intention to adopt. By integrating these theories, the conceptual model will provide a better understanding of how the internal organisational resources (digital readiness) and certain institutional constructs external to the organisation will impact operations managers' intention to adopt I4.0 technologies for managing risks and building organisational resilience. Therefore, our proposed theoretical model meets Dubin's critical needs (Lynham, 2002) in the sense that it offers improved understanding and interesting insights stemming from the relationship between the literature-informed theoretical constructs, comprises variables measured using proxies, contains no composite variables, and includes boundary criteria governed by control variables.

2.7.Knowledge gaps

Table 1 shows a summary of the contributions presented in the literature review. Despite the reported value of I4.0 technologies for risk and crisis management and in digital manufacturing (Akter and Fosso-Wamba, 2019; Kshetri, 2018; Akter, Michael, Uddin, McCarthy and Rahman, 2020; Fosso-Wamba, Bawack, Guthrie, Queiroz and Carillo, 2020), we found limited empirical evidence in the existing research focused on examining the intention to adopt these technologies for risk management. Although examining and understanding the factors influencing the adoption of emerging technologies is slowly gaining momentum within Operations Management research (Zheng, Ardolino, Bacchetti and Perona, 2021), it has rarely addressed the context of risk management, which is a critical dimension in achieving sustainable performance, business competitiveness and organisational resilience (Marcucci, Antomarioni, Ciarapica and Bevilacqua, 2021) The context of risk management and use of I4.0 technologies has been increasingly discussed and gained momentum in light of the COVID-19 pandemic, which has led to supply chain disruptions on all fronts stemming from demand uncertainties, government lockdown strategies and limited availability of labour, making it difficult to work on-site (Mubarik, Naghavi, Mubarik, Kusi-Sarpong, Khan, Zaman and Kazmi, 2021). Whilst the COVID-19 pandemic is an unprecedented crisis, the adoption of I4.0 technologies is likely to facilitate enhancing resilience in the manufacturing sector whilst addressing the rising regulatory and cost pressures (recovering productivity). Therefore, the context of this study (risk management) fully aligns with the current business environment created by the pandemic, which is unexplored, and rightly examines the factors influencing the perception of operations managers to adopt I4.0 technologies, as poor implementation of emergent technologies can have counterproductive effects (Lohmer, Bugert and Lasch, 2020).

Many of the studies presented concerning the adoption of these technologies have been reported in India, the US, Brazil, and Malaysia, with little analysis in other countries such as the UK, where the government has put in place strategies, incentives and policies for increasing the adoption of I4.0 in the manufacturing sector (BEIS, 2019). Furthermore, the context of adoption in most of these studies is unclear, except for the articles explicitly examining the relationship between the intention to adopt and organisational performance. Additionally, the behavioural intention to adopt all four of these technologies (in any context) has never been empirically examined in a single piece of research using the same sample population, except Akter, Michael, Uddin, McCarthy and Rahman (2020), who have comprehensively reported various applications of these technologies and their role in digitally transforming business operations. Nevertheless, their study does not cover risk management.

This review highlights that much of the existing work in supply chain resilience has emphasised the significance of risk management to avoid service disruption. However, resilience is yet to be examined as a critical influencing factor in the adoption of I4.0 technologies. Moreover, the global SARS-CoV-2 pandemic has clearly shown how digitalisation and adoption of technologies support business processes, people and services, and make businesses resilient to combat negative impacts on economies (Verma and Gustafsson, 2020). Therefore, the study makes a unique contribution by examining the relationship between the digital readiness of the organisation, building operational resilience within the organisation, and the intention to adopt I4.0 technologies from a managerial perspective in risk management (Fatorachian and Kazemi, 2021).

In summary, this research intends to examine adapting I4.0 technologies, namely DA, AI, CC and BC, to improve the identification, analysis, and development of responses to risks through actionable insights into the UK manufacturing sector. It is important to consider the impact of organisational resources (i.e., digital readiness), market pressure, existing regulations and policies, and usage perceptions when evaluating operations managers' intentions to adopt these technologies. This paper sets out to achieve that aim.

Table 1. Summary of the literature

Authors	Theory/Framework	Antecedents to DA	Antecedents to AI	Antecedents to BC	Antecedents to CC	Risk mgmt
Chen et al. (2015)	TOE	Expected benefits technological compatibility top management support organization readiness competitive pressure	X	X	X	X
Sun et al. (2018)	TOE, DOI and Institutional Theory	Relative advantage Human resources Technology resources Management support Cost of adoption Security privacy and ethics concerns in collecting data Technology readiness Trading partner readiness Complexity Regulatory environment Uncertainty/risk concern Institutional based trust Organization/IT structure Decision-making culture Business strategy orientation Business resources Change efficacy IS strategy orientation Competitive pressure Firm size Appropriateness Compatibility Market turbulence Observability Trialability IS fashion	X	X	X	X

Dubey, Gunasekaran, Childe, Blome and Papadopoulos (2019)	RBV and institutional Theory	Human skills Tangible resources	X	X	X	X
Dubey et al. (2020b)	Dynamic capabilities and contingency theory	Entrepreneurial orientation		X	X	X
Bag et al. (2021b)	Institutional theory and RBV	Tangible resources workforce skills		X	X	X
Grover et al. (2020)	Extension of the factors used by Thompson et al. (1991)	X	Perceived ease of using the technology performance expectancy social influencers facilitating conditions	X	X	X
Kuberkar and Singhal (2020)	UTAUT	X	Performance expectancy effort expectancy social influence facilitating conditions anthropomorphism trust	X	X	X
AlSheibani et al. (2018)	TOE and DOI	X	Relative advantage Compatibility top management support organisation size resources competitive pressure government regulatory issues	X	X	X
Jöhnk et al. (2020)	Readiness for change, Readiness in IS, TAM,	X	Strategic alignment Resources Knowledge culture and data management strategy	X	X	X

	TRA, TPB, DOI, TOE					
Pillai and Sivathanu (2020)	TOE and Task-Technology-Fit	X	Competitive advantage organisational leadership digital readiness external market pressure partnership with AI vendors	X	X	X
Chatterjee et al. (2021)	TAM and TOE	X	Perceived usefulness perceived ease of use	X	X	X
Kamble et al. (2018)	TAM, TRI and TPB	X	X	Attitude perceived usefulness	X	X
Kamble et al. (2020)	TAM and Technology-organisation-Environment framework	X	X	Perceived usefulness perceived ease of use	X	X
Queiroz and Fosso-Wamba (2019)	TAM and UTAUT	X	X	Performance expectancy (both countries) social influence (India) facilitating conditions (USA)	X	X
Queiroz et al. (2020)	UTAUT	X	X	Facilitating conditions social influence trust effort expectancy	X	X
Wong et al. (2020b)	UTAUT	X	X	Relative advantage Complexity competitive pressure	X	X
Wong et al. (2020a)	TOE	X	X	Technology readiness facilitating conditions technology affinity	X	X
Oliveira et al. (2014)	TOE and DOI	X	X	X	Relative advantage Complexity technological readiness top management support firm size	X

Lian et al. (2014)	TOE and HOT-fit	X	X	X	Data security perceived technical competence cost top manager support complexity	X
Gutierrez et al. (2015)	TOE	X	X	X	Competitive pressure Complexity technology readiness trading partner pressure	X
Khayer et al. (2020)	RBV, expectation-conformation theory	X	X	X	End-user satisfaction information quality system quality managerial information technology (IT) capability technical IT capability	X
Jianwen and Wakil (2019)	-	X	X	X	Innovation and knowledge within the organisations limited resources and commitment from senior management systems integration and cyberspace security regulatory environment competitive pressure	X

3. Model development

The model proposed in this research examines the effects of RBV and institutional theory on managers' perceptions of the adoption of emergent technologies for risk management. The integration of both views has been found very useful in the past to account for internal and external factors affecting organisations (Dubey, Gunasekaran, Childe, Blome and Papadopoulos, 2019; Hughes, Powell, Chung and Mellahi, 2017). The purpose is to look at the way these factors influence user acceptance for risk management in organisations. The impact of manager perceptions on user acceptance is analysed through the use of TAM. TAM was useful to examine the adoption of emergent technologies in previous research (Kamble, Gunasekaran and Arha, 2018; Albayati, Kim and Rho, 2020).

3.1.External factors

Institutional theory considers the environments in which companies work and evolve and the structures they develop to comply with rules and acquire legitimacy (Meyer and Rowan, 1977; Euske and Euske, 1991). A company's environment has a social framework of norms that defines acceptable behaviour (Dubey, Gunasekaran, Childe, Blome and Papadopoulos, 2019). Market pressures can cause firms to strategically plan their activities and innovate their processes (Paulraj and Chen, 2007; Thanki and Thakkar, 2018). The regulatory framework and the pressure caused by the interaction of stakeholders in the market are relevant components of that environment (Chen, Preston and Swink, 2015). The effects of regulatory support and market pressure on the intention of adopting a technology have been studied in the context of blockchain for operations management (Wong, Leong, Hew, Tan and Ooi, 2020). The model proposed in this research, however, looks at their role as factors affecting managers' perceptions. Investigation into the role of governmental policies for the successful adoption of emergent technology is needed (Kamble, Gunasekaran and Arha, 2018) because policy changes can hinder investment and prevent technology implementation (Bonnín Roca, Vaishnav, Morgan, Fuchs and Mendonça, 2021). At the same time, regulatory guidance and support can provide more information to managers about emergent technologies, thereby providing further insights about their usefulness and reducing the uncertainty that could cause insecurity among users. Additionally, some companies are discouraged by the large investments required for digital manufacturing (Horváth and Szabó, 2019), especially less obvious investments such as training to facilitate the use of technology (Bag, Sahu, Kilbourn, Pisa, Dhamija and Sahu, 2021). Overall, regulatory guidance can provide information about best practices using emergent technologies for risk management and motivate organisations to make investments that can mitigate the impact of disruptions in productive systems.

The importance of supply chain trading partners and stakeholders and the relationships between them in the global supply chain ecosystem have been investigated as part of pressures in the market (Scholten and Schilder, 2015). Emerging I4.0 technologies can face limited diffusion because of their technological uncertainty (Bonnín Roca, Vaishnav, Morgan, Fuchs and Mendonça, 2021). New technologies are perceived as risky because of the limited information available about their use and implementation (Arora, Foley, Youtie, Shapira and Wiek, 2014), which makes them seem overly complicated. The adoption of technologies by networks of partners and competitors can increase the diffusion of information through communication (Geroski, 2000) because when enough stakeholders decide to engage with an innovation, the motivation of all the stakeholders related to them increases (Chakravorti, 2004). This allows the development of reports, white papers, user guides, and training that can affect users' perception and ultimately support the intention to use the technology. Similarly, more information about practical implementations can highlight key advantages for the organisation, thereby encouraging the adoption of technology. In the context of the study, this is relevant because it can facilitate the integration of the supply chain to identify, analyse and manage risks. Thus, the following hypotheses are tested in this research:

- H1: Regulatory guidance and support have a significant effect on the perceived ease of use of the technology.
- H2: Regulatory guidance and support have a significant effect on the perceived usefulness of the technology.
- H3: Market pressure has a significant effect on the perceived ease of use of the technology.
- H4: Market pressure has a significant effect on the perceived usefulness of the technology.

3.2.Organisational factors

The RBV looks at the relationship between a company's internal resources its performance (Bowman and Ambrosini, 2003). It argues that an organisation can produce a competitive advantage through the use or development of internal resources and capabilities (Dubey, Gunasekaran, Childe, Blome and Papadopoulos, 2019; Hughes, Powell, Chung and Mellahi, 2017). Hence, this theory suggests that the company can achieve higher performance through the production of internal unique resource-based advantages (Hughes, Powell, Chung and Mellahi, 2017). Nandi Madhavi, Nandi, Moya and Kaynak (2020) argue that information and communication technology capabilities are key resources that can be used to produce a competitive advantage in companies. This research agrees with that view and investigates the role of technological readiness in the adoption of emergent technologies for risk management. Technological readiness, referred to here as the level of digital transformation, involves the inclination to embrace new technologies (Ramírez-Correa, Grandón and Rondán-Cataluña, 2020) and can be achieved through investment in infrastructure and the training of human resources. That investment is commonly preceded by understanding and acknowledging the organisational requirements for the introduction of technology in the company. These include the importance of preparing human resources, understanding organisational change, promoting a culture of innovation, and acquiring an adaptive capacity. Given the perceived risk associated with using emergent technologies and the limited information about them (Arora, Foley, Youtie, Shapira and Wiek, 2014), we argue that the level of awareness of the requirements influences perceptions of the easiness of use and usefulness of implementing emergent technologies. Achieving more efficient and effective risk management leverages from a high level of awareness about the requirements, especially because it reduces uncertainty about factors affecting successful implementation. Therefore, the following hypothesis are tested in this research:

- H5: Awareness of the organisational requirements has a significant effect on the level of digital transformation.
- H6: Awareness of the organisational requirements has a significant effect on the perceived ease of use of the technology.
- H7: Awareness of the organisational requirements has a significant effect on the perceived usefulness of the technology.

The experience gained through previous investment in infrastructure and human resources can influence the perception of the usefulness and ease of use of emergent technologies. Digital transformation involves the transformation and evolution of processes, activities and competencies to take advantage of emergent technologies (He, Meadows, Angwin, Gomes and Child, 2020). Organisations with more technological expertise and knowledge can become early adopters because they are more capable of understanding new technologies at early stages than other companies, which become late-stage adopters (Geroski, 2000). A higher level of digital transformation is reflected in more prepared human resources and infrastructure to manage multiple sensors, capture, and analyse information, and identify and react swiftly to relevant risks.

Additionally, claims have been made about the value of harnessing emergent technologies to strengthen organisations facing disruptions because these technologies can introduce flexibility and robustness in operations (Lohmer, Bugert and Lasch, 2020; Ivanov, Dolgui and Sokolov, 2019; Gejke, 2018). This means that engaging with technology can enhance the level of resilience in organisations (Yang, Fu and Zhang, 2021) because it affects the capacity of organisations to absorb disruptions, adapt quickly and react effectively. Likewise, claims have been made about the importance of risk management in building resilience because it can help organisations mitigate the impact of disruptions and ensure continuity (El Baz and Ruel, 2021). This can be further supported by the introduction of emergent technologies because these can facilitate, expedite, and increase the accuracy of risk management activities. However, little empirical evidence has been provided to examine that relationship. Hence, Hypotheses 8 – 10 investigated in this research are as follows:

- H8: Digital transformation has a significant effect on the perceived ease of use of the technology.
- H9: Digital transformation has a significant effect on the perceived usefulness of the technology.
- H10: Digital transformation has a significant effect on organisational resilience.

On the other hand, Asamoah, Agyei-Owusu and Ashun (2020) argue that RBV resources can support the development of capabilities such as resilience that can drive performance and enhance customer satisfaction. Embedding resilience in the company can affect the intention to implement emergent technologies, because of the emphasis on continuous improvement and the benefits of leveraging the advantages of these technologies. The capability of organisations constantly to monitor risks, cope with disruptions, and quickly adapt and respond to changing situations is a desirable quality shaping the organisational culture. Therefore, the following hypothesis is tested:

- H11: Organisational resilience has a significant effect on the behavioural intention of using the technology.

3.3.TAM model

One of the most significant barriers to the implementation of digital manufacturing involves human resources (Bag, Sahu, Kilbourn, Pisa, Dhamija and Sahu, 2021). As a result, the final part of the model involves the traditional TAM model, which is based on the perceptions of the potential users. Emergent technologies have significant potential to support processes undertaken under uncertain conditions such as risk management (Kim and Kim, 2020). Ivanov, Dolgui and Sokolov (2019) mention that as digital technologies affect supply chains, and supply chains are affected by risks, it is logical to assume a link between digital technologies and risk management. The TAM model is based on perceived usefulness and perceived ease of use as two key theoretical constructs driving user behaviour (Davis, 1989). Its predictive power can be a major asset to understanding user acceptance (Kamble, Gunasekaran and Arha, 2018). Perceived usefulness is understood as the potential benefits from the implementation of the emergent technology from the perspective of the manager (Kamble, Gunasekaran and Arha, 2018), whereas the perceived degree of difficulty associated with any technology is referred to as perceived ease of use, and it can hinder the willingness of managers to engage with that technology (Davis, 1989). The perception of the benefits of use and the ease of use can be very important for emergent technologies, which often carry potential advantages but with a degree of uncertainty about their easiness to adopt (Rodríguez-Espíndola, Chowdhury, Beltagui and Albores, 2020). The benefits for risk management vary depending on the characteristics and uses of the technology, especially because these are connected to the likely impact of the disruption and the responsiveness gained by the firm. Blockchain carries the potential to produce a decentralised database, enact the use of smart contracts, increase traceability, and introduce near real-time information, but it is at a nascent stage and concerns exist about the integration with legacy systems, scalability and resources which can affect their use (Kamble, Gunasekaran, Kumar, Belhadi and Foropon, 2020). Although CC can be a platform to share information and facilitate interaction between stakeholders, it carries concerns about privacy, infrastructure and effort expectancy (Ali, Mehmood, Majeed, Muhammad, Khan, Song and Malik, 2019). Additionally, the expertise and infrastructure needed for the use of AI and big data need to be balanced with the potential of big data analytics to capture and process large amounts of data especially for the prediction of risks (Akter and Fosso-Wamba, 2019) and the support AI can provide for decision-making before and during disruptions based on the combination of data from different sources (Rodríguez-Espíndola, Chowdhury, Beltagui and Albores, 2020). Considering the importance of the perceptions of the advantages and ease of use of these technologies, the hypothesis tested in this research include:

- H12: Perceived usefulness has a significant effect on the behavioural intention of using the technology.
- H13: Perceived ease of use has a significant effect on the behavioural intention of using the technology.

The different constructs and hypotheses tested in this research can be seen in Figure 1.

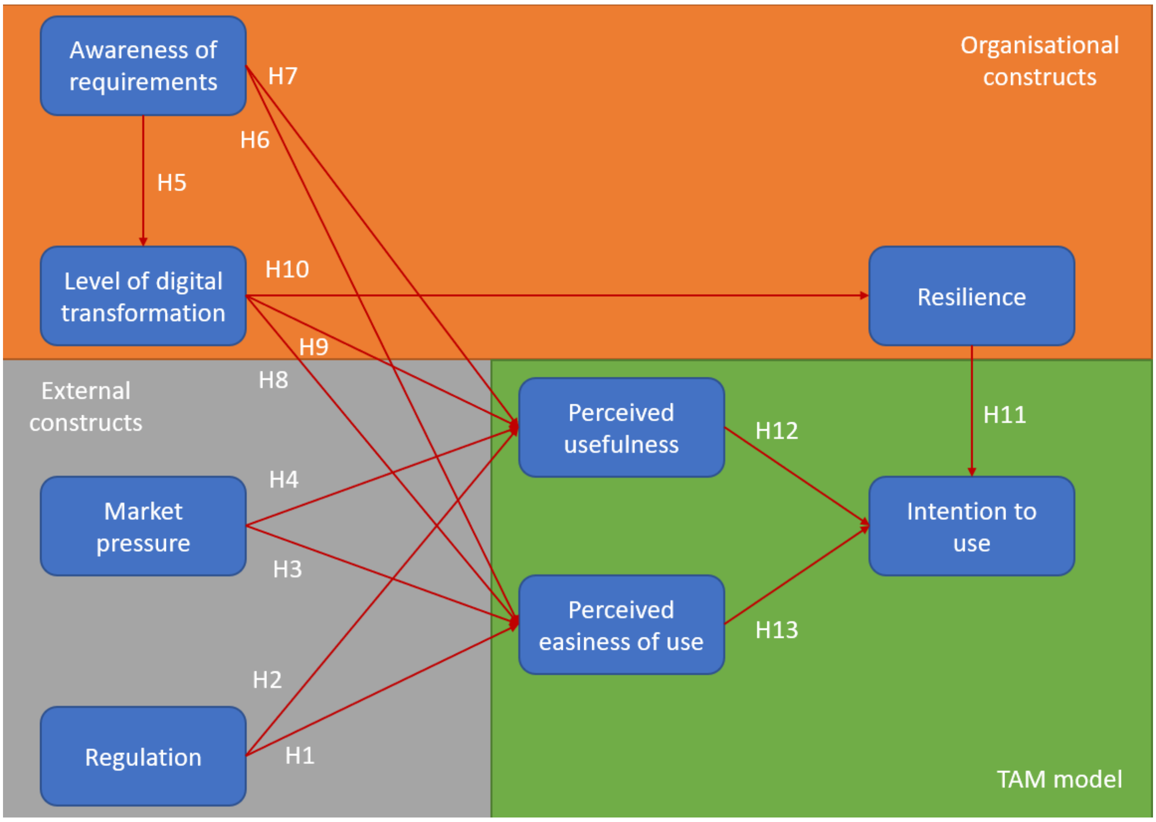


Figure 1. Model for the adoption of emergent technologies for risk management

4. Research design

4.1.Construct operationalisation

The findings from the literature review and the theoretical underpinning presented in Section 2 were used to produce the model presented and explained in Section 3. The items used to measure each one of the different constructs were obtained from scales previously validated in the literature to ensure reliability and validity (Churchill, 1979). These constructs along with their supporting literature can be found in Table 7 in the Appendix. The constructs were measured using a five-point Likert scale (1 = completely disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = completely agree) to allow for enough statistical variability among responses (Chen, Paulraj and Lado, 2004; Dubey, Altay, Gunasekaran, Blome, Papadopoulos and Childe, 2018). The model was pre-tested with three academics for further validation to ensure the constructs were clear and appropriate for the subject area. We amended the questions according to the recommendations obtained before applying the survey.

4.2.Sample selection

The UK has developed a strategy for leveraging emergent technologies in industry (https://tinyurl.com/y2jngwn5) and programmes promoting the use of emergent technologies to enhance the skillset of organisations (https://tinyurl.com/yyjpmzx3). Therefore, this research used a cross-sectional electronic survey to delve into the aspects affecting user acceptance of emergent technologies for risk management in the manufacturing industry in the UK.

Data were collected electronically using Qualrics to recruit participants. The sample size was decided considering the nature of the data analysis method to obtain robust and reliable results. Different thresholds and rules of thumb were proposed to determine adequate sample sizes for SEM. Although some traditional sources suggest including ten times as many participants as variables (Nunnally, 1978), other articles suggest a minimum of 100 and 200 responses (Boomsma, 1985) with at least 100 respondents for average models (Bollen and Noble, 2011). Recent studies based on Monte Carlo simulation analysis re-evaluate the standard rules of thumb for sample size selection with suggestions below the thresholds presented (Singh, Shukla and Mishra, 2018; Sideridis, Simos, Papanicolaou and Fletcher, 2014). Following those guidelines, this research obtained a sample size of 117 responses. Based on the medium complexity of our model with no missing values, the database collected was deemed sufficient for analysis to obtain meaningful results using SEM. Further conformation about the adequacy of the sample size was undertaken using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for the model.

Considering the level of expertise required to provide rich information for analysis, this research employed purposive sampling to identify potential responders (Maspaitella, Garnevska, Siddique and Shadbolt, 2018). The type of participants recruited included operations managers, risk managers and crisis managers in companies operating in the UK. The reason these participants were selected was their in-depth knowledge of risk management operations inside their manufacturing companies.

4.3.Sample details

The survey was prepared on Qualtrics (www.qualtrics.com), the link was distributed among UK companies and the data was saved anonymously on the platform. Information was gathered from 117 companies using the online survey tool. The details of the sample are included in Table 2. The sample gathered practitioners working on operations management, project management and risk and crisis management. Inclusion criteria were incorporated as a set of screening questions in the survey to ensure that that all participants: (1) belonged to a company operating in the UK; (2) had knowledge about risk and crisis management in the company; and (3) had a working understanding about the use of technology in their companies. Respondents not involved in a role linked to risk and crisis management and not being employed full-time were excluded from the sample. The purpose was to have respondents with first-hand knowledge and the capacity to make decisions that could deliver meaningful information for this study.

Table 2. *Sample demographics*

Size of the company	Frequency
Fewer than 10 employees	6
Between 11 and 50 employees	17
Between 51 and 100 employees	13
Between 101 and 250 employees	18
More than 250 employees	62
Experience at the company	**Frequency**
Less than 1 year	22
Between 1 and 5 years	48
More than 5 years but less than 10 years	25
More than ten years	21
Risk and crisis management experience	**Frequency**
Less than 1 year	4
Between 1 and 5 years	31
More than 5 years but less than 10 years	31
More than ten years	50

*One participant decided not to disclose the information about demographics

As it can be seen in the table, the sample includes managers with a good working knowledge of practices in a good range of organisations from small and medium-sized enterprises to large companies. More than two-thirds of the sample has more than five years of experience in risk and crisis management.

4.4.Data analysis

The sample collected was considered adequate based on the findings from Muthén and Muthén (2002). The database was checked for any missing values and non-engaged responses, which were not found in the data. The analysis process involved the use of exploratory factor analysis (EFA), SEM and the analysis of the hypothesis.

EFA allows identification of the main constructs or dimensions found in the data, to ensure only relevant items are included (Kline, 1994). It involves data screening, analysis of descriptives, factor analysis, results interpretation, and a reliability test. Harman's single-factor test was used to test common variance. The process includes running the EFA and looking at the unrotated solution to determine the number of factors to account for variance (Podsakoff, MacKenzie, Jeong-Yeon and Podsakoff, 2003). Once the EFA was done, the different items and constructs were included in AMOS for SEM to compare the theoretical model presented with the information from the responses (Kline, 1994). SEM uses quantitative information to examine casual relationships between constructs (Bollen, 1989). It is a widely used approach because of its potential to create path diagrams and the availability of goodness-of-fit indices to allow for model validation (Dey, Malesios, De, Chowdhury and Abdelaziz, 2020). For the analysis, maximum likelihood was used as the extraction method. The hypotheses presented in the previous sections were tested for each of the four emergent technologies, namely: AI, blockchain, CC and big data. Finally, the results of the analysis were used to evaluate the different hypotheses and draw conclusions.

5. Results

5.1. Exploratory factor analysis

EFA was undertaken in SPSS Statistics 26 using principal components analysis for extraction. Table 3 presents Bartlett's test and the KMO measure for the four models, with values showing no multicollinearity and KMO values in the range of good sample size (Hutcheson, 1999).

Table 3. *KMO's and Bartlet's tests of the four models*

Test		*Coefficient artificial intelligence*	*Coefficient blockchain*	*Coefficient cloud computing*	*Coefficient big data*
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.834	.832	.812	.786
Bartlett's Test of Sphericity	Approx. Chi-Square	1557.704	1734.590	1448.893	1260.926
	df	300	325	276	253
	Sig.	.000	.000	.000	.000

The common method bias test on the four models revealed a total variance explained by a single factor of 29.75% for AI, 28.72% for BC, 27.48% for CC, and 27.21% for DA. All values were below the threshold of 50% (Podsakoff, MacKenzie, Jeong-Yeon and Podsakoff, 2003), which suggests the information used for analysis is not affected by common method bias.

Table 4 exhibits the alpha values for the eight-factor solution of all the models. The alpha reliabilities for most of the constructs were satisfactory by the cut-off point of 0.7 (Kline, 2000), whereas the alpha reliability of perceived ease of use and perceived usefulness in the CC model were accepted because a value of 0.6 or more was considered adequate (Hair, Black and Babin, 2010).

Table 4. *Alpha values of the four models*

Construct	**Cronbach's α AI**	**Cronbach's α BC**	**Cronbach's α CC**	**Cronbach's α DA**
Perceived easiness of use	0.707	0.846	0.685	0.794
Perceived usefulness	0.850	0.800	0.659	0.704
Behavioural intention to use	0.890	0.932	0.909	0.825
Awareness of requirements	0.870			
Digital technology adoption	0.828			
Organisational resilience	0.833			
Regulations	0.820			

Market pressure	0.750

Additionally, composite reliability (CR), average variance extracted (AVE) and correlation matrices were obtained to ensure the reliability of the measures used. Tables 8-11 in the Appendix show the values obtained for each of the models, with values of AVE above 0.5 and CR above 0.6 in all cases, which are considered acceptable for analysis (Fornell and Larcker, 1981). The results from the correlation matrices confirm the discriminant and convergent validity of the models.

5.2.Structural equation modelling

The goodness-of-fit (GoF) coefficients of the structural equation models for the four technologies are presented in Table 5. Different measures of GoF were estimated to check the model fit to the data. We used the root mean square error of approximation (RMSEA), the goodness-of-fit index (GFI), the Tucker Lewis index (TLI), the comparative fit index (CFI), and the normed X^2 to examine the model fit. Values of CFI≥0.9 and TLI>0.9, (Schumacker and Lomax, 2004), RMSEA≤0.08 (Hair, Black and Babin, 2010; Byrne, 1989), and normed $X^2 \leq 2.0$ (Papke-Shields, Malhotra and Grover, 2002) show good fit, whereas the value of GFI≥0.8 represents reasonable fit (Doll, Xia and Torkzadeh, 1994).

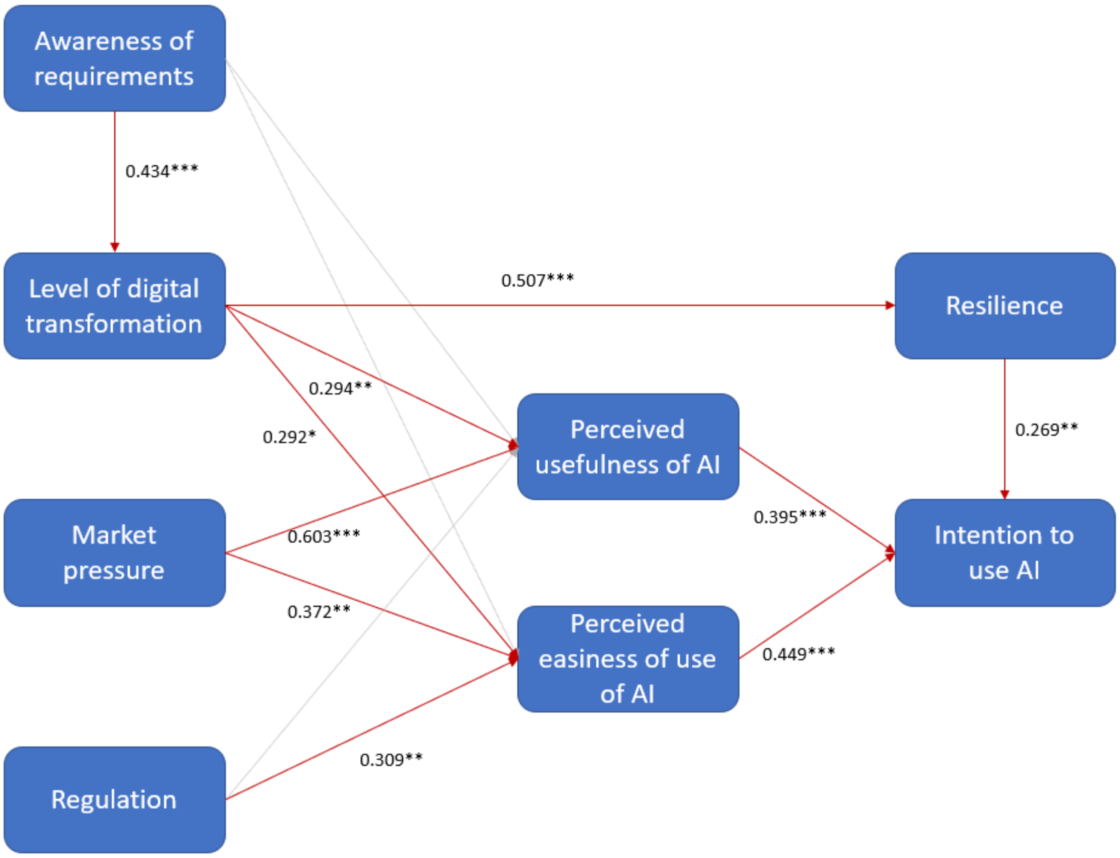
Table 5. *Goodness of fit of the four models*

GoF measure	Model AI	Model BC	Model CC	Model DA
CFI	0.942	0.952	0.954	0.943
TLI	0.934	0.945	0.947	0.933
GFI	0.823	0.825	0.837	0.838
X^2/DF	1.308	1.265	1.247	1.293
RMSEA	0.052	0.048	0.046	0.050

5.3.Parameter estimation and hypothesis testing results

The results of the SEM models for AI, blockchain, CC and big data are presented in Figures 2 - 5, respectively. The figures show the estimates of the standardised path regression coefficients and their significance for the links between the constructs used for each model. The continuous lines with coefficients represent significant relationships, whereas the dotted lines represent non-significant relationships. The significance of the relationships is evaluated based on the p-value obtained from the analysis. SEM provides p-values indicating the statistical significance of the coefficients obtained (Byrne, 2001). The p-value tests the null hypothesis that the coefficient is equal to 0, which means no effect from one construct to another. Low p-values (<0.05) indicate that changes in the predictor value lead to changes in the predicted value, whereas p-values above 0.05 are considered insignificant, implying a lack of relationship between the constructs.

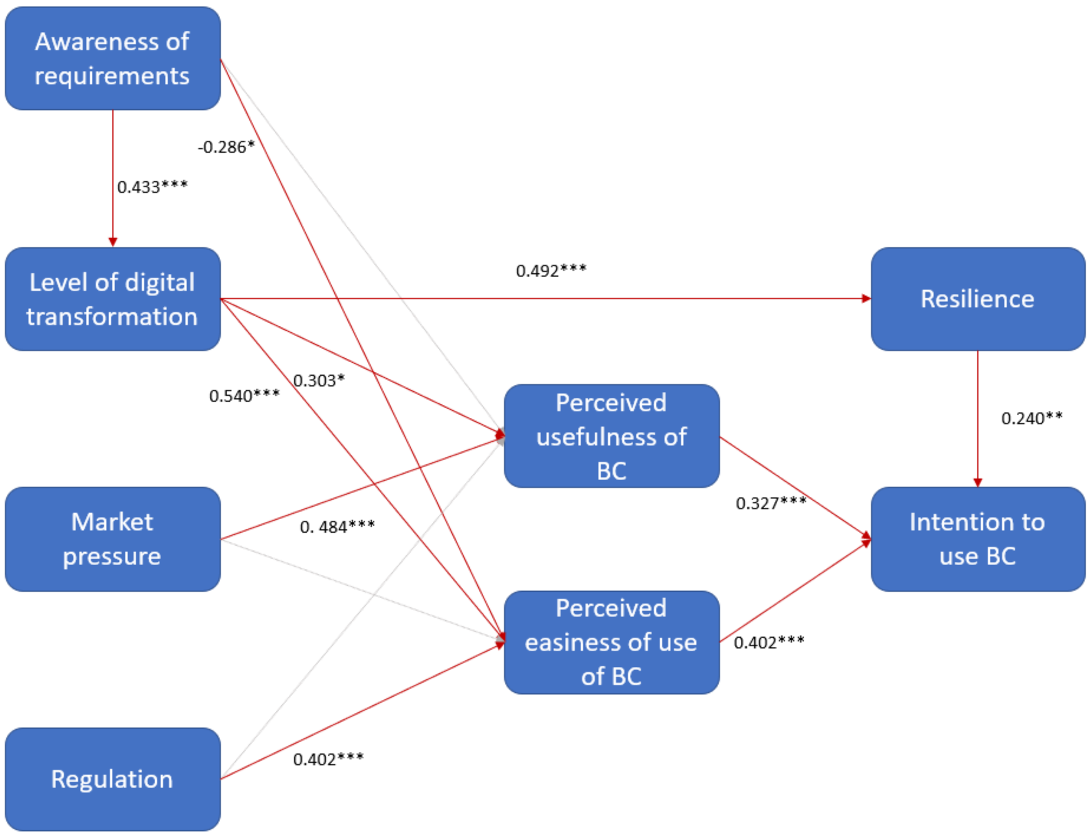
Figure 2 presents the results for the adoption of AI. Significant effects of organisational factors include awareness of the requirements on the level of digital transformation, level of digital transformation on perceived usefulness, perceived ease of use and organisational resilience; and organisational resilience on intention to use AI. The most significant effects of external factors include market pressure on perceived usefulness and perceived easiness of use and regulation on the perceived easiness of use. Examining the TAM section of the model, we found that perceived usefulness and ease of using AI have significant and positive effects on the behavioural intention of using AI.



*: p< 0.05; **: p<0.01; ***: p<0.001

Figure 2. Standardised path coefficient estimates of the model for AI adoption

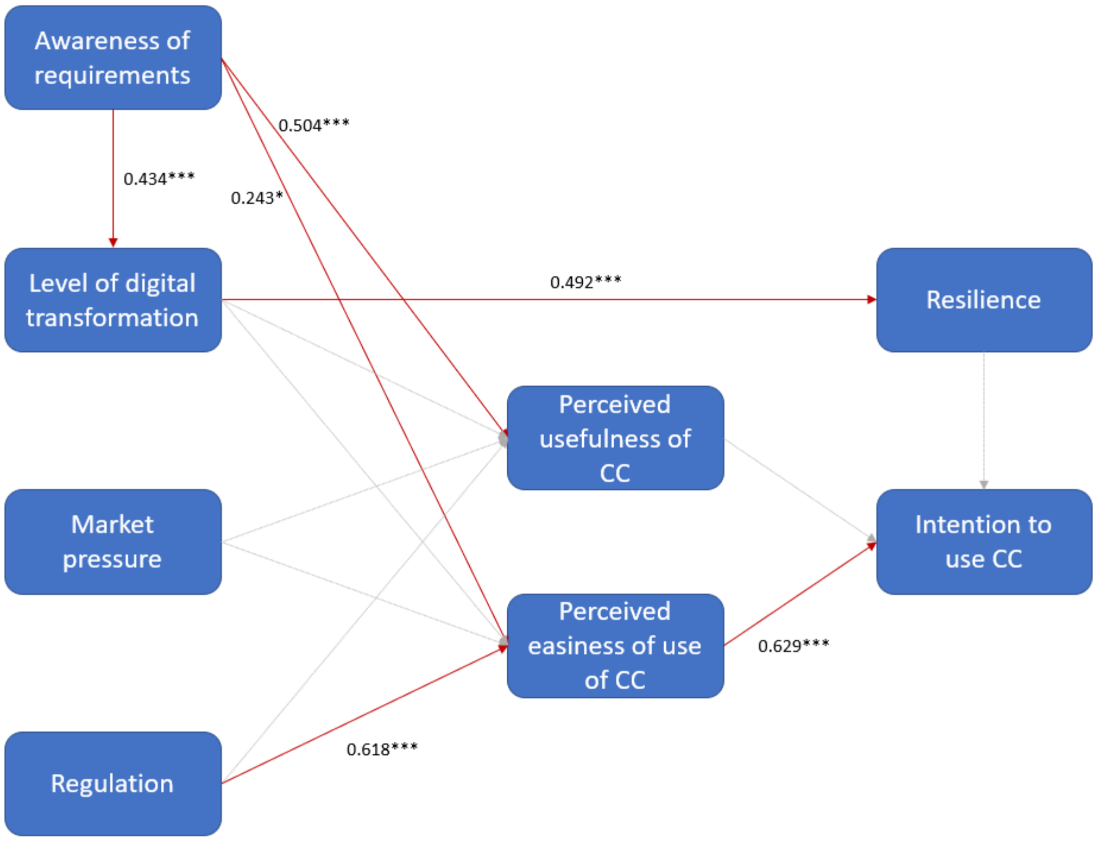
Figure 3 shows the adoption of blockchain technology. Significant effects of organisational factors include awareness of the requirements on the level of digital transformation (positive) and perceived easiness of use (negative); significant positive effects from the level of digital transformation on perceived usefulness, perceived ease of use, and organisational resilience; and organisational resilience on intention to use AI. The most significant effects of external factors include regulation on the perceived easiness of use and market pressure on perceived usefulness. The TAM section of the model shows significant results, as both perceived usefulness and ease of use significantly and positively influence the behavioural intention of using BC.



*: p< 0.05; **: p<0.01; ***: p<0.001

Figure 3. Standardised path coefficient estimates of the model for BC adoption

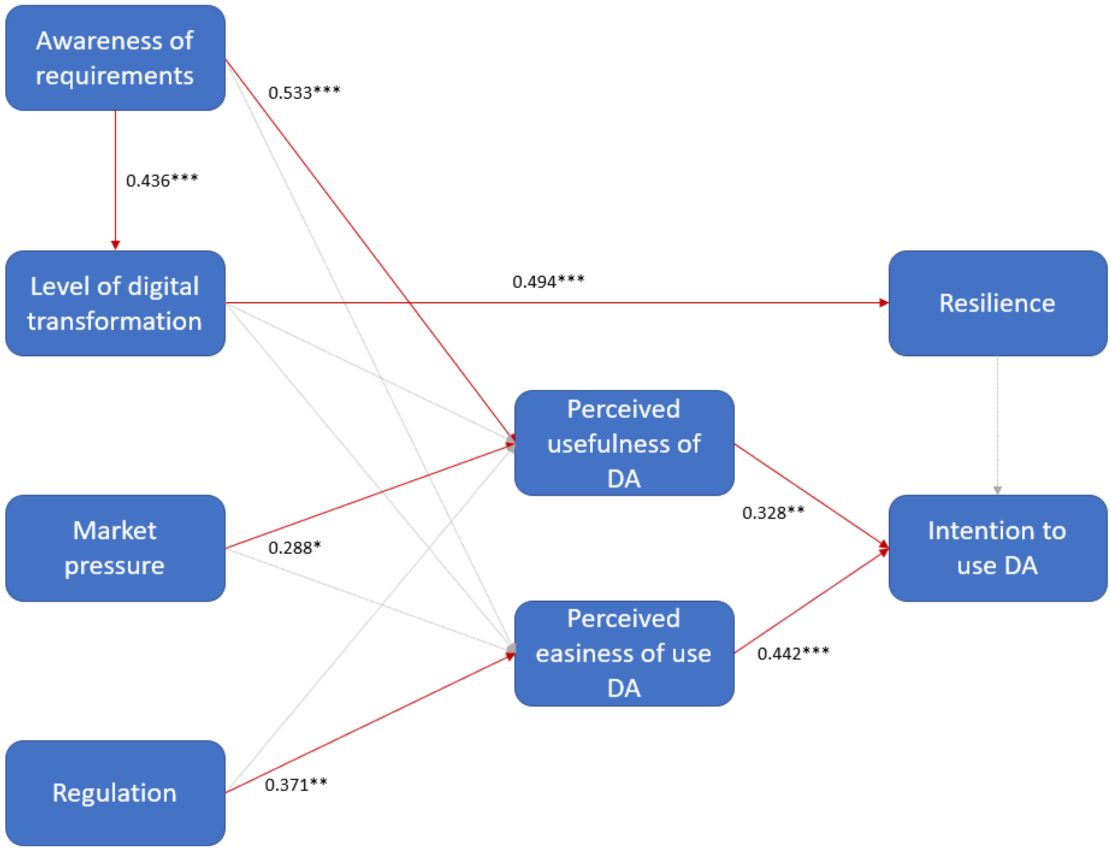
Figure 4 shows the results for the adoption of CC technology. Significant and positive effects of organisational factors include awareness of the requirements on the level of digital transformation, perceived usefulness, perceived easiness of use, and level of digital transformation on organisational resilience. Additionally, the most significant effect of external factors involves regulation on the perceived easiness of use. The TAM section of the model shows that perceived ease of use has a significant positive effect on the behavioural intention of using CC.



*: p< 0.05; **: p<0.01; ***: p<0.001

Figure 4. Standardised path coefficient estimates of the model for CC adoption

The model examining the adoption of big data is presented in Figure 5. Organisational factors have significant and positive effects: awareness of the requirements on the level of digital transformation and perceived usefulness and level of digital transformation on organisational resilience. Significant and positive effects involving external factors include regulation on the perceived easiness of use and market pressure on perceived usefulness. Finally, the behavioural intention of using big data is significantly and positively influenced by perceived ease of use and perceived usefulness.



*: p< 0.05; **: p<0.01; ***: p<0.001

Figure 5. Standardised path coefficient estimates of the model for DA adoption

The summary of results is presented in Table 6. Digital transformation arises as an important driver of organisational resilience and is an influencing factor for perceived usefulness and easiness of use in the cases of AI and BC. At the same time, as expected, it is consistently affected by the awareness of the organisational requirements for the implementation of technology. The effect of regulations on the perceived easiness of use is consistently positive, similar to the case of market pressures on perceived usefulness, except in the case of CC. Organisational resilience has a significant effect on the behavioural intention to use the cases of AI and BC. Perceived easiness of use affects behavioural intention in all cases, whilst perceived usefulness influences intention to use in most cases, except for the case of CC. The relevance of these results is discussed in the next section.

Table 6. Summary of the standardised path coefficients and significance of the four models

Hypothesis	Relationship	AI	BC	CC	DA
H1	*Regulations - Easiness*	0.309**	0.402***	0.618***	0.371**
H2	*Regulations - Usefulness*	n.s.	n.s.	n.s.	n.s.
H3	*Market - Easiness*	0.372**	n.s.	n.s.	n.s.
H4	*Market - Usefulness*	0.603***	0.484***	n.s.	0.288*
H5	*Requirements – Digital transformation*	0.434***	0.433***	0.434***	0.436***
H6	*Requirements - Easiness*	n.s.	-0.286*	0.243*	n.s.
H7	*Requirements - Usefulness*	n.s.	n.s.	0.504***	0.533***

H8	*Digital transformation - Easiness*	0.297*	0.540***	n.s.	n.s.
H9	*Digital transformation - Usefulness*	0.294**	0.303*	n.s.	n.s.
H10	*Digital transformation - Resilience*	0.507***	0.492***	0.492***	0.494***
H11	*Resilience – Intention*	0.269**	0.240**	n.s.	n.s.
H12	*Usefulness – Intention*	0.395***	0.327***	n.s.	0.328**
H13	*Easiness – Intention*	0.449***	0.402***	0.629***	0.442***

*: $p < 0.05$; **: $p<0.01$; ***: $p<0.001$

6. Discussion

Previous research has argued that digital manufacturing technologies can enhance the circular use of resources in supply chains (Lopes de Sousa Jabbour, Jabbour, Godinho Filho and Roubaud, 2018). We are extending that idea by targeting the need to allow the integration of risk management in the digital transformation of manufacturing (Borangiu, Trentesaux, Thomas, Leitão and Barata, 2019) to create more resilient organisations. Hence, using the theoretical foundations of TAM (Davis, 1989), institutional theory, and the RBV, this paper introduces and validates a model for the adoption of emergent technologies for risk management. The model proposed was applied to the implementation of four technologies to improve the identification, analysis and response to potential risks: AI, blockchain, CC and big data.

6.1.User acceptance

In the digital manufacturing and I4.0 sphere, it is important to look at the adoption of emergent technologies (Shakina, Parshakov and Alsufiev, 2021). The TAM model provides a good foundation from which to examine the adoption of emergent technologies for risk management. These emergent technologies can enhance and even redefine the way processes are performed. Although the advantages of introducing I4.0 technologies are well recognised (Dalenogare, Benitez, Ayala and Frank, 2018), the limited level of adoption combined with the absence of studies looking at the aspects affecting their implementation is an area that needs to be tackled (Bag, Sahu, Kilbourn, Pisa, Dhamija and Sahu, 2021). Perceived usefulness and perceived ease of use have been related to user acceptance in the past, where the findings have shown that adoption can be enhanced when users are aware of the potential benefits of the implementation of technology and can use it without major difficulties. These relations are consistent with the results of this study, which represent a major finding of the analysis. Previous studies have shown the value of both constructs for individual technologies underpinned by the work of Davis (1989). However, this study provides an analysis of four different technologies. It highlights the importance of both constructs for the implementation of emergent technologies in risk management; at the same time, the insignificant link between CC and perceived usefulness shows the effect of the distinct perceived characteristics of each technology on adoption. This stresses that the type of technology and the context of the application (i.e. risk management) can affect the TAM constructs.

Perceived ease of use is essential in risk management because instances in which people have a satisfactory experience with technology, especially in highly pressured circumstances, can encourage continuity of use (Meechang, Leelawat, Tang, Kodaka and

Chintanapakdee, 2020). Perceived easiness of use affected behavioural intention in all the models, which highlights the importance of having a clear understanding of the technology to facilitate user adoption. It is key for instances in which the users require close connection and interaction with the process, such as risk management (Meechang, Leelawat, Tang, Kodaka and Chintanapakdee, 2020). That result aligns with findings by Chatterjee, Rana, Dwivedi and Baabdullah (2021) in the implementation of AI, and by Albayati, Kim and Rho (2020) and Kamble, Gunasekaran, Kumar, Belhadi and Foropon (2020) in the implementation of blockchain, but contradicts findings by Kamble, Gunasekaran and Arha (2018) in the use of blockchain for supply chains in India. The reason can be linked to the context; the perceptions of the easiness of use represent a major deciding factor in the use of emergent technologies in risk management because the pressure, sense of urgency and uncertainty found in those settings (Anand and Forshner, 1995) allow minimal room for error whilst using the technologies.

Although perceived usefulness is commonly a major factor affecting intention to use technology (Davis, 1989) because knowledge about the benefits of the technology tends to incentivise users, it was found to be significant for only three out of the four technologies, which aligns with findings by Kamble, Gunasekaran and Arha (2018) and Kamble, Gunasekaran, Kumar, Belhadi and Foropon (2020) for BC, and Chatterjee, Rana, Dwivedi and Baabdullah (2021) for AI. The usefulness of BC, AI and DA is linked to improved ability to merge data from different sources, enhanced capability to filter and sort data, increased capacity to draw information from big data, enhanced communication between stakeholders, data-driven decision-making, and increased transparency and accountability (Rodríguez-Espíndola, Chowdhury, Beltagui and Albores, 2020; Queiroz and Fosso-Wamba, 2019; Xu, Xu and Li, 2018). Meechang, Leelawat, Tang, Kodaka and Chintanapakdee (2020) identify that perceptions of a technology can be domain-specific, as each technology plays a different role, and perceived usefulness becomes relevant for those technologies that improve the perceived performance. Users seem to perceive cloud services more as an enabler than as a key alternative enhancing the processes or outputs from their activities, which is reflected in perceived usefulness not having a significant relationship with adoption intentions in the case of CC. This result aligns with arguments in the literature about the marginal benefits of the isolated implementation of cloud services (Tortorella Guilherme, Giglio and van Dun Desirée, 2019) and because the perceived value of CC seems to be linked to data storage and computation on the eyes of users (Xu, Xu and Li, 2018; Koh, Orzes and Jia, 2019). This means that even when cloud services are being increasingly adopted, from the perspective of risk management the benefits of that technology are seen as passive compared to the advantages advertised for the other technologies.

Overall, the findings of the study highlight the importance of engaging potential users in the implementation of I4.0 technologies. Despite the widely known benefits of these technologies (Dalenogare, Benitez, Ayala and Frank, 2018), briefing potential users about the way each technology can help make their activity more efficient is essential to promote successful adoption. Additionally, users have to be given abundant information and training for each technology to facilitate its use and achieve the expected aims.

Otherwise, failure to convince them about the potential benefits and to facilitate the use of the technology can significantly hinder the successful adoption of technology.

6.2.Organisational resilience

Emergent technologies are useful tools to enable supply chain resilience (Min, 2019). Nevertheless, evidence is lacking for the effects of organisational resilience on the successful implementation of emergent technologies. Moreover, despite concerns about the importance of the lack of preparation and digital culture for the implementation of digital manufacturing (Bag, Sahu, Kilbourn, Pisa, Dhamija and Sahu, 2021), fewer studies have looked into the effects of capabilities such as resilience and their importance for the introduction of digital solutions. This is particularly important in risk management, as developing technical infrastructures can enable integrated approaches for supply chain risk management (Belhadi, Kamble, Jabbour, Gunasekaran, Ndubisi and Venkatesh, 2021). The findings of this study suggest that organisational resilience is only relevant for the adoption of BC and AI. The reason can be that these technologies are more widely advertised and commonly associated with the term 'disruptive technologies' (Fosso-Wamba and Queiroz, 2020; Rodríguez-Espíndola, Chowdhury, Beltagui and Albores, 2020; Cichosz, 2018). From the perspective of RBV, the need for novel approaches and new competences is associated with the paradigm-changing perception of disruptive technologies (Nair and Boulton William, 2008). The flexibility and capability to adapt found in resilient organisations (Ambulkar, Blackhurst and Grawe, 2015) would be warranted to implement and fully leverage these technologies, in contrast with CC and data analytics. Hence, organisational resilience can become a key enabler to facilitate the implementation of technologies perceived to be more complex, such as AI and BC. As the organisation is more responsive to changes in its processes and capable of adapting to new conditions and requirements caused by those changes, it is less averse to adopting disruptive technologies such as BC and AI. In contrast, organisations with lower levels of organisational resilience can find the introduction of these technologies riskier and less likely to succeed. In the case of CC and DA, it seems once technologies are more widely used and information is more readily available, the ability to adapt to unexpected conditions can become less important. That has been shown in this research, which concludes that managers do not perceive these characteristics as vital when the aim is to adopt CC and big data, which have already been used by several companies as part of the IoT and which rely on well-known and readily available best practices and accounts of experiences by other companies (Ancarani, Di Mauro, Legenvre and Cardella Marco, 2019). The established availability of information and resources around these technologies allows them to mitigate unexpected circumstances and causes less uncertainty about their implementation, which makes their implementation less risky and more attractive for all companies.

Overall, the results suggest that organisational resilience can facilitate the implementation of disruptive technologies because of the ability to react quickly and adapt to evolving conditions. This finding suggests that more innovative companies interested in these disruptive technologies can benefit from the capabilities generated in the organisation by fostering resilience.

6.3. Internal factors

Several organisational challenges exist for digital manufacturing as related to human and material resources. Investment costs and staff training can be significant barriers (Mak, Li, Tang, Wu and Lai, 2020). Hence, findings about digital transformation and its effect on TAM constructs provide insights into the role of these resources and capabilities to support disruptive technologies. This is related to the degree of organisational and technical infrastructure available in the company to foster the use of the system, which is aligned with the facilitating conditions described by Venkatesh, Morris, Davis and Davis (2003). This research acknowledges the importance of developing these conditions based on the level of technical expertise gained through the degree of digital transformation and the preparedness for implementation based on awareness of the requirements for technology implementation. The degree of digital transformation has a significant effect on perceived usefulness and ease of use of AI and BC only, which is consistent with results obtained by Grover, Kar and Dwivedi (2020), Kuberkar and Singhal (2020) and Pillai and Sivathanu (2020) for AI, and Queiroz and Fosso-Wamba (2019), Queiroz, Fosso-Wamba, De Bourmont and Telles (2020) and Wong, Leong, Hew, Tan and Ooi (2020) for BC. This can be due to the expected level of technical savviness required to introduce these disruptive technologies in risk management. Companies engaged with digital transformation have more experience leveraging technological advances, which gives them more confidence and affects their ease in adopting new technologies, as they have more certainty about the benefits that can be obtained from it. In the case of using CC and big data, numerous reports and applications (Xu, Xu and Li, 2018) make organisations less engaged with digital transformation more comfortable with the adoption of technology. More information and guidance facilitate understanding of the needs for adoption and provide more confidence about the advantages of implementing technology.

Interestingly, awareness of the requirements is significant for perceived usefulness in the cases of DA and CC, unlike the level of digital transformation. It seems that more widely known and established technologies rely more on gathering readily available information about the requirements than on having a high level of digital savviness. An unexpected finding about the awareness of requirements, however, is the contrasting impact on perceived ease of use between blockchain and CC. Although both are clustered as digital technologies (Lorenz, Benninghaus, Friedli and Netland, 2020), the results suggest that increased awareness of these requirements negatively affects the perceived easiness of use of blockchain, as opposed to the effect on the perceived easiness of use of CC. That can be because of the difference in the perceptions of the complexity of those requirements. Blockchain is at a very early stage and the requirements to harness the technology have yet to be mastered by managers (Fosso-Wamba and Queiroz, 2020), which can make the technology appear less user-friendly for employees and suggests a subsequent need for training. This result agrees with findings from the literature stressing the importance of accumulating competencies and skills in companies to improve the adoption of emergent technologies in digital manufacturing (Shakina, Parshakov and Alsufiev, 2021) and the need to increase the level of digital culture among employees through alternatives such as training (Ślusarczyk, 2018). On the other hand, CC belongs to a set of technologies developed before 2011, which were adopted by companies before the advent of the I4.0 concept (Tortorella Guilherme, Giglio and van Dun Desirée, 2019), thus benefiting from several practitioner cases (Ancarani, Di Mauro, Legenvre and Cardella Marco, 2019) that can be combined with current infrastructure to enhance technology adoption. Considering the prominence of the technical and organisational conditions of the company to promote technology adoption (Venkatesh, Morris, Davis and Davis, 2003), the results confirm the importance of the type of technology and its perceived characteristics in the effect of emergent technologies, as the influence of the level of digital transformation and the awareness of the requirements showed variations across technologies.

Digital transformation is understood as a never-ending process of leveraging capabilities brought by new technologies for organisations to transform and thrive (Li, 2020). Digital transformation has been suggested as a potential approach to prepare, manage and adapt to the conditions caused by disruptions (Papagiannidis, Harris and Morton, 2020). Managing risks and crises has been commonly linked to the concept of resilience. Organisational resilience creates the potential to react and adapt to changing and unforeseen circumstances (Cotta and Salvador, 2020). The findings of this study provide empirical evidence of the value of digital transformation to provide support to enhance organisational resilience across all the technologies studied. This means that organisations introducing the capabilities and infrastructure to harness technological advances along with the required training for adoption are reinforcing their ability to withstand disruptions, adapt to unforeseen circumstances and leverage them to move forward. Hence, organisations committed to digital transformation can leverage that expertise to build resilience inside their organisations, which in turn can allow them to manage risk and crises more effectively. That transformation, however, needs to be underpinned by an awareness of the organisational requirements for the successful adoption of technology.

6.4. External factors

External factors stemming from the institutional view represent another important part of the model. Beyond the internal barriers for digital manufacturing found in companies, environmental factors related to external stakeholders and collaboration can have a significant effect on implementation (Bag, Sahu, Kilbourn, Pisa, Dhamija and Sahu, 2021). Wong, Leong, Hew, Tan and Ooi (2020) found that regulatory support and market dynamics were not significant factors affecting the behavioural intention to use blockchain. However, we argue that regulatory support and market pressure can be factors affecting managers' perceptions. Our findings suggest a significant effect of governmental policies and support on the perceived easiness of using emergent technologies for risk management across the different technologies tested. This can be explained because regulatory guidance can enhance the confidence and level of information about the adoption of novel technologies, whereas financial motivations can allow organisations to introduce training, human resources, and support for the transition. This finding aligns with current evidence from multiple developed countries promoting governmental and industrial plans for enhanced manufacturing performance through the use of new technologies (Mariani and Borghi, 2019) and evidence that the regulatory framework can affect technology adoption (AlSheibani, Yen and Messom, 2018; Jianwen and Wakil, 2019). On the other hand, evidence of market pressure affecting the adoption of emergent technologies (Chen, Preston and Swink, 2015; AlSheibani, Yen and Messom, 2018; Pillai and Sivathanu, 2020; Wong, Leong, Hew, Tan and Ooi, 2020) are consistent with the results indicating that market pressure has a significant effect on the perceived usefulness of these technologies except in the case of CC. This means that in the cases of AI, BC, and DA the benefits for the risk management function observed in benchmarked companies or partners in the supply chain are important for understanding and acknowledging the potential benefits for the company. Conversely, the case of CC can be linked to the perception of marginal benefits from its implementation (Tortorella Guilherme, Giglio and van Dun Desirée, 2019). Even if the benefits of this technology are observed in several other organisations, it seems that these are less attractive for risk management given that it can be seen as a more passive technology compared to other alternatives.

7. Research implications

7.1. Theoretical implications

The study has used the lenses of RBV, institutional theory and TAM to develop a novel behavioural adoption model for AI, BC, CC, and DA for risk management. The model has been examined through the analysis of 117 responses using SEM to test the relationships between constructs to provide a deeper understanding of the adoption behaviour and influences of professionals from a developed economy perspective. The literature review has shown limited research looking into the adoption of I4.0 technologies in risk management, particularly looking at and contrasting the factors for the adoption of different I4.0 technologies and the role of organisational resilience and user acceptance. Hence, the contribution of this research to knowledge is threefold: It develops and empirically tests a model for user acceptance of emergent technologies in risk management combining RBV, TAM and institutional theory, it investigates the relationship between organisational resilience and user acceptance of technology in risk management, and it provides insights into the differences between the user acceptance of four different I4.0 technologies in the risk management context. Therefore, the set of implications stemming from our results for management and environmental science includes:

- Organisational resources are relevant factors affecting the adoption of emergent technologies for risk management. The involvement of companies in digital transformation can be beneficial by encouraging the adoption of cutting-edge and disruptive technologies, whereas information about the requirements and requisites of the implementation need to be considered for more known technologies.

- External factors influence users' perceptions of the adoption of emergent technologies. Guidance and regulations can affect perceptions of the easiness of the use of emergent technologies, whereas market pressure can affect the perceived usefulness of emergent technologies.
- Organisational resilience fosters an environment that can support the adoption of disruptive technologies such as BC and AI. The flexibility, adaptability, and capability to adapt that are embedded in resilient organisations facilitate the implementation of complex and less widely adopted technologies.

7.2.Practical implications

This research has shown not only theoretical contributions but also contributions to operations managers wanting to adopt these technologies:

- Regulatory support can make a significant difference in the perceptions of managers and user acceptance of emergent technologies in general. The boundaries of uncertainty and lack of understanding about technology adoption can be reduced through policies encouraging organisations to implement training and use resources to facilitate the transition to the introduction of emergent technologies for risk management. This can encourage policymakers to introduce further programmes to support companies to continue the digital transformation, aiming to support regional development and create more robust organisations to cope with disruptions in the digital manufacturing era.
- Stakeholder pressure helps organisations realise the value of technologies. Practices from other supply chain stakeholders such as customers, suppliers and competitors are relevant to value the benefits of implementing emergent technologies for risk management. This finding can encourage managers to advocate for visibility and share best practices with other supply chain partners to achieve benefits and to show the impact of I4.0 technologies in their processes.
- Investing in organisational resilience can enhance the willingness for technology adoption for risk management. Organisations aware of vulnerabilities and the potential impact of disruptions value the prospective benefits of disruptive technologies and can leverage capabilities such as flexibility and adaptability to support the implementation of technologies such as blockchain and AI. This result shows managers the importance of the relationship between enhanced capabilities and the benefits of technology adoption.
- Digital transformation can help develop necessary capabilities for organisational resilience. Harnessing technology can help companies to cope and manage risks and crises more easily. This finding can help managers to introduce digital transformation as part of their business strategy to develop capabilities that can help

them prevent and manage disruptions, along with the operational benefits advertised for the use of technology.

8. Conclusions

I4.0 has become a critical enabler for the digitalisation of processes and redefining activities in companies globally. Increasing environmental challenges have shown the importance of integrating risk management in the digital transformation of manufacturing companies. However, it is one of the processes that are lagging in that evolution. Moreover, the general implementation of I4.0 is still at a very nascent stage (Büchi, Cugno and Castagnoli, 2020). Understanding the different factors influencing user acceptance and facilitating that transformation can make a major difference in facilitating the adoption of I4.0 technologies to redefine key processes such as risk management. This paper has empirically investigated the impact of organisational and external factors in the adoption of AI, blockchain, CC and big data for risk management based on the lenses of the RBV, institutional theory and TAM. The purpose is to provide a further understanding of the impact of those factors to enable the implementation of emergent technologies and improve risk management processes.

A total of 117 responses from managers obtained from a survey instrument were analysed using SEM to validate the model and examine the relationships between constructs. These responses were used to analyse the influence of internal and external factors in user acceptance. Regulatory support and guidance have a significant positive relationship with perceived ease of use in the case of the four technologies, whilst market pressure has a significant positive relationship with perceived usefulness for the implementation of AI, blockchain and big data. On the other hand, internal factors were particularly relevant for the adoption of AI and blockchain. Digital transformation had a positive relationship with both perceived usefulness and perceived ease of use in both cases, whereas organisational resilience showed a positive effect on the behavioural intention to adopt both technologies. This outcome suggests the importance of accounting for internal and external factors as key enablers in the adoption of emergent technologies for risk management and support in redefining and enhancing processes in companies.

This work extends current knowledge on the implementation of emergent technologies for risk management to support digital manufacturing. However, various limitations need to be acknowledged. Although considering manufacturing companies in the UK was decided to enhance the internal validity of the study, this complicates generalisability. The results of this analysis must be carefully considered for different sectors. That can be addressed through the use of larger samples from different sectors in future research. This study cannot confirm the lack of existence of factors mediating the external factors. We propose the use of case-based research to look into any other aspects that could have mediating effects on the implementation of emergent technologies for risk management to support digital manufacturing.

Opportunities for future work are diverse. A similar study on alternative countries would allow the identification of differences in managers' perceptions and the relationships of the constructs included. The comparison between the perceived use of these technologies and their actual use after an emergency has occurred would deepen our understanding of the value and use of emergent technologies. That analysis could involve the comparison of firms regarding different characteristics and technological proficiencies, to look at the variations among them. Additionally, an interesting opportunity for further work involves exploring the links between the particular features of each emergent technology and the different stages of risk management to identify their effects on the behavioural intention of implementation of these technologies. Finally, the addition of other emergent technologies could be valuable to gather further insights about the constructs included.

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Appendix

Table 7. Survey items

Survey construct	*Questions*	*Reference*
Digital technology adoption	• My company is engaging in digital transformation • My company has relevant sensors/technology to collect and sense information from multiple sources in real time • My company employs technology solutions to transform data into a usable format, to help understand the collected information • My company employs technology solutions to use the data for making forecasts that will help prepare for the future • My company employs technology solutions to automate the processes relevant to data-driven decision making • My company has strategies in place for workforce skills development, to effectively manage and use the technology solutions	*Dubey, Gunasekaran, Childe, Bryde, Giannakis, Foropon, Roubaud and Hazen (2020), Fosso-Wamba, Queiroz and Trinchera (2020)*
Organisational resilience	• We are able to cope with changes brought by disruptions/ emergency situations. • We are able to adapt to the disruption easily. • We are able to provide a quick response to disruptions • We are able to maintain high situational awareness at all times	*Ambulkar, Blackhurst and Grawe (2015)*
Regulations	• Emergent technologies' development and implementation receives financial support from government or relevant authorities • Relevant policies are introduced by the government to boost emergent technology implementation • There is legal support for the integration of emergent technologies • The laws and regulations that exist nowadays are sufficient to protect the integration and use of emergent technologies.	*Wong, Leong, Hew, Tan and Ooi (2020)*
Market pressure	• Stakeholder's (e.g. suppliers and customers) expectations about the integration of emergent technologies on risk management are increasing • Other companies are planning or starting to integrate emergent technologies for risk management • The requirements for accuracy, transparency, enhanced decision-making, and traceability for risk management are rising. • Companies need to introduce cutting-edge technology for risk management such as BC, cloud computing, artificial intelligence, and data analytics continuously to satisfy stakeholders	*Wong, Leong, Hew, Tan and Ooi (2020)*
Awareness of requirements of technology adoption	• Requires strategic leadership from within the organisation • Requires a vision and long-term plan which are effectively communicated across the organisation • It can enhance business reputation in the sector and among the consumers • Requires creating the right balance between people and technology, through clear allocation of resources, tasks, and identifying roles and responsibilities • Requires engaging the employees and establishing trust among the workforce	*Ślusarczyk (2018)*

	• Requires developing relations with business partners and stakeholders to effectively engage them • Requires awareness of technology needs and developing skills through training • Requires alignment with organisation, structure values, culture, and strategy • Requires understanding the organisational change – i.e. what will be the change and its impact on people, process, and profits • Developing and promoting a culture of innovation within the organisation • Requires adaptive capacity, i.e. acknowledging uncertainty and demonstrate agility to change •	
Perceived easiness of use AI	• I think AI is easy and understandable • It would be easy for me to become skilful at using AI for risk management • I think integrating AI will be easy compared to conventional practices used for risk management • I would find it easy to get AI to do what I need to do for risk management	*Davis (1989), Kamble, Gunasekaran and Arha (2018)*
Perceived easiness of use BC	• I think BC is easy and understandable • It would be easy for me to become skilful at using BC for risk management • I think integrating BC will be easy compared to conventional practices used for risk management • I would find it easy to get BC to do what I need to do for risk management	
Perceived easiness of use CC	• I think CC is easy and understandable • It would be easy for me to become skilful at using CC for risk management • I think integrating CC will be easy compared to conventional practices used for risk management • I would find it easy to get CC to do what I need to do for risk management	
Perceived easiness of use DA	• I think DA is easy and understandable • It would be easy for me to become skilful at using DA for risk management • I think integrating DA will be easy compared to conventional practices used for risk management • I would find it easy to get DA to do what I need to do for risk management	
Perceived usefulness AI	• AI enhances predictive risk identification assessment • AI facilitates drawing insights from big data for risk management • AI encourages having qualitative understanding of the risks and recommendations to enhance trust and reliability for risk management • AI supports the efficient allocation of resources for risk management • AI enhances decision-making during crises	*Davis (1989), Venkatesh and Davis (2000)*
Perceived usefulness BC	• BC facilitates tracing and tracking information related to processes for risk management	

	• BC allows us to perform secure transactions for risk management • BC allows us to effectively communicate with customers and suppliers to manage risks • BC enhances information quality and reliability for risk management • BC facilitates swifter data-driven decision-making for risk management	
Perceived usefulness CC	• CC facilitates collaboration with internal and external stakeholders for risk management • CC reduces in-house operability risks • CC enhances data management within the organisation for risk management • CC facilitates data driven decision making for risk management	
Perceived usefulness DA	• DA allows to combine data from different sources to increase the reliability of forecasts about risks and potential crises • DA permits the company to react swiftly to manage risks and crises • DA provides an overview of the data and help to understand its value for risk management • DA enable data-driven decision-making during risk management	
Behavioural intention to use AI	• I predict my organisation will adopt AI for risk management in the future • I plan to integrate AI for risk management in the near future • I expect that my organisation will integrate AI to enhance risk management in the future • My organisation plans to digitally transform risk management operations through integrating AI	*Kamble, Gunasekaran and Arha (2018), Wong, Leong, Hew, Tan and Ooi (2020), Venkatesh and Davis (2000)*
Behavioural intention to use BC	• I predict my organisation will adopt BC for risk management in the future • I plan to integrate BC for risk management in the near future • I expect that my organisation will integrate BC to enhance risk management in the future • My organisation plans to digitally transform risk management operations through integrating BC	
Behavioural intention to use CC	• I predict my organisation will adopt CC for risk management in the future • I plan to integrate CC for risk management in the near future • I expect that my organisation will integrate CC to enhance risk management in the future • My organisation plans to digitally transform risk management operations through integrating CC	
Behavioural intention to use DA	• I predict my organisation will adopt DA for risk management in the future • I plan to integrate DA for risk management in the near future • I expect that my organisation will integrate DA to enhance risk management in the future • My organisation plans to digitally transform risk management operations through integrating DA	

Table 8. CR, AVE and correlations matrix of the AI model

	CR	AVE	MSV	MaxR(H)	EAI	MAR	REQ	ADO	RES	REG	IAI	UAI
EAI	0.713	0.556	0.480	0.733	**0.746**							
MAR	0.750	0.501	0.473	0.759	0.443	**0.708**						
REQ	0.871	0.629	0.181	0.872	-0.002	0.312	**0.793**					
ADO	0.834	0.626	0.242	0.839	0.280	0.178	0.426	**0.791**				
RES	0.834	0.627	0.242	0.847	0.150	-0.020	0.285	0.492	**0.792**			
REG	0.820	0.603	0.345	0.822	0.491	0.587	0.072	0.239	0.134	**0.777**		
IAI	0.893	0.735	0.480	0.899	0.693	0.447	0.274	0.443	0.385	0.442	**0.858**	
UAI	0.851	0.589	0.473	0.855	0.549	0.688	0.336	0.395	0.197	0.465	0.667	**0.768**

Table 9. CR, AVE and correlations matrix of the BC model

	CR	AVE	MSV	MaxR(H)	EBC	MAR	REQ	ADO	RES	REG	IBC	UBC
EBC	0.847	0.649	0.338	0.847	**0.806**							
MAR	0.749	0.500	0.345	0.760	0.226	**0.707**						
REQ	0.872	0.629	0.181	0.872	0.003	0.322	**0.793**					
ADO	0.834	0.627	0.243	0.839	0.478	0.187	0.425	**0.792**				
RES	0.834	0.628	0.243	0.844	0.189	-0.005	0.285	0.493	**0.792**			
REG	0.821	0.604	0.345	0.821	0.484	0.587	0.070	0.235	0.131	**0.777**		
IBC	0.933	0.777	0.338	0.941	0.581	0.389	0.054	0.410	0.364	0.464	**0.882**	
UBC	0.802	0.575	0.334	0.805	0.513	0.578	0.321	0.382	0.144	0.399	0.541	**0.758**

Table 10. CR, AVE and correlations matrix of the CC model

	CR	AVE	MSV	MaxR(H)	ECC	MAR	REQ	ADO	RES	REG	ICC	UCC
ECC	0.686	0.522	0.448	0.687	**0.723**							
MAR	0.751	0.502	0.349	0.755	0.393	**0.709**						

REQ	0.871	0.629	0.324	0.872	0.302	0.324	**0.793**					
ADO	0.834	0.627	0.240	0.843	0.354	0.173	0.428	**0.792**				
RES	0.834	0.627	0.240	0.845	0.254	-0.011	0.287	0.490	**0.792**			
REG	0.819	0.602	0.448	0.820	0.669	0.591	0.074	0.224	0.130	**0.776**		
ICC	0.912	0.723	0.442	0.938	0.665	0.419	0.317	0.235	0.020	0.446	**0.851**	
UCC	0.668	0.504	0.350	0.690	0.592	0.387	0.569	0.387	0.089	0.296	0.406	**0.710**

Table 11. CR, AVE and correlations matrix of the DA model

	CR	**AVE**	**MSV**	**MaxR(H)**	**ECC**	**MAR**	**REQ**	**ADO**	**RES**	**REG**	**ICC**	**UCC**
ECC	0.797	0.568	0.319	0.818	**0.754**							
MAR	0.752	0.502	0.339	0.753	0.418	**0.709**						
REQ	0.871	0.629	0.368	0.872	0.326	0.333	**0.793**					
ADO	0.834	0.627	0.241	0.842	0.313	0.170	0.429	**0.792**				
RES	0.834	0.627	0.241	0.844	0.149	-0.010	0.287	0.491	**0.792**			
REG	0.820	0.603	0.339	0.821	0.483	0.582	0.073	0.230	0.131	**0.777**		
ICC	0.832	0.713	0.319	0.857	0.565	0.562	0.474	0.343	0.169	0.334	**0.844**	
UCC	0.708	0.549	0.368	0.720	0.354	0.417	0.607	0.388	0.135	0.214	0.431	**0.741**

Table 12. List of abbreviations

Abbreviation	Meaning
AI	Artificial intelligence
BC	Blockchain technology
CC	Cloud computing
CFI	the comparative fit index
DA	Big data
GFI	Goodness-of-fit index
GoF	Goodness-of-fit (GoF)
IT	Information Technology
KMO	Kaiser-Meyer-Olkin
RBV	Resource-based view
RMSEA	Root mean square error of approximation
SEM	Structural equation modelling
TAM	Technology Acceptance Model
TLI	Tucker Lewis index
TOE	Technology-Organisations-Environment
UTAUT	Unified Theory of Acceptance and Use of Technology