

Identification and analysis of adoption barriers of disruptive technologies in the logistics industry

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Abstract

Purpose – Recently, disruptive technologies (DTs) have proposed several innovative applications in managing logistics and promise to transform the entire logistics sector drastically. Often, this transformation is not successful due to the existence of adoption barriers to DTs. This study aims to identify the significant barriers that impede the successful adoption of DTs in the logistics sector and examine the interrelationships amongst them.

Design/methodology/approach – Initially, 12 critical barriers were identified through an extensive literature review on disruptive logistics management, and the barriers were screened to ten relevant barriers with the help of Fuzzy Delphi Method (FDM). Further, an Interpretive Structural Modelling (ISM) approach was built with the inputs from logistics experts working in the various departments of warehouses, inventory control, transportation, freight management and customer service management. ISM approach was then used to generate and examine the interrelationships amongst the critical barriers. Matrices d'Impacts Croises-Multiplication Applique a Classement (MICMAC) analysed the barriers based on the barriers' driving and dependence power.

Findings – Results from the ISM-based technique reveal that the lack of top management support (B6) was a critical barrier that can influence the adoption of DTs. Other significant barriers, such as legal and regulatory frameworks (B1), infrastructure (B3) and resistance to change (B2), were identified as the driving barriers, and



industries need to pay more attention to them for the successful adoption of DTs in logistics. The MICMAC analysis shows that the legal and regulatory framework and lack of top management support have the highest driving powers. In contrast, lack of trust, reliability and privacy/security emerge as barriers with high dependence powers.

Research limitations/implications – The authors' study has several implications in the light of DT substitution. First, this study successfully analyses the seven DTs using Adner and Kapoor's framework (2016a, b) and the Theory of Disruptive Innovation (Christensen, 1997; Christensen *et al.*, 2011) based on the two parameters as follows: emergence challenge of new technology and extension opportunity of old technology. Second, this study categorises these seven DTs into four quadrants from the framework. Third, this study proposes the recommended paths that DTs might want to follow to be adopted quickly.

Practical implications – The authors' study has several managerial implications in light of the adoption of DTs. First, the authors' study identified no autonomous barriers to adopting DTs. Second, other barriers belonging to any lower level of the ISM model can influence the dependent barriers. Third, the linkage barriers are unstable, and any preventive action involving linkage barriers would subsequently affect linkage barriers and other barriers. Fourth, the independent barriers have high influencing powers over other barriers.

Originality/value – The contributions of this study are four-fold. First, the study identifies the different DTs in the logistics sector. Second, the study applies the theory of disruptive innovations and the ecosystems framework to rationalise the choice of these seven DTs. Third, the study identifies and critically assesses the barriers to the successful adoption of these DTs through a strategic evaluation procedure with the help of a framework built with inputs from logistics experts. Fourth, the study recognises DTs adoption barriers in logistics management and provides a foundation for future research to eliminate those barriers.

Keywords Disruptive technologies, Internet of things, Blockchain, Bigdata, Drone, Driverless vehicle, Artificial intelligence, 3D printing, Logistics management

Paper type Research paper

1. Introduction and motivation

Disruptive innovation has influenced the logistics industry, with most firms attempting to adapt to a rapidly changing environment. Many organisations are transforming their logistics networks to remain competitive and sustainable in the continuously evolving technological environment (Winkelhaus and Groose, 2020). For instance, Kouvolo Innovation, a Finnish company, has collaborated with International Business Machines (IBM) to build a blockchain-based system for shipping containers (Del Castillo, 2017). Recently, major European operators have joined *Tradelens* to enable information-sharing across diverse supply chains (SCs), increase industry innovation, reduce trade friction and endorse more global trade [1]. Although experts expect that blockchains will deliver significant benefits (Hughes *et al.*, 2019), freight logistics firms prefer to operate with simpler technologies rather than adopt more advanced ones (Janjevic *et al.*, 2019).

With more focus on the Internet of Things (IoT), logistics firms and SCs immensely benefit from IoT adoption. IoTs are expected to generate US\$1.9 trillion in economic value globally across the SCs and logistics sectors [2]. Further, according to DHL, IoTs help track shipments, manage warehouse inventory and optimise vehicle fleets. Recently, Saia LTL Freight [2] incorporated Intel's IoT on its truck fleets to track maintenance schedules, the health and safety of the drivers and the frequency of refuelling. However, IoT adoption in the logistics sector is not without challenges. A critical challenge is maintaining the consistency between the centralised information technology (IT) records and data feeds from the installed IoT sensors (Tu, 2018). Further, a big challenge with IoT adoption is the highly uncertain financial returns on technology investment [3]. Finally, realising the full potential of IoTs may require significant managerial attention for handling issues such as *analytics challenges* and *cybersecurity* [4].

As firms focus more on improving the operational efficiency of their SCs and logistics, they are opting for automation technologies more frequently, such as drone-based delivery. For instance, Swiss Post and Matternet are conducting trial drone-based deliveries [5]. Recently, Aha has been delivering food items and small consumer goods with the help of drones within a limited radius of 2.5 miles [6]. However, there are obstacles (such as *poor*

weather, other flying objects and drone loudness) that current market players such as Amazon face whilst serving drone-based deliveries [7]. Further, drone-based deliveries in densely populated urban areas are too risky [8]. Whilst many research projects have proven the success of drone-based deliveries, in reality, infrastructural support and regulatory factors can determine its commercial viability [9, 10].

Global logistics firms are also expected to increase their digital technologies, such as artificial intelligence (AI) to meet the growing e-commerce demand [11]. Traditional logistics and transportation firms still depend heavily on human labour for logistical processes [12], which can improve with the adoption of AI. Many logistics firms use robots and AI-based mechanical arms to reduce human intervention in logistical operations. For instance, XPO Logistics, Rakuten and JD.com are using AI-based robots for delivering the goods ordered by customers [13, 14]. However, these firms face problems due to the enormous range of items these robots need to lift and carry in the warehouses [13]. In another instance, KNAPP AG, the Austrian logistics firm, reported that AI-based robots could successfully handle only about 15% of all items [15]. Further, most of these robots could not grip soft objects properly, leading to inefficient usage of AI-based technologies [16].

The current competitive environment in the logistics industry leads to a huge increase in business data. Big Data Analytics can be a solution to handle these challenges and provide a competitive advantage to logistics firms. For instance, service delivery time can be *optimised* through advanced predictive techniques. DHL Smart Trucks operate on real-time geographical, traffic and weather data to plan the delivery routes dynamically. Big Data Analytics can also provide a versatile platform to create valuable customer insights and recommendations built from existing data, customer feedback and demographics to improve delivery [17]. However, the implementation of Big Data projects is not without its challenges. First, a strong alignment between business units and the IT departments must be maintained (Bean and Davenport, 2019; Wamba *et al.*, 2018). Second, organisational data must be accessible to all stakeholders [17]. Third, organisations need to hire data scientists to manage these projects efficiently [18].

Many logistics firms and organisations plan to adopt autonomous vehicles (AVs) to ease transportation hurdles. For instance, TuSimple [19] collaborates with major Third-party logistics (3PL) operators to improve freight delivery with AVs [20]. Next, Amazon plans to adopt AVs to overcome logistical challenges [21]. However, opting for AVs is costlier for logistics firms, and they need regular maintenance [22]. AVs have inadequate scope in the trucking industry due to their obvious disadvantage whilst long-distance driving on highways [23]. Besides, the global adoption of AVs in the logistics sector has safety concerns. For instance, Uber's autonomous car was involved in a fatal accident [24], whilst the image-processing algorithms of AVs could not identify objects as accurately as predicted [25].

Next, there is growing hype and excitement about 3D printing (or additive manufacturing) technologies that can potentially revolutionise the logistics sectors. For instance, Amazon has designed delivery trucks fitted with 3D printers to manufacture products on the way to a customer destination. Therefore, it can drastically reduce the lead time of customised delivery [26]. However, many challenges prevent the successful adoption of 3D printing in the logistics sector. For instance, Ford Motors is adopting 3D printers to mass produce spare parts. However, the production speed of these 3D printers is much lower than the traditional machines, leading to a higher lead time. Again, 3D printing is a fast-developing technology, and organisations fear that their initial investments will be obsolete within the next few years. Thus, the feasibility of 3D printing remains a significant challenge.

Therefore, firms must identify various barriers before considering the implementation of disruptive technologies (DTs) (Christensen, 2013; Rogers *et al.*, 2016; Zhong *et al.*, 2016; Hofmann and Rüschi, 2017; Kim *et al.*, 2017; Hopkins and Hawking, 2018; McDonald, 2019; Sah *et al.*, 2021). Thus, in this study, (1) we list the barriers, (2) select the relevant barriers with the

Fuzzy Delphi Method (FDM) and (3) analyse their interrelationship using an Interpretive Structural Modelling (ISM)-based structural model. Further, we analyse their driving and dependence powers using Matrics d'Impacts Croises-Multiplication Applique a Classement (MICMAC) analysis. For this study, we consider the following seven DTs (see Table 1) in the logistics sector: *Unmanned aerial vehicle (UAV)/Drone technologies*, *Driverless car/AVs*, *Big Data*, *blockchains*, *AI*, *IoT* and *3D printing* (Hopkins and Hawking, 2018; McDonald, 2019; Hughes *et al.*, 2019). These seven DTs are applied extensively in the logistics sector, and these are viable for large scale adoption (Rogers *et al.*, 2016; Zhong *et al.*, 2016; Hofmann and Rüschi, 2017; Kim *et al.*, 2017; Kellermann *et al.*, 2020). In this exploratory study, we also apply the classical theory of disruptive innovations by Christensen (Christensen, 1997; Christensen and Raynor, 2013; Christensen *et al.*, 2015) and ecosystems framework (Adner and Kapoor, 2016a, b)

S. No	DTs in the logistics sector	Description
1	Blockchain	D: "Blockchain technology refers to a fundamentally decentralised, distributed, shared and immutable database ledger that stores the registry of assets and transactions across a peer-to-peer (P2P) network" (Khan and Salah, 2018) U: It enforces transparency and safe system-wide consensus on the validity of a transaction using its entire history (Risius and Spohrer, 2017, p. 386)
2	Internet of Things	D: A transparent and massive network of intelligent objects capable of sharing information and services through the internet to record, monitor and optimise their activities in real-time (Madakam <i>et al.</i> , 2015) U: A vehicle can be controlled automatically by IoTs according to the host specifications, enabling them to operate at pre-defined intervals and at standard speed to maximise fuel economy
3	Drone	D: An aviation device that can function without a human driver but can be controlled remotely or fly autonomously (Sah <i>et al.</i> , 2021) U: It allows delivering lightweight parcels with a low operational cost, especially last-mile delivery
4	Artificial Intelligence	D: Algorithms that enable machines to work similarly to a human brain, such as evaluating complicated datasets for patterns and trends (Syam and Sharma, 2018) U: AI techniques such as genetic algorithms, artificial neural networks and fuzzy logic models are being introduced in the logistics sectors in route optimisation problems and dynamic traffic modelling (Pannu, 2015)
5	Big Data	D: It refers to data sets whose attributes follow the 3Vs (variety, velocity and volume) (Yin and Kaynak, 2015). They require new technology such as Hadoop, Hbase, MapReduce, MongoDB or CouchDB U: It allows service providers to improve logistics management and enhance customer satisfaction (Sivarajah <i>et al.</i> , 2017)
6	Driverless car/AVs	D: Defined as vehicles that do not require human intervention for controlling actions such as braking, accelerating or steering (NHTSA, 2017) U: Vehicles used in warehouses are based on an autonomous navigation system, and they are not only ideal for the transport of goods but also for the loading, unloading and execution of orders (Benzidia <i>et al.</i> , 2019)
7	3D printing	D: It is a computer-controlled process that generates three-dimensional or physical objects, usually in layers, by depositing appropriate raw materials (Attaran, 2017) U: Mass customisation of the finished product helps reduce inventory levels and last-mile shipping by printing products closer to the customer (Khorram and Nonino, 2017)

Note(s): D: Definition; U: Use

Table 1.
Description of DTs in
the logistics sector

to corroborate our choice of these seven DTs for the logistics industry. Therefore, we address these research gaps in the form of the research questions as follows:

RQ1. What are the different DTs in the logistics sector?

RQ2. How does the Theory of Disruptive Innovation and Ecosystems Framework map the logistics industry's business models (i.e. seven DTs)?

RQ3. What are the relevant barriers to the successful adoption of these DTs?

RQ4. What are the hierarchical relationships and interaction(s) amongst those barriers?

The rest of the study proceeds as follows. [Section 2](#) provides detailed background literature on DTs for the logistics sector, followed by relevant theoretical frameworks. [Section 3](#) presents the proposed research methodology. [Section 4](#) presents the application of the proposed methodology, followed by the results. [Section 5](#) presents the discussion and findings of this study, followed by their managerial and research implications in [Section 6](#). The study concludes with a future research direction and limitations in [Section 7](#).

2. Literature review and theoretical foundation

In this section, we review the relevant literature on the seven DTs in the logistics sector and the barriers that inhibit their adoption, as presented in [Table A1](#). Later, we present and discuss the theoretical frameworks to examine the feasibility of these seven DTs.

2.1 Barriers to the adoption of disruptive technologies: identification

2.1.1 Legal and regulatory frameworks (B1). The federal and state governments play an essential role in evaluating unforeseen economic, health and safety issues whilst implementing and using 3D printing ([US GAO, 2015](#)). Similarly, blockchain-based platforms have no dependency on regulatory frameworks due to their decentralised nature ([Biswas and Gupta, 2019](#)). In the context of a driverless car, regulatory actions are necessary to address several issues, such as vehicle licensing and liability requirements ([Fagnant and Kockelman, 2015](#)). Therefore, developing robust regulatory and legal frameworks is mandatory to enable faster adoption of DTs ([Hughes et al., 2019](#)).

2.1.2 Resistance to change (B2). Adopting DTs across logistics firms can also arise from various factors such as resistance to change, associated social scepticism, stakeholders' attitude and perceptions ([Kostoff et al., 2004](#)). Fear is often an attitudinal factor that creates resistance to the successful adoption of commercial drones in logistics ([Kwon et al., 2017](#)). Similarly, the perception of security risks, technology anxiety and perceived complexity cause resistance to IoT adoption ([Mani and Chouk, 2018](#)). Factors such as changing jobs, tasks and work practices resist the successful adoption of 3D printing ([Mellor et al., 2014](#)). Finally, inadequate administrative support for IT and related practices creates resistance to adopting Big Data amongst organisations ([Bean and Davenport, 2019](#)).

2.1.3 Infrastructure (B3). The successful adoption of DTs requires a preliminary investment for associated hardware and software to analyse the data. But most organisations are not ready to upgrade their existing IT systems to meet the requirement of Big Data ([Alharthi et al., 2017](#)). Similarly, IoT implementation in an organisation requires high infrastructure readiness and support to manage the interconnected devices efficiently ([Luthra et al., 2018](#)). Likewise, infrastructure issues may hinder the adoption of AVs ([Zhang et al., 2018](#)). In the context of 3D printing, a lack of technical infrastructure may impede its adoption ([Dwivedi et al., 2017](#)). Improper security infrastructure and connectivity are considered critical barriers to adopting DTs ([Kaur and Rampersad, 2018](#)).

2.1.4 Data management (B4). The data centres are not ready to deal with the massive amount of data due to their heterogeneous nature ([Gartner, 2014](#); [Chen and Zhang, 2014](#)).

The drones used for last-mile deliveries generate real-time data from multiple sources (Alwateer *et al.*, 2019). In such circumstances, an effective data management framework needs to be implemented to resolve issues arising from the data centres (Finn and Wright, 2016; Alwateer *et al.*, 2019). Similarly, additive manufacturing generates enormous data in different formats and from diverse sources that lead to adoption challenges (Liu *et al.*, 2020).

2.1.5 Lack of trust (B5). The lack of trust can be a big challenge to the adoption of DTs (Hsiao, 2003). Trust is an important issue in the adoption of IoT and blockchains (Heiskanen, 2017). Similarly, trust issues in organisations, such as inefficient transactions, frauds and pilferage, are highlighted in many studies (Hsiao, 2003). Similarly, the lack of trust leads to safety issues that may threaten the commercial use of DTs (Finn and Donovan, 2016).

2.1.6 Lack of top management support (B6). Poor organisational policies did not support blockchains, leading to problems with resource allocation in organisations (Mendling *et al.*, 2018). The lack of budgeting and financial support from top management hindered the adoption of Big Data (LaValle *et al.*, 2011). A lack of top management support may discourage the adoption of additive manufacturing (Dwivedi *et al.*, 2017).

2.1.7 Lack of adequate resources (B7). Availability of resources such as IT skills, access to finances and the latest software can lead to the successful implementation of DTs in the logistics sector and provide a competitive advantage (Danneels, 2004). For instance, adopting blockchain-based platforms requires investment in new information collection and processing software. This adoption is expensive for organisations and their network partners (Mougayar, 2016). In another instance, challenges such as unskilled employees, insufficient computing resources and low data storage can cause problems to handle Big Data and hinder its adoption (LaValle *et al.*, 2011). Similarly, Janssen *et al.* (2019) found that the lack of resources posed a significant challenge in developing an efficient IoT-based platform.

2.1.8 Lack of reliability (B8). The reliability of a logistics system refers to the effective facilitation of materials and the flow of information throughout the entire SC (Saber *et al.*, 2019). In additive manufacturing, a lack of reliability can cause issues in quality, consistency and repeatability (Kim *et al.*, 2014). If blockchains cannot maintain the promised reliability, then complications may arise related to the traceability of the process (Biswas and Gupta, 2019). In the context of drones, Colefax *et al.* (2019) addressed the reliability of components that cause hindrance in the detection, monitoring and surveillance.

2.1.9 Privacy and security (B9). Privacy concerns the right of a user to evaluate *when, how* and *to what level* the associated information is to be shared with others. Similarly, security refers to protecting data against intentional and accidental breaches. IoTs collect confidential information and can cause a privacy and security breach by third parties (Janssen *et al.*, 2019). In the context of Big Data, several challenges may hinder its adoption, such as poor data protection, lack of data storage and data privacy threats (Chen and Zhang, 2014). Biswas and Gupta (2019) identified data privacy and security issues in blockchain platforms that can hinder their adoption. The US Federal Aviation Administration reported that data privacy and security issues could delay the operation of civil drones (Finn and Wright, 2016). Similarly, privacy is a primary concern in adopting additive manufacturing (Niaki and Nonino, 2017; Dwivedi *et al.*, 2017).

2.1.10 Technical issues (B10). The technical barrier refers to restricted access to useful, meaningful, relevant and appropriate hardware and software. Sah *et al.* (2021) reported major technical issues such as limited payload carrying capacity, poor range and bad weather conditions that could increase delivery risks in the context of drones. In the context of IoTs, Janssen *et al.* (2019) identified technical challenges such as networking issues, sensing issues, poor standardisation and lack of interoperability that impede their successful adoption. In additive manufacturing adoption, Mellor *et al.* (2014) reported barriers such as poor technical standards, low performance and low consistency issues.

2.2 Theoretical frameworks to examine disruptive technologies in the logistics industry

In this exploratory study, we examine the seven DTs (Table 1) using the *Theory of Disruptive Innovation* (Christensen, 1997; Christensen et al., 2011; Christensen and Raynor, 2013) and the *Ecosystems Framework* (Adner and Kapoor, 2016a, b). Next, we validate the seven DTs using the 2×2 matrix (Figure 1) proposed by Adner and Kapoor (2016a). The matrix consists of four types of substitution of DTs. It helps us gauge the relationship between the seven chosen DTs and evaluate how rapidly a transformation may happen in the logistics sector. Typically, the best position for a DT within the matrix is the “creative destruction” quadrant with the fastest substitution speed. In contrast, the riskiest position for a DT is the “robust resilience” quadrant with the slowest substitution speed. A typical DT which is currently in the “robust resilience” quadrant and aspires to be adopted quickly (i.e. to become creative destruction) must follow a route either through the “illusion of resilience” or the “robust coexistence” (shown as the green or red arrows in the matrix).

2.2.1 Creative destruction. This form of DT faces weak challenges in the emergence of the ecosystem (i.e. new technologies) whilst also demonstrating inadequate opportunities for extension (i.e. old technologies) (Adner and Kapoor, 2016a, b). Based on our matrix, this type of DT has the highest substitution speed within the entire logistics sector. A good example of “creative destruction” is the adoption of IoTs within the global logistics sector. For instance, when a worker scans a shipment fitted with IoTs, it helps to collect real-time data, increasing coordination amongst the other agents in the delivery process and reducing information asymmetry. Whilst an IoT component is simply a “plug-and-play” feature, it possesses the ability to replace many labour-intensive practices within the old logistics ecosystems. Firms can install IoT ecosystems quickly and without many technological challenges. Additionally, the coronavirus disease 2019 (COVID-19) pandemic has forced businesses to adopt IoT-based logistics ecosystems [27]. As a result, the adoption of IoT can swiftly “disrupt” the old technology or, in other words, lead to a “destructive” replacement.

2.2.2 Illusion of resilience. This form of DT faces strong challenges in emerging ecosystem (i.e. new technologies) whilst demonstrating weak extension opportunities (i.e. old technologies). Based on our matrix (see Figure 1), this DT has a moderate pace of substitution within the logistics sector. Examples of this type are 3D printers and AI, which still face strong challenges whilst adopting these technologies. For instance, successful adoption of 3D printing in the mainstream logistics sector is delayed due to many reasons such as escalated production costs of machine parts, unavailability of cost-effective 3D printing plastics and low speed of fabrication [28]. Next, in adopting AI-based practices, businesses face many challenges, such as the sceptical behaviour of managers and a prevalent belief that AI will replace human jobs (De Cremer and Kasparov, 2021). Therefore, a weak opportunity to extend old technologies signifies that the incumbent ecosystem players

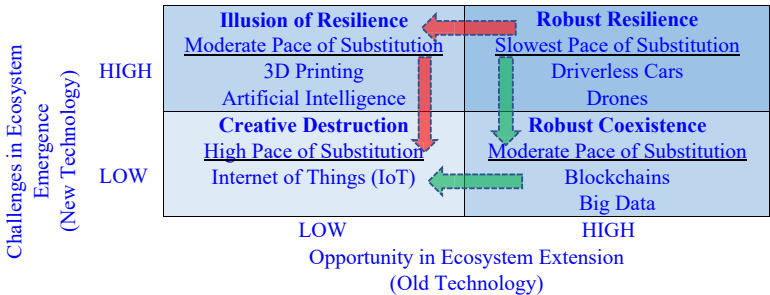


Figure 1.
Positioning of DTs in
the logistics sector

Source(s): Adapted from Adner and Kapoor (2016a)

cannot advance as fast as expected. This phenomenon leads to an imaginary scenario where these incumbent players, still dependent on old technology, do not sense an immediate threat and remain in a “state of inertia,” only to be replaced swiftly in the future.

2.2.3 Robust coexistence. This form of DT faces weak challenges in the emergence of an ecosystem (i.e. new technologies) but indicates abundant opportunities for extension (i.e. old technologies). Based on our matrix, this type of DT has a moderate pace of substitution within the logistics sector, for example, blockchains and Big Data technologies. It is now evident that the widespread adoption of blockchains across logistics firms will be much slower (Biswas and Gupta, 2019; Hughes *et al.*, 2019; Yadav *et al.*, 2020) than the initially predicted hype (Mougayar, 2016; Heiskanen, 2017; Saberi *et al.*, 2019). It will lead to a gradual readjustment or coexistence of *new processes* that migrate to blockchains, whilst the *traditional ones* still follow the same old technologies. Also, many logistics firms choose to work with simple software platforms instead of adopting a more complex and advanced blockchain-based platform (Janjevic *et al.*, 2019). This reluctance was also reflected in the mild success of Tradelens, signifying that the competitors and subcontractors would have to join the platform and share data (Lacity and Van Hoek, 2021). Similar is the case with low responses of businesses towards adopting the Big Data technologies. Although much was proposed about their miraculous capabilities, improvement of financial performance and efficient business processes (McAfee *et al.*, 2012; Alharthi *et al.*, 2017), firms should be cautious whilst implementing Big Data functionalities to reduce the overall risks of adoption (Bean and Davenport, 2019; Wamba *et al.*, 2018). These DTs have yet to attain their full potential, leaving ample time for their competitors to upgrade. In other words, blockchain and Big Data must function as complementary opportunities in established ecosystems and “coexist”.

2.2.4 Robust resilience. This form of DT faces strong challenges in the emergence of an ecosystem (i.e. new technologies) and shares many opportunities for extension (i.e. old technologies). Based on our matrix, this type of DT has a very slow pace of substitution within the logistics sector, for example, driverless cars and drones. Although logistics firms are progressively using more AVs and drones for parcel deliveries, they have not fully replaced their “traditional” delivery systems. For instance, the global adoption of AVs and drones has safety concerns, the inability to operate in bad weather conditions and regulatory challenges. That is why they cannot compete with the traditional delivery systems. Although these DTs are making significant developments, they are still in their early stages and require developing a fully validated ecosystem that can be adopted universally.

2.3 Background work on multi-criteria decision-making (MCDM) techniques

Multi-criteria decision-making (MCDM) techniques are tools for decision-makers (DMs) to solve complex problems where DMs may have different knowledge, characteristics and experience (Aoun *et al.*, 2021). Before applying any MCDM technique, it is important to identify the barriers from the previous literature. Once researchers identify the barriers from literature, it is important to filter the relevant barriers based on their importance and appropriateness. Researchers often use qualitative techniques such as in-depth interviews and Delphi methods to collect expert opinions. However, these techniques consume more time and have high chances of generating exploratory findings (Phellas *et al.*, 2011). In contrast, FDM addresses the vagueness and ambiguity of experts’ judgements with the help of fuzzy set theory (Gupta *et al.*, 2022). In this manner, it addresses the situations in which humans cannot precisely conclude (Rathore, 2021; Rathore and Gupta, 2021).

Similarly, other MCDM techniques, such as Decision making trial and evaluation laboratory (DEMATEL) and ISM, are available in the previous literature to identify the barriers’ interrelations (Dwivedi *et al.*, 2017; Biswas and Gupta, 2019). Using ISM has the advantage over DEMATEL by transforming poorly articulated models into a hierarchy of systematic barriers and well-defined models (Singh and Bhanot, 2020). Many recent studies

have applied ISM to analyse the barriers to the successful adoption of technologies (Yadav *et al.*, 2020; Rana *et al.*, 2019). Table 2 presents a brief literature review on the ISM technique.

3. Proposed research methodology

We prepared an FDM questionnaire (refer to Table A2 in Appendix) to collect experts' opinions to identify the relevant barriers. Then, we sent the questionnaires to 15 experts in India. Each expert had over ten years of work experience in logistics management, such as managing warehouses, handling inventory, exports and imports, transportation and procurement of raw materials. Many previous studies have collected inputs from 15 experts to apply MCDM-based techniques (Nassereddine and Eskandari, 2017; Singh and Sarkar, 2020). Therefore, the sample size of experts in our study is well within the prescribed limit. We present the demographic details of the experts in Table 3. We asked the experts to determine the importance of each adoption barrier using a linguistic scale (refer to Table A3 in Appendix). After finalising the relevant barriers, we analysed them to develop a robust structured hierarchical model using ISM. This technique can collectively examine all barriers and identify their interdependencies (Kamble *et al.*, 2018). Then, we included the relevant barriers in the ISM questionnaire (refer to Table A4 in Appendix) and sent it to those 15 experts to determine their contextual relationships. The experts were requested to fill the questionnaire with the help of V, A, X and O symbols. Figure 2 presents the proposed methodology for this study.

Table 2.
Application of ISM
technique in articles on
"barrier analysis"

Study	Objective
Yadav <i>et al.</i> (2020)	Barriers analysis for the blockchain adoption in the Indian agriculture SCs
Singh and Bhanot (2020)	Analysis of barriers to implementing IoT in the Indian manufacturing industry
Gardas <i>et al.</i> (2018)	Identifying and analysing the critical barriers to reverse logistics of used oil in developing economies context
Kamble <i>et al.</i> (2018)	Study on barriers analysis of Industry 4.0 adoption in the Indian manufacturing industry
Rana <i>et al.</i> (2019)	Analysis of barriers to the m-commerce adoption in UK SMEs
Movahedipour <i>et al.</i> (2017)	Analysis of barriers to the implementation of sustainable SCs
Shukla <i>et al.</i> (2018)	Study on the dynamic interaction of critical barriers that inhibit 3D printing/additive manufacturing (AM) for mass customisation
Vasanthakumar <i>et al.</i> (2016)	Study on analysis of factors influencing lean remanufacturing practices in the Indian automotive industry
Our study	Identification and evaluation of barriers affecting the DTs adoption in the logistics industry

Table 3.
Demographic details of
experts from the
logistics sector

No. of experts	Logistics domain/academia	Profile	Experience (years)
2	Warehouse management	Warehouse manager	11–14
1	Distribution management	Supplier planning manager	16
1	Customer relationship management	Customer relation manager	11
2	Inventory management	Assistant inventory manager	9–12
1	Academia	Head of department	13
4	Transport management	Chief technology officer	12–17
2	Export and import management	Clearance manager	12
2	Vendor management	Logistics manager	14

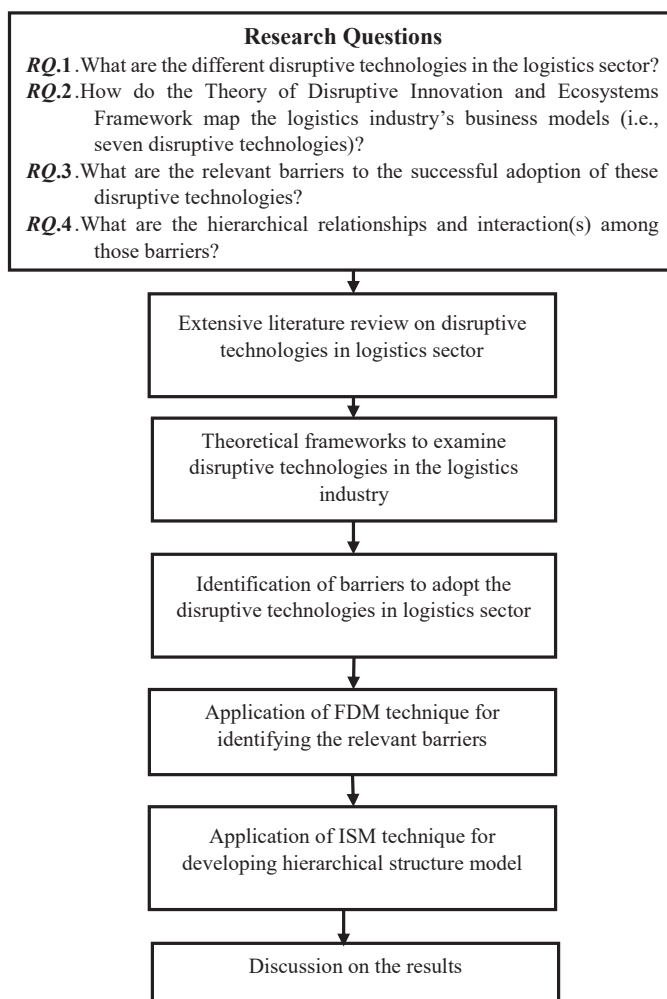


Figure 2.
Methodology for
developing a
hierarchical structure
model for the adoption
of DTs in the logistics
sector

3.1 Fuzzy Delphi Method

The following are the steps involved in FDM (adapted from Ishikawa *et al.*, 1993) and are given below:

- (1) Identify the barriers from literature;
- (2) Prepare a questionnaire with all barriers and ask experts (n) to rate the importance of barriers (m) related to the study with the help of the fuzzy linguistic scale (Table A3 in Appendix) and
- (3) Convert all expert opinions into fuzzy numbers and use the geometric mean model to evaluate the aggregate experts' opinions.

Let us assume X_{ij} is the fuzzy number corresponding to the j th barrier by the i th expert is present as given below:

$$X_{ij} = (a_{ij}, b_{ij}, c_{ij}) \text{ for } i = 1, 2, 3 \dots n; j = 1, 2, 3 \dots m;$$

where n represents the number of experts and m represents the number of barriers.

- (4) Calculate the fuzzy weights of barriers as follows:

$$a_j = \min[a_{ij}]; b_j = \left[\sum_{i=1}^n (b_{ij})^{\frac{1}{n}} \right]; c_j = \max[c_{ij}]$$

- (5) The centre of gravity method is used to estimate the defuzzification value D_j as follows:

$$d_j = \frac{a_j + b_j + c_j}{3}, \quad j = 1, 2, 3 \dots m$$

- (6) Compare the weights of all barriers by setting the desired threshold value (α). If $d_j \geq \alpha$, then the barrier is accepted; if $d_j < \alpha$, then the barrier is rejected.

3.2 ISM analysis

ISM is an interactive learning technique that directly integrates the barriers into a systematic and structured model. It is an efficient modelling methodology to evaluate the effect of one barrier on another. Warfield (1974) reported that the ISM technique is powerful for identifying the relationships within the specific elements in an interdependent system. It also helps analysts identify and recognise relationships between specific items that may lead to an issue or an ensuing problem.

Ravi and Shankar (2017) examined the reverse-logistics barriers and their relationships in the automotive sector with the ISM technique. Raj *et al.* (2008) applied ISM to identify the mutual relationships amongst enablers that assisted the implementation of flexible manufacturing systems and then classified them based on individual drives and dependency powers. We enlist the critical features of the ISM technique, as adapted from Raj *et al.* (2008):

- (1) Interpretive, as the decision recommended by experts, can decide the relationships amongst the individual barriers;
- (2) Helps build a hierarchy map based on a complex set of barriers;
- (3) Leads to a diagraph representing the fundamental interactions amongst the barriers and their overall structure and
- (4) Allows the imposition of a ranking and the direction on the complexities within the relationships amongst those barriers.

Next, we enlist the steps of the ISM methodology adapted from Kannan *et al.* (2009):

- (1) List the identified barriers to the adoption of DTs in logistics sectors.
- (2) Establish a contextual relationship between the identified barriers.
- (3) Prepare a structural self-interaction matrix (SSIM) comprised of the barriers.
- (4) Develop the reachability matrix from the SSIM matrix and check for transitivity. (Transitivity is a preliminary assumption in the ISM technique. This relationship says that if a barrier X is linked to Y ; and Y to Z , then X must be linked to Z .)

- (5) Partition the final reachability matrix (FRM) (derived from *Step 4*) into various stages.
- (6) Draw a diagraph based on the relationships represented in the FRM. The transitive connections are omitted from the diagraph.
- (7) By replacing vector nodes with statements, convert the diagraph into an ISM-based model.
- (8) Recheck the ISM-based model for conceptual inconsistency and take necessary actions.

3.3 MICMAC analysis

We performed the MICMAC analysis to identify indirect relationships amongst the barriers with the help of the driving and dependence power of each barrier (Ravi and Shankar, 2017). The sum of each row barrier and column barrier becomes the coordinates of each individual barrier, and they are positioned in the two-dimensional graph based on these coordinates. Then, the barriers were classified into four quadrants (Rana *et al.*, 2019) as follows:

- (1) *Autonomous* (Quadrant I) – Barriers under this quadrant have low driving and dependence powers. Therefore, they do not yield much influence.
- (2) *Dependent* (Quadrant II) – Barriers in this quadrant have weak driving power but strong dependence power. Other barriers usually influence these barriers in the lower level of the ISM model.
- (3) *Linkage* (Quadrant III) – Barriers that come under this quadrant have strong driving power and strong dependence power. They are unstable, and any action involving these barriers would result in a subsequent reaction that affects them and other barriers.
- (4) *Independent or driver* (Quadrant IV) – Barriers under this quadrant are considered the most important ones with strong driving powers but weak dependence. It means that they can highly influence other barriers. Therefore, they require immediate attention because other barriers that depend on them might be affected.

4. Results from our study

4.1 Results from the Fuzzy Delphi Method

After an extensive literature review on DTs in the logistics sector, we identified 12 barriers that hinder their adoption. Then, we examined these 12 barriers with the help of experts' opinions using FDM steps. According to the FDM steps described in Section 3.1, we performed defuzzification for barriers utilising the *centre of gravity* method. Then, we compared the values obtained after the defuzzification of all barriers with the desired *threshold value* (α). This threshold is considered a benchmark for accepting or rejecting any barrier (Kannan *et al.*, 2009). Finally, we identified ten relevant barriers to applying this method. The FDM results are shown in Table 4.

4.2 Results from ISM and MICMAC

After successfully identifying ten relevant barriers, we developed a robust structured hierarchical model and examined the interrelationship amongst those barriers using the ISM technique. We prepared a SSIM matrix using ISM steps to depict these interrelationships, as described in Section 3.2. Then, we constructed an SSIM (Table 5) with the help of experts' opinions which we collected through questionnaires. Next, we developed the initial

Table 4.
Fuzzy Delphi Method
(FDM) results

S.No	Barriers	Fuzzy weights	Defuzzification (d _j)	Result
1	Legal and regulatory framework (B1)	(0.5,0.77,0.9)	0.72	Accepted
2	Resistance to change (B2)	(0.5,0.74,0.9)	0.71	Accepted
3	Infrastructure (B3)	(0.3,0.75,0.9)	0.65	Accepted
4	Data Management (B4)	(0.3,0.77,0.9)	0.66	Accepted
5	Lack of trust (B5)	(0.3,0.75,0.9)	0.65	Accepted
6	Lack of communication	(0.1,0.37,0.7)	0.39	Rejected
7	Lack of top management support (B6)	(0.3,0.75,0.9)	0.65	Accepted
8	Lack of adequate resources (B7)	(0.5,0.81,0.9)	0.74	Accepted
9	Lack of advanced analytics skills	(0.1,0.35,0.7)	0.38	Rejected
10	Lack of reliability (B8)	(0.3,0.77,0.9)	0.66	Accepted
11	Privacy and Security (B9)	(0.5,0.81,0.9)	0.74	Accepted
12	Technical issues (B10)	(0.3,0.75,0.9)	0.65	Accepted
Threshold value		0.63		

Note(s): The accepted factor(s) are coded, and the rejected ones are left uncoded

Table 5.
SSIM matrix for
barriers to the adoption
of DTs

Code	Name of barrier	B10	B9	B8	B7	B6	B5	B4	B3	B2
B1	Legal and regulatory framework	V	O	O	V	A	V	V	V	V
B2	Resistance to change	O	V	V	V	A	V	V	A	
B3	Infrastructure	V	O	V	V	O	V	V		
B4	Data management	X	V	V	O	A	V			
B5	Lack of Trust	A	O	V	O	A				
B6	Lack of top management support	V	V	V	V					
B7	Lack of adequate resources	X	O	V						
B8	Reliability	A	A							
B9	Privacy/security	A								
B10	Technical issues									

reachability matrix (IRM), as shown in Table 6. Then, we checked the IRM for transitivity to create the FRM, as presented in Table 7.

Then, we obtained the reachability and antecedent sets for each critical barrier from the FRM. The reachability set consisted of the barrier itself and other barriers affected by it.

Table 6.
Initial reachability
matrix (IRM)

S.No	Barriers code	B10	B9	B8	B7	B6	B5	B4	B3	B2	B1
1	B1	1	0	0	1	0	1	1	1	1	1
2	B2	0	1	1	1	0	1	1	0	1	0
3	B3	1	0	1	1	0	1	1	1	1	0
4	B4	1	1	1	0	0	1	1	0	0	0
5	B5	0	0	1	0	0	1	0	0	0	0
6	B6	1	1	1	1	1	1	1	0	1	1
7	B7	1	0	1	1	0	0	0	0	0	0
8	B8	0	0	1	0	0	0	0	0	0	0
9	B9	0	1	1	0	0	0	0	0	0	0
10	B10	1	1	1	1	0	1	1	0	0	0

Note(s): B1 = legal and regulatory framework; B2 = resistance to change; B3 = infrastructure; B4 = data management; B5 = lack of trust; B6 = lack of top management support; B7 = lack of adequate resources; B8 = lack of reliability; B9 = privacy and security; B10 = technical issues

S.No	Barriers code	B10	B9	B8	B7	B6	B5	B4	B3	B2	B1	Driving power	Rank
1	B1	1	1*	1*	1	0	1	1	1	1	1	9	2
2	B2	1*	1	1	1	0	1	1	0	1	0	7	4
3	B3	1	1*	1	1	0	1	1	1	1	0	8	3
4	B4	1	1	1	1*	0	1	1	0	0	0	6	5
5	B5	0	0	1	0	0	1	0	0	0	0	2	6
6	B6	1	1	1	1	1	1	1	1*	1	1	10	1
7	B7	1	1*	1	1	0	1*	1*	0	0	0	6	5
8	B8	0	0	1	0	0	0	0	0	0	0	1	7
9	B9	0	1	1	0	0	0	0	0	0	0	2	6
10	B10	1	1	1	1	0	1	1	0	0	0	6	5
	Dependence power	7	8	10	7	1	8	7	3	4	2	57/57	
	Rank	3	2	1	3	7	2	3	5	4	6		

Note(s): *Denotes the values which are changed from “0” to “1” during transitivity check

B1 = legal and regulatory framework; B2 = resistance to change; B3 = infrastructure; B4 = data management; B5 = lack of trust; B6 = lack of top management support; B7 = lack of adequate resources; B8 = lack of reliability; B9 = privacy and security; B10 = technical issues

Table 7.
Final reachability matrix (FRM)

The antecedent set consisted of the barrier itself and other barriers that may have affected it. Then, we generated the intersection of these two sets for all other critical barriers. A barrier with the same reachability and intersection sets secures the top level in the ISM hierarchy. These barriers have high dependence power, so the remaining barriers drive them. After finding the top barriers, they were removed from the other barriers. Finally, these top level barriers helped us in developing the ISM hierarchy. We completed the detailed analysis of the level partition of these ten critical barriers within seven iterations (see [Table A5](#) from [Appendix](#)). We developed the ISM hierarchical structural model (see [Figure 3](#)) with the help of FRM. Finally, we performed MICMAC analysis to examine the barriers based on their driving and dependence powers, which were calculated from the FRM. The summation of each row and column score for each barrier becomes the coordinates in which the barrier is positioned on the diagram ([Figure 4](#)). Then, we categorised the ten barriers into these four quadrants as follows: Autonomous barriers, Dependent barriers, Linkage barriers and Independent barriers.

5. Discussion

The key research questions for this study were: *RQ1. What are the different DTs in the logistics sector?* *RQ2. How does the Theory of Disruptive Innovation and Ecosystems Framework map the logistics industry's business models (i.e. seven DTs)?* *RQ3. What are the relevant barriers to the successful adoption of these DTs?* *RQ4. What are the hierarchical relationships and interaction(s) amongst those barriers?*

To answer *RQ1*, first, we identified the seven DTs with the help of an extensive literature review. Further, we explained each DT with the help of unique use cases ([Table 1](#)).

To answer *RQ2*, we analysed the seven DTs using *Adner and Kapoor's framework* and the *Theory of Disruptive Innovation*. Then, we categorised these seven DTs into four groups, namely *creative destruction*, *robust coexistence*, *illusion of resilience* and *robust resilience*. We also recommended how each of these DTs could be adopted quickly.

To answer *RQ3* and *RQ4*, we identified significant barriers with the help of inputs from logistic experts and an in-depth examination of background literature. We then analysed the interrelationships between the barriers and developed a hierarchical framework using the ISM technique. The structured hierarchy model was developed in seven levels, as shown in

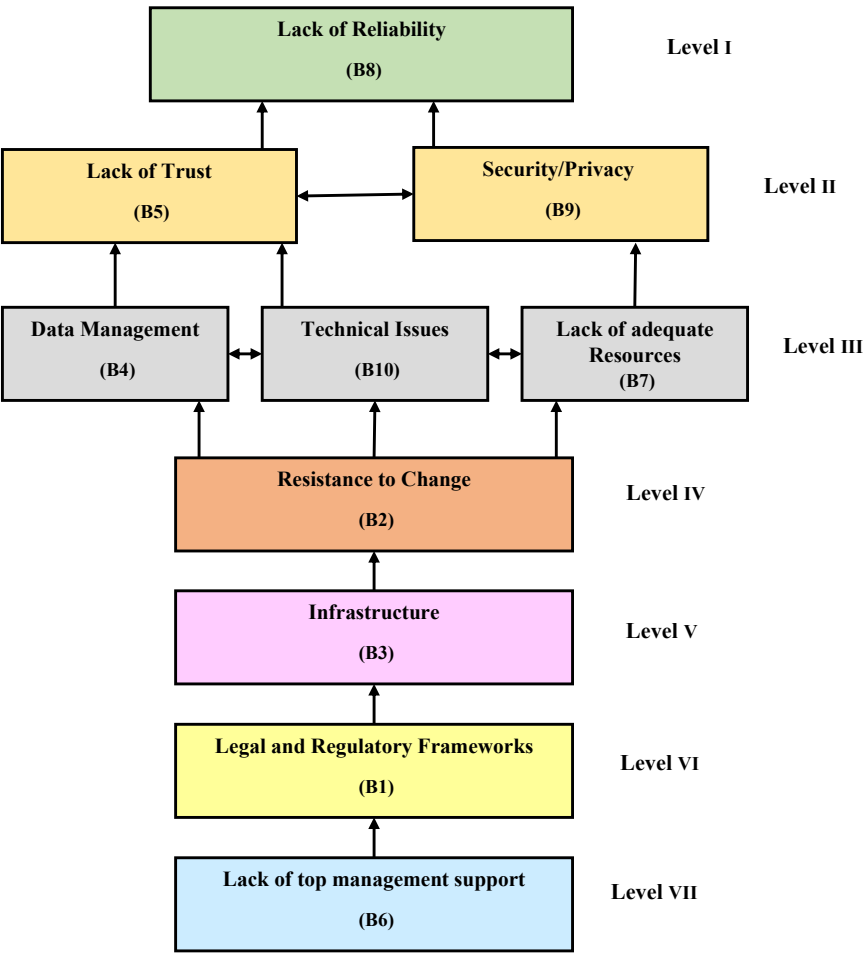
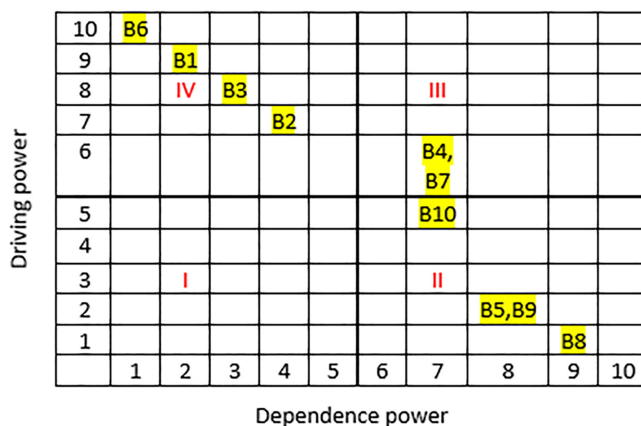


Figure 3.
ISM-based structural
model comprising the
barriers to the adoption
of DTs

Figure 3. It helped to portray the interrelations amongst the barriers that could increase the efficacy of DTs adoption in the logistics sector.

From our analysis, the *lack of top management support* (B6) at Level VII emerges as a potentially critical barrier to building a foundation and might act as the single driving force behind Level VI. This barrier is related to *legal and regulatory frameworks* (B1) in the ISM model. Therefore, the risks associated with the adoption of DTs will impact other associated barriers. For instance, the exploratory findings from our study indicate that the top management might not be supportive of the adoption of DTs. Other barriers could appear stronger because logistics managers might try to prevent the associated risks from those barriers. Previous literature has addressed the lack of *top management support* from an adoption perspective only (LaValle *et al.*, 2011; Dwivedi *et al.*, 2017). However, Govindan and Hasanagic (2018) suggested that managers should not consider *top management support* as a singular barrier because it might encapsulate many other barriers. This finding supports our result, indicating that *lack of top management support* potentially serves as a key barrier that has a greater influence on other connecting barriers in the ISM model.



Note(s): B1= Legal and regulatory framework;
B2 = Resistance to change; B3 = Infrastructure;
B4 = Data Management; B5 = Lack of Trust;
B6 = Lack of top management support;
B7 = Lack of adequate resources; B8 = Lack of Reliability;
B9 = Privacy and Security; B10 = Technical issues

Figure 4.
MICMAC-based
analysis of the barriers
to the adoption of DTs

The lack of *top management support* (B6) is directly related to the *legal and regulatory frameworks* (B1) barrier at Level VI (Figure 3). Barrier B1 possess a high driving power and low dependence power, and so it is placed in Quadrant IV (Figure 4). Therefore, the lack of suitable adoption frameworks and policies might cause difficulties in adopting DTs in logistics firms. Biswas and Gupta (2019) found that blockchains lacked adherence to legal procedures and regulations due to their decentralised structure. Similarly, obsolete regulatory policies can potentially restrict the adoption of DTs in logistics. Therefore, top management in the logistics industry needs to intervene and create a flexible environment with regulations that can scale, adapt and enable disruptive innovations.

The *infrastructure* (B3) barrier at Level V is an outcome of the previous Level VI (Figure 3). Exploratory findings from our study indicate that barrier B3 possesses a high driving power but low dependency power and is positioned in Quadrant IV (Figure 4). Therefore, it can possibly influence other barriers from higher levels but, in turn, is controlled by the barriers from its lower level. Previous studies have found that organisations lacking upgraded IT systems and low infrastructure readiness may be affected by quick adoption decisions of DTs in the logistics sector (Kaur and Rampersad, 2018). These infrastructure issues might be prevailing due to the *lack of top management support* (B6) and *legal and regulatory frameworks* (B1). Therefore, they could possibly be an extended concern because of their strong driving power on *infrastructure* (B3).

Next, the barrier *resistance to change* (B2) exists at Level IV (Figure 3). Its driving power is relatively low as compared to the *lack of top management support* (B6), *legal and regulatory frameworks* (B1) or *infrastructure* (B3). Still, it acts as an independent barrier and is positioned in Quadrant IV (Figure 4). From the exploratory findings, barrier B2 is influenced directly by B3 and might create other barriers such as *technical issues*, *data management* and *inadequate resources*. Mellor et al. (2014) found that *changing jobs, tasks* and *work practices* were often responsible for increasing resistance amongst logistics workers during the

adoption of novel DTs. After years of traditional manufacturing processes, firms were often uncomfortable acquiring new technology in maintaining logistics operations. This could possibly lead to the *resistance to change* (B2) that emerged as a critical barrier to adopting DTs.

Next, the group of barriers at Level III (Figure 3) are generated from the *linkage* and *dependent* category. Whilst *technical issue* (B10) is a dependent barrier and is placed in Quadrant II (Figure 4), *data management* (B4) and *lack of adequate resources* (B7) belong to the *linkage* category. They are positioned in Quadrant III (Figure 4). Although they are placed in different quadrants, they are closely related due to their driving and dependence power. Therefore, findings from our exploratory study indicate that *technical issues* (B10) such as limited payload-carrying capacity and low range could increase the associated risks of a logistics firm that operates drones for parcel delivery (Sah *et al.*, 2021).

Similarly, Janssen *et al.* (2019) identified some technical challenges, such as networking issues, sensing issues, standardisation and interoperability, impeding the successful deployment of IoTs. These issues also raised privacy and security concerns amongst logistics users, leading to distrust within the organisation. This exploratory finding revealed that an organisation might often pay lesser attention to such barriers and that they needed to be possibly reinvented and restructured, especially for gaining trust and addressing existing users' security and privacy concerns.

Level II (Figure 3) contains two barriers, *lack of trust* (B5) and *security and privacy* (B9). Whilst their driving powers are very low, their dependency powers are extremely high, positioning them in Quadrant II (Figure 4). These barriers could be influenced by other barriers from the lower levels in the ISM model. Extant studies suggested that greater attention must be paid to privacy and security issues to gain customer trust (Dwivedi *et al.*, 2017). Therefore, based on the exploratory findings from our study, a secure information-sharing and data protection framework might be needed for logistics firms.

Level I (Figure 3) of the ISM model consists of a single barrier, i.e. *lack of reliability* (B8). It possesses a high dependence power and is placed in Quadrant II (Figure 4). In the ISM model, other barriers from lower levels can affect the *lack of reliability* (B8). Therefore, B8 is possibly an outcome of the lower-level obstacles (i.e. Level II), and there might be a direct link between these two levels. This direct connection could also suggest that *reliability* issues can reduce system performance during the adoption of DTs if the logistic managers cannot provide a reliable system.

6. Research and managerial implications

6.1 Research implications

Our study has several research implications in light of the adoption of DTs. First, this study successfully analyses the seven DTs using Adner and Kapoor's framework and the *Theory of Disruptive Innovation* based on the two parameters as follows: *emergence challenge of new technology* and *extension opportunity of old technology*. Second, this study categorises the seven DTs into four quadrants (see Figure 1), namely *creative destruction*, *robust coexistence*, *illusion of resilience* and *robust resilience*. In particular, (1) IoT belongs to the "creative destruction" quadrant, (2) blockchains and Big Data belong to the "robust coexistence" quadrant, (3) 3D printing and AI belong to the "illusion of resilience" and (4) driverless cars and drones belong to "robust resilience". Third, this study proposes the recommended paths for DTs in the "robust resilience" quadrant, which aspires to be adopted quickly by firms. It needs to follow either of the two approaches: (1) reduce the opportunity in *old technology extension* from high to low and then reduce the challenges in *new technology emergence* from high to low; (2) reduce the challenges in *new technology emergence* from high to low and then reduce the challenges in *old technology extension* from high to low.

6.2 Managerial implications

Our study has several managerial implications in light of the adoption of DTs. First, our study identified no autonomous barriers to adopting DTs (Figure 4). This finding implies that all the barriers in our study have significant driving and dependence powers for the successful adoption of DTs. Second, other barriers belonging to any lower level of the ISM model can influence the *dependent* barriers. Therefore, logistic managers should focus on these barriers to achieve less resistance to DTs adoption. Third, the *linkage* barriers are unstable, and any preventive action involving them would subsequently affect themselves and other barriers. However, if they are appropriately implemented, that could result in a positive environment for the successful adoption of DTs. Therefore, managers should take care of these linkage barriers. Fourth, the *independent* barriers have high influencing powers over other barriers. Due to this reason, they are considered key barriers to the successful adoption of DTs. Hence, logistics managers should pay attention to these critical barriers whilst implementing DTs.

7. Conclusion and future directions of research

Our research presented potential DTs with use cases from the logistics sector and the significant barriers that may have prevented their adoption. We validated and categorised these DTs into possible four groups according to the *Theory of Disruptive Innovation*. Next, we examined and evaluated these significant barriers in terms of their contextual relationships using the ISM technique. Although we do not claim to be fully inclusive in our analysis, the proposed framework helps us identify a potential set of barriers that may have affected the adoption of DTs in the logistics sector. Finally, we described the interrelationships amongst these barriers to develop a structural hierarchy model.

Our exploratory findings reveal that the *ten barriers are the legal and regulatory framework, resistance to change, privacy/security, infrastructure, data management, lack of trust, lack of top management support, lack of adequate resources, reliability and technical issues*. Amongst them, *lack of top management support, legal and regulatory framework and infrastructure* are vital and might need immediate attention of managers to adopt DTs successfully. However, *lack of trust, reliability and privacy/security issues* demonstrate a very high dependence power than other barriers. Therefore, managers might not be much concerned about their influence on adoption.

The main contributions of this exploratory study are fourfold. First, it identifies the seven DTs in the logistics sector. Second, it applies the theory of disruptive innovations and the framework of the ecosystems to rationalise the choice of these seven DTs and categorise them into four possible groups. Third, it identifies and critically assesses the barriers to the successful adoption of these DTs through the ISM method. Fourth, it builds the interrelationships amongst the identified barriers.

Despite these contributions, this study has a few limitations. First, our analysis was exploratory in nature, owing to the application of the Delphi Approach. Future studies could adopt questionnaire-based surveys and collect responses from logistics managers to examine the possible barriers of DTs and their interrelationships. Second, our analysis was limited to a specific selection of ten barriers. Future research in logistics management could extend our study by reviewing other innovative technologies. Third, future studies can adopt empirical analysis to offer additional evidence on the applicability of our research and thus build a generalised framework to identify the adoption barriers in the logistics sector.

Notes

1. Tradelens Ecosystem: <https://www.tradelens.com/ecosystem>

2. Internet of Things reaches into the trucking business: <https://www.wsj.com/articles/internet-of-things-reaches-into-the-trucking-business-1430342965>
3. <https://blogs.wsj.com/cio/2018/08/06/internet-of-things-adoption-to-rise-despite-security-data-integration-challenges/>
4. <https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/an-executives-guide-to-the-internet-of-things>
5. <https://www.wsj.com/articles/are-drones-the-future-of-air-freight-1436468089>
6. <https://www.wsj.com/articles/your-drone-delivered-coffee-is-almost-here-11553918415>
7. <https://www.wsj.com/articles/the-drones-are-coming-11571995806>
8. <https://www.economist.com/business/2018/06/09/how-e-commerce-with-drone-delivery-is-taking-flight-in-china>
9. <https://www.wsj.com/articles/commentary-drone-delivery-projects-must-look-beyond-the-hype-11574875675>
10. <https://www.economist.com/business/2019/06/15/drone-deliveries-are-advancing-in-health-care>
11. <https://www.wsj.com/articles/logistics-ai-startup-covariant-reaps-40-million-in-funding-round-11588719951>
12. <https://blogs.wsj.com/cio/2018/12/04/retail-transportation-among-industries-most-impacted-by-ai/>
13. <https://www.wsj.com/articles/warehouses-test-a-new-breed-of-ai-robots-11546948800>
14. <https://www.wsj.com/articles/retailers-bring-ai-into-brick-and-mortar-operations-11547675716>
15. <https://www.wsj.com/articles/as-e-commerce-booms-robots-pick-up-human-slack-11596859205>
16. <https://www.wsj.com/articles/smarter-delivery-hinges-on-smarter-robots-11580288408>
17. https://www.dhl.com/content/dam/downloads/g0/about_us/innovation/CSI_Studie_BIG_DATA.pdf
18. <https://hbr.org/2012/10/data-scientist-the-sexiest-job-of-the-21st-century/>
19. TuSimple is the world's largest and most advanced self-driving truck company.
20. <https://www.wsj.com/articles/tusimple-adds-logistics-operators-to-self-driving-trucks-effort-11593604800>
21. <https://www.wsj.com/articles/amazon-team-focuses-on-exploiting-driverless-technology-1493035203>
22. <https://www.wsj.com/articles/future-of-driverless-deliveries-depends-on-large-auto-makers-11558542006>
23. <https://www.wsj.com/articles/self-driving-technology-threatens-nearly-300-000-trucking-jobs-report-says-1536053401>
24. <https://www.theguardian.com/technology/2018/mar/19/uber-self-driving-car-kills-woman-arizona-tempe>
25. <https://www.economist.com/business/2016/01/09/the-driverless-car-sharing-road-ahead>
26. <https://3dprintingindustry.com/news/amazon-sets-out-to-conquer-entire-3d-printing-industry-with-new-patent-application-43263/>
27. Global industry accelerates IoT adoption in response to COVID: <https://www.computerweekly.com/news/252507082/Global-industry-accelerates-IoT-adoption-in-response-to-Covid>
28. <https://www.wsj.com/articles/3-d-companies-tackle-coronavirus-supply-shortages-11585832400>

References

- Adner, R. and Kapoor, R. (2016a), "Innovation ecosystems and the pace of substitution: re-examining technology S-curves", *Strategic Management Journal*, Vol. 37 No. 4, pp. 625-648.
- Adner, R. and Kapoor, R. (2016b), "Right tech, wrong time", *Harvard Business Review*, Vol. 94 No. 11, pp. 60-67.
- Alharthi, A., Krotov, V. and Bowman, M. (2017), "Addressing barriers to big data", *Business Horizons*, Vol. 60 No. 3, pp. 285-292.
- Alwateer, M., Loke, S.W. and Zuchowicz, A.M. (2019), "Drone services: issues in drones for location-based services from human-drone interaction to information processing", *Journal of Location Based Services*, Vol. 13 No. 2, pp. 94-127.
- Aoun, J., Quaglietta, E., Goverde, R.M., Scheidt, M., Blumenfeld, M., Jack, A. and Redfern, B. (2021), "A hybrid Delphi-AHP multi-criteria analysis of Moving Block and Virtual Coupling railway signalling", *Transportation Research Part C: Emerging Technologies*, Vol. 129, 103250.
- Attaran, M. (2017), "The rise of 3-D printing: the advantages of additive manufacturing over traditional manufacturing", *Business Horizons*, Vol. 60 No. 5, pp. 677-688.
- Bean, R. and Davenport, T.H. (2019), "Companies are failing in their efforts to become data-driven", *Harvard Business Review*, Vol. 5.
- Benzidia, S., Ageron, B., Bentahar, O. and Husson, J. (2019), "Investigating automation and AGV in healthcare logistics: a case study-based approach", *International Journal of Logistics Research and Applications*, Vol. 22 No. 3, pp. 273-293.
- Biswas, B. and Gupta, R. (2019), "Analysis of barriers to implement blockchain in industry and service sectors", *Computers and Industrial Engineering*, Vol. 136, pp. 225-241.
- Chen, C.P. and Zhang, C.Y. (2014), "Data-intensive applications, challenges, techniques and technologies: a survey on Big Data", *Information Sciences*, Vol. 275, pp. 314-347.
- Christensen, C.M. (1997), "Marketing strategy: learning by doing", *Harvard Business Review*, Vol. 75 No. 6, pp. 141-151.
- Christensen, C. and Raynor, M. (2013), *The Innovator's Solution: Creating and Sustaining Successful Growth*, Harvard Business Review Press, Boston, MA.
- Christensen, C.M. (2013), *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*, Harvard Business Review Press, Boston, MA.
- Christensen, C., Raynor, M. and McDonald, R. (2011), *Disruptive Innovation*, Perseus Book LLC (Ingram), New York.
- Christensen, C.M., Raynor, M.E. and McDonald, R. (2015), "What is disruptive innovation", *Harvard Business Review*, Vol. 93 No. 12, pp. 44-53.
- Colefax, A.P., Butcher, P.A., Pagendam, D.E. and Kelahe, B.P. (2019), "Reliability of marine faunal detections in drone-based monitoring", *Ocean and Coastal Management*, Vol. 174, pp. 108-115.
- Danneels, E. (2004), "Disruptive technology reconsidered: a critique and research agenda", *Journal of Product Innovation Management*, Vol. 21 No. 4, pp. 246-258.
- Da Xu, L., He, W. and Li, S. (2014), "Internet of things in industries: a survey", *IEEE Transactions on Industrial Informatics*, Vol. 10 No. 4, pp. 2233-2243.
- De Cremer, D. and Kasparov, G. (2021), "AI should augment human intelligence, not replace it", *Harvard Business Review*, available at: <https://hbr.org/2021/03/ai-should-augment-human-intelligence-not-replace-it>.
- Del Castillo, M. (2017), "Finnish city awarded €2.4 million to test Blockchain-powered shipping – CoinDesk", available at: www.coindesk.com/finnishcity-wins-2-4m-blockchain-shipping/ (accessed 7 December 2021).

- Dwivedi, G., Srivastava, S.K. and Srivastava, R.K. (2017), "Analysis of barriers to implement additive manufacturing technology in the Indian automotive sector", *International Journal of Physical Distribution and Logistics Management*, Vol. 47 No. 10, pp. 972-991.
- Fagnant, D.J. and Kockelman, K. (2015), "Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations", *Transportation Research A: Policy and Practice*, Vol. 77, pp. 167-181.
- Finn, R.L. and Wright, D. (2016), "Privacy, data protection and ethics for civil drone practice: a survey of industry, regulators and civil society organizations", *Computer Law and Security Review*, Vol. 32 No. 4, pp. 577-586.
- Finn, R. and Donovan, A. (2016), "Big data, drone data: privacy and ethical impacts of the intersection between big data and civil drone deployments", *The Future of Drone Use*, TMC Asser Press, The Hague, pp. 47-67.
- Gardas, B.B., Raut, R.D. and Narkhede, B. (2018), "Reducing the exploration and production of oil: reverse logistics in the automobile service sector", *Sustainable Production and Consumption*, Vol. 16, pp. 141-153.
- Gartner (2014), "Gartner says the Internet of Things will transform the data center", available at: <http://www.gartner.com/newsroom/id/268461> (accessed 7 December 2021).
- Govindan, K. and Hasanagic, M. (2018), "A systematic review on drivers, barriers, and practices towards circular economy: a supply chain perspective", *International Journal of Production Research*, Vol. 56 No. 2, pp. 278-311.
- Gupta, R., Rathore, B., Srivastava, A. and Biswas, B. (2022), "Decision-making framework for identifying regions vulnerable to transmission of COVID-19 pandemic", *Computers and Industrial Engineering*, Vol. 169, 108207, doi: [10.1016/j.cie.2022.108207](https://doi.org/10.1016/j.cie.2022.108207) (in press).
- Heiskanen, A. (2017), "The technology of trust: how the Internet of Things and blockchain could usher in a new era of construction productivity", *Construction Research and Innovation*, Vol. 8 No. 2, pp. 66-70.
- Hofmann, E. and Rüscher, M. (2017), "Industry 4.0 and the current status as well as future prospects on logistics", *Computers in Industry*, Vol. 89, pp. 23-34.
- Hopkins, J. and Hawking, P. (2018), "Big data analytics and IoT in logistics: a case study", *The International Journal of Logistics Management*, Vol. 29 No. 2, pp. 575-591.
- Hsiao, R.L. (2003), "Technology fears: distrust and cultural persistence in electronic marketplace adoption", *Journal of Strategic Information Systems*, Vol. 12 No. 3, pp. 169-199.
- Hughes, L., Dwivedi, Y.K., Misra, S.K., Rana, N.P., Raghavan, V. and Akella, V. (2019), "Blockchain research, practice and policy: applications, benefits, limitations, emerging research themes and research agenda", *International Journal of Information Management*, Vol. 49, pp. 114-129.
- Ishikawa, A., Amagasa, M., Shiga, T., Tomizawa, G., Tatsuta, R. and Mieno, H. (1993), "The max-min Delphi method and fuzzy Delphi Method via fuzzy integration", *Fuzzy Sets and Systems*, Vol. 55 No. 3, pp. 241-253.
- Janjevic, M., Knoppen, D. and Winkenbach, M. (2019), "Integrated decision-making framework for urban freight logistics policy-making", *Transportation Research D: Transport and Environment*, Vol. 72, pp. 333-357.
- Janssen, M., Luthra, S., Mangla, S., Rana, N.P. and Dwivedi, Y.K. (2019), "Challenges for adopting and implementing IoT in smart cities: an integrated MICMAC-ISM approach", *Internet Research*, Vol. 29 No. 3, pp. 1589-1616.
- Kamble, S.S., Gunasekaran, A. and Sharma, R. (2018), "Analysis of the driving and dependence power of barriers to adopt industry 4.0 in Indian manufacturing industry", *Computers in Industry*, Vol. 101, pp. 107-119.
- Kannan, G., Pokharel, S. and Kumar, P.S. (2009), "A hybrid approach using ISM and fuzzy TOPSIS for the selection of reverse logistics provider", *Resources, Conservation and Recycling*, Vol. 54 No. 1, pp. 28-36.

- Kaur, K. and Rampersad, G. (2018), "Trust in driverless cars: investigating key factors influencing the adoption of driverless cars", *Journal of Engineering and Technology Management*, Vol. 48, pp. 87-96.
- Kellermann, R., Biehle, T. and Fischer, L. (2020), "Drones for parcel and passenger transportation: a literature review", *Transportation Research Interdisciplinary Perspectives*, Vol. 4, 100088.
- Khan, M.A. and Salah, K. (2018), "IoT security: review, blockchain solutions, and open challenges", *Future Generation Computer Systems*, Vol. 82, pp. 395-411.
- Khorram, N. M. and Nonino, F. (2017), "Additive manufacturing management: a review and future research agenda", *International Journal of Production Research*, Vol. 55 No. 5, pp. 1419-1439.
- Kim, G.H., Trimi, S. and Chung, J.H. (2014), "Big-data applications in the government sector", *Communications of the ACM*, Vol. 57 No. 3, pp. 78-85.
- Kim, S.J., Lim, G.J., Cho, J. and Côté, M.J. (2017), "Drone-aided healthcare services for patients with chronic diseases in rural areas", *Journal of Intelligent and Robotic Systems*, Vol. 88 No. 1, pp. 163-180.
- Kostoff, R.N., Boylan, R. and Simons, G.R. (2004), "Disruptive technology roadmaps", *Technological Forecasting and Social Change*, Vol. 71 Nos 1-2, pp. 141-159.
- Krombholz, K., Judmayer, A., Gusenbauer, M. and Weippl, E. (2016), "The other side of the coin: user experiences with bitcoin security and privacy", *International Conference on Financial Cryptography and Data Security*, Springer, Berlin, Heidelberg, pp. 555-580.
- Kwon, H., Kim, J. and Park, Y. (2017), "Applying LSA text mining technique in envisioning social impacts of emerging technologies: the case of drone technology", *Technovation*, Vol. 60, pp. 15-28.
- Lacity, M. and Van Hoek, R. (2021), "What we've learned so far about blockchain for business", *MIT Sloan Management Review*, Vol. 62 No. 3, pp. 48-54.
- LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S. and Kruschwitz, N. (2011), "Big data, analytics and the path from insights to value", *MIT Sloan Management Review*, Vol. 52 No. 2, pp. 21-32.
- Liu, C., Le Roux, L., Körner, C., Tabaste, O., Lacan, F. and Bigot, S. (2020), "Digital twin-enabled collaborative data management for metal additive manufacturing systems", *Journal of Manufacturing Systems*, Vol. 62, pp. 857-874.
- Luthra, S., Garg, D., Mangla, S.K. and Berwal, Y.P.S. (2018), "Analyzing challenges to Internet of Things (IoT) adoption and diffusion: an Indian context", *Procedia Computer Science*, Vol. 125, pp. 733-739.
- Madakam, S., Lake, V., Lake, V. and Lake, V. (2015), "Internet of things (IoT): a literature review", *Journal of Computer and Communications*, Vol. 3 No. 5, p. 164.
- Mani, Z. and Chouk, I. (2018), "Consumer resistance to innovation in services: challenges and barriers in the Internet of Things era", *Journal of Product Innovation Management*, Vol. 35 No. 5, pp. 780-807.
- McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J. and Barton, D. (2012), "Big data: the management revolution", *Harvard Business Review*, Vol. 90 No. 10, pp. 60-68.
- McDonald, W. (2019), "Drones in urban stormwater management: a review and future perspectives", *Urban Water Journal*, Vol. 16 No. 7, pp. 505-518.
- Mellor, S., Hao, L. and Zhang, D. (2014), "Additive manufacturing: a framework for implementation", *International Journal of Production Economics*, Vol. 149, pp. 194-201.
- Mendling, J., Weber, I., Aalst, W.V.D., Brocke, J.V., Cabanillas, C., Daniel, F. and Zhu, L. (2018), "Blockchains for business process management-challenges and opportunities", *ACM Transactions on Management Information Systems*, Vol. 9 No. 1, pp. 1-16.
- Mougayar, W. (2016), *The Business Blockchain: Promise, Practice, and Application of the Next Internet Technology*, John Wiley & Sons, New York.
- Movahedipour, M., Zeng, J., Yang, M. and Wu, X. (2017), "An ISM approach for the barrier analysis in implementing sustainable supply chain management", *Management Decision*, Vol. 55 No. 8, pp. 1824-1850.

- Nassereddine, M. and Eskandari, H. (2017), "An integrated MCDM approach to evaluate public transportation systems in Tehran", *Transportation Research Part A: Policy and Practice*, Vol. 106, pp. 427-439.
- National Highway Traffic Safety Administration (NHTSA) (2017), "Preliminary statement of policy concerning automated vehicles", available at: https://www.nhtsa.gov/staticfiles/rulemaking/pdf/Automated_Vehicles_Policy.pdf (accessed 11 December 2021).
- Niaki, M.K. and Nonino, F. (2017), "Impact of additive manufacturing on business competitiveness: a multiple case study", *Journal of Manufacturing Technology Management*, Vol. 28 No. 1, pp. 56-74.
- Pannu, A. (2015), "Artificial intelligence and its application in different areas", *Artificial Intelligence*, Vol. 4 No. 10, pp. 79-84.
- Phellas, C.N., Bloch, A. and Seale, C. (2011), "Structured methods: interviews, questionnaires and observation", *Researching Society and Culture*, Vol. 3 No. 1, pp. 23-32.
- Raj, T., Shankar, R. and Suhaib, M. (2008), "An ISM approach for modelling the enablers of flexible manufacturing system: the case for India", *International Journal of Production Research*, Vol. 46 No. 24, pp. 6883-6912.
- Rana, N.P., Barnard, D.J., Baabdullah, A.M., Rees, D. and Roderick, S. (2019), "Exploring barriers of m-commerce adoption in SMEs in the UK: developing a framework using ISM", *International Journal of Information Management*, Vol. 44, pp. 141-153.
- Rathore, B. (2021), "Analysis of enablers to implement ergonomic interventions in Indian manufacturing industry: a multi-criteria decision-making approach", *Global Business Review*, 09721509211044293, doi: [10.1177/09721509211044293](https://doi.org/10.1177/09721509211044293) (in press).
- Rathore, B. and Gupta, R. (2021), "A fuzzy based hybrid decision-making framework to examine the safety risk factors of healthcare workers during COVID-19 outbreak", *Journal of Decision Systems*, Vol. 31 Nos 1-2, pp. 68-101.
- Ravi, V. and Shankar, R. (2017), "An ISM-based approach analyzing interactions among variables of reverse logistics in automobile industries", *Journal of Modelling in Management*, Vol. 12 No. 1, pp. 36-52.
- Risius, M. and Spohrer, K. (2017), "A blockchain research framework", *Business and Information Systems Engineering*, Vol. 59 No. 6, pp. 385-409.
- Rogers, H., Baricz, N. and Pawar, K.S. (2016), "3D printing services: classification, supply chain implications and research agenda", *International Journal of Physical Distribution and Logistics Management*, Vol. 46 No. 10, pp. 886-907.
- Saberi, S., Kouhizadeh, M., Sarkis, J. and Shen, L. (2019), "Blockchain technology and its relationships to sustainable supply chain management", *International Journal of Production Research*, Vol. 57 No. 7, pp. 2117-2135.
- Sah, B., Gupta, R. and Bani-Hani, D. (2021), "Analysis of barriers to implement drone logistics", *International Journal of Logistics Research and Applications*, Vol. 24 No. 6, pp. 531-550.
- Sander, F., Semeijn, J. and Mahr, D. (2018), "The acceptance of blockchain technology in meat traceability and transparency", *British Food Journal*, Vol. 120 No. 9, pp. 2066-2079.
- Shukla, M., Todorov, I. and Kapletia, D. (2018), "Application of additive manufacturing for mass customization: understanding the interaction of critical barriers", *Production Planning and Control*, Vol. 29 No. 10, pp. 814-825.
- Singh, P.K. and Sarkar, P. (2020), "A framework based on fuzzy Delphi and DEMATEL for sustainable product development: a case of Indian automotive industry", *Journal of Cleaner Production*, Vol. 246, 118991.
- Singh, R. and Bhanot, N. (2020), "An integrated DEMATEL-MMDE-ISM based approach for analyzing the barriers of IoT implementation in the manufacturing industry", *International Journal of Production Research*, Vol. 58 No. 8, pp. 2454-2476.
- Sivarajah, U., Kamal, M.M., Irani, Z. and Weerakkody, V. (2017), "Critical analysis of Big Data challenges and analytical methods", *Journal of Business Research*, Vol. 70, pp. 263-286.

- Syam, N. and Sharma, A. (2018), "Waiting for a sales renaissance in the fourth industrial revolution: machine learning and artificial intelligence in sales research and practice", *Industrial Marketing Management*, Vol. 69, pp. 135-146.
- Tu, M. (2018), "An exploratory study of Internet of Things (IoT) adoption intention in logistics and supply chain management", *The International Journal of Logistics Management*, Vol. 29 No. 1, pp. 131-151.
- US GAO (2015), *3D Printing: Opportunities, Challenges, and Policy Implications of Additive Manufacturing*, No. GAO-15-505SP, United States Government Accountability Office, Washington, DC, available at: <https://www.gao.gov/assets/gao-15-505sp.pdf> (accessed 11 December 2021).
- Vasanthakumar, C., Vinodh, S. and Ramesh, K. (2016), "Application of interpretive structural modelling for analysis of factors influencing lean remanufacturing practices", *International Journal of Production Research*, Vol. 54 No. 24, pp. 7439-7452.
- Wamba, S.F., Gunasekaran, A., Papadopoulos, T. and Ngai, E. (2018), "Big data analytics in logistics and supply chain management", *International Journal of Logistics Management*, Vol. 29 No. 2, pp. 478-484.
- Warfield, J.N. (1974), "Developing interconnection matrices in structural modelling", *IEEE Transactions on Systems, Man, and Cybernetics* No. 1, pp. 81-87.
- Winkelhaus, S. and Grosse, E.H. (2020), "Logistics 4.0: a systematic review towards a new logistics system", *International Journal of Production Research*, Vol. 58 No. 1, pp. 18-43.
- Yadav, V.S., Singh, A.R., Raut, R.D. and Govindarajan, U.H. (2020), "Blockchain technology adoption barriers in the Indian agricultural supply chain: an integrated approach", *Resources, Conservation and Recycling*, Vol. 161, 104877.
- Yin, S. and Kaynak, O. (2015), "Big data for modern industry: challenges and trends [point of view]", *Proceedings of the IEEE*, Vol. 103 No. 2, pp. 143-146.
- Zhang, W., Guhathakurta, S. and Khalil, E.B. (2018), "The impact of private autonomous vehicles on vehicle ownership and unoccupied VMT generation", *Transportation Research Part C: Emerging Technologies*, Vol. 90, pp. 156-165.
- Zhong, R.Y., Newman, S.T., Huang, G.Q. and Lan, S. (2016), "Big Data for supply chain management in the service and manufacturing sectors: challenges, opportunities, and future perspectives", *Computers and Industrial Engineering*, Vol. 101, pp. 572-591.

References

- Abduljabbar, R., Dia, H., Liyanage, S. and Bagloee, S.A. (2019), "Applications of artificial intelligence in transport: an overview", *Sustainability*, Vol. 11 No. 1, p. 189.
- Abramova, S. and Böhme, R. (2016), "Perceived benefit and risk as multidimensional determinants of bitcoin use: a quantitative exploratory study", in *Proceedings of the Thirty Seventh International Conference on Information Systems (ICIS)*, Dublin, 2016.
- Ali, S.S., Deka, S., Ahmad, Z., Ahmed, S., Jaswal, M. and Alsulami, H. (2019), *Feasibility of Drone Integration as Last Mile Delivery*, Emerald Emerging Markets Case Studies.
- Andrychowicz, M., Dziembowski, S., Malinowski, D. and Mazurek, Ł. (2015), "On the malleability of bitcoin transactions", *International Conference on Financial Cryptography and Data Security*, Springer, Berlin, Heidelberg, pp. 1-18.
- Apostolaki, M., Zohar, A. and Vanbever, L. (2017), "Hijacking bitcoin: routing attacks on cryptocurrencies", *2017 IEEE Symposium on Security and Privacy (SP)*, IEEE, pp. 375-392.
- Baldassarre, G., Santucci, V.G., Cartoni, E. and Caligiore, D. (2017), "The architecture challenge: future artificial-intelligence systems will require sophisticated architectures, and knowledge of the brain might guide their construction", *Behavioral and Brain Sciences*, Vol. 40.
- Balthazar, P., Harri, P., Prater, A. and Safdar, N.M. (2018), "Protecting your patients' interests in the era of big data, artificial intelligence, and predictive analytics", *Journal of the American College of Radiology*, Vol. 15 No. 3, pp. 580-586.

- Bamburry, D. (2015), "Drones: designed for product delivery", *Design Management Review*, Vol. 26 No. 1, pp. 40-48.
- Bansal, P., Kockelman, K.M. and Singh, A. (2016), "Assessing public opinions of and interest in new vehicle technologies: an Austin perspective", *Transportation Research C: Emerging Technologies*, Vol. 67, pp. 1-14.
- Barbierato, E., Gribaudo, M. and Iacono, M. (2014), "Performance evaluation of NoSQL big-data applications using multi-formalism models", *Future Generation Computer Systems*, Vol. 37, pp. 345-353.
- Bashir, M., Strickland, B. and Bohr, J. (2016), "What motivates people to use Bitcoin?", *International Conference on Social Informatics*, Springer, Cham, pp. 347-367.
- Basnayake, B.A.D.J.C.K., Amarasinghe, Y.W.R., Attalage, R.A., Udayanga, T.D.I. and Jayasekara, A.G.B.P. (2015), "Artificial intelligence based smart building automation controller for energy efficiency improvements in existing buildings", *International Journal of Advanced Automation Science and Technology*, Vol. 40 No. 40.
- Baumers, M., Dickens, P., Tuck, C. and Hague, R. (2016), "The cost of additive manufacturing: machine productivity, economies of scale and technology-push", *Technological Forecasting and Social Change*, Vol. 102, pp. 193-201.
- Beck, R., Müller-Bloch, C. and King, J.L. (2018), "Governance in the blockchain economy: a framework and research agenda", *Journal of the Association for Information Systems*, Vol. 19 No. 10, p. 1.
- Böhme, R., Christin, N., Edelman, B. and Moore, T. (2015), "Bitcoin: economics, technology, and governance", *Journal of Economic Perspectives*, Vol. 29 No. 2, pp. 213-238.
- Boucher, P. (2016), "'You wouldn't have your granny using them': drawing boundaries between acceptable and unacceptable applications of civil drones", *Science and Engineering Ethics*, Vol. 22 No. 5, pp. 1391-1418.
- Chan, S.L., Lu, Y. and Wang, Y. (2018), "Data-driven cost estimation for additive manufacturing in cybermanufacturing", *Journal of Manufacturing Systems*, Vol. 46, pp. 115-126.
- Chang, V., Chundury, P. and Chetty, M. (2017), "Spiders in the sky: user perceptions of drones, privacy, and security", *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pp. 6765-6776.
- Chen, J., Chen, Y., Du, X., Li, C., Lu, J., Zhao, S. and Zhou, X. (2013), "Big data challenge: a data management perspective", *Frontiers of Computer Science*, Vol. 7 No. 2, pp. 157-164.
- Clarke, R. and Moses, L.B. (2014), "The regulation of civilian drones' impacts on public safety", *Computer Law and Security Review*, Vol. 30 No. 3, pp. 263-285.
- Clothier, R.A., Greer, D.A., Greer, D.G. and Mehta, A.M. (2015), "Risk perception and the public acceptance of drones", *Risk Analysis*, Vol. 35 No. 6, pp. 1167-1183.
- Collingwood, L. (2017), "Privacy implications and liability issues of autonomous vehicles", *Information and Communications Technology Law*, Vol. 26 No. 1, pp. 32-45.
- Croman, K., Decker, C., Eyal, I., Gencer, A.E., Juels, A., Kosba, A. and Song, D. (2016), "On scaling decentralized blockchains", *International Conference on Financial Cryptography and Data Security*, Springer, Berlin, Heidelberg, pp. 106-125.
- Decker, C., Berchtold, M., Chaves, L.W.F., Beigl, M., Roehr, D., Riedel, T., ... and Herzig, D. (2008), "Cost-benefit model for smart items in the supply chain", *The Internet of Things*, Springer, Berlin, Heidelberg, pp. 155-172.
- Diedrichs, A.L., Tabacchi, G., Grünwaldt, G., Pecchia, M., Mercado, G. and Antivilo, F.G. (2014), "Low-power wireless sensor network for frost monitoring in agriculture research", *2014 IEEE Biennial Congress of Argentina (ARGENCON)*, IEEE, pp. 525-530.
- Duffy, J.P., Cunliffe, A.M., DeBell, L., Sandbrook, C., Wich, S.A., Shutler, J.D., ... and Anderson, K. (2018), "Location, location, location: considerations when using lightweight drones in challenging environments", *Remote Sensing in Ecology and Conservation*, Vol. 4 No. 1, pp. 7-19.

- Edwards, C., Edwards, A., Spence, P.R. and Lin, X. (2018), "I, teacher: using artificial intelligence (AI) and social robots in communication and instruction", *Communication Education*, Vol. 67 No. 4, pp. 473-480.
- Fairley, P. (2017), "Blockchain world-Feeding the blockchain beast if bitcoin ever does go mainstream, the electricity needed to sustain it will be enormous", *IEEE Spectrum*, Vol. 54 No. 10, pp. 36-59.
- Fast, N.J. and Jago, A.S. (2020), "Privacy matters Or does it? Algorithms, rationalization, and the erosion of concern for privacy", *Current Opinion in Psychology*.
- Fawcett, S.E., Ogden, J.A., Magnan, G.M. and Cooper, M.B. (2006), "Organizational commitment and governance for supply chain success", *International Journal of Physical Distribution and Logistics Management*.
- Fuller, B. (2016), "Cautious optimism about driverless cars and land use in American metropolitan areas", *Cityscape*, Vol. 18 No. 3, pp. 181-184.
- Gandomi, A. and Haider, M. (2015), "Beyond the hype: big data concepts, methods, and analytics", *International Journal of Information Management*, Vol. 35 No. 2, pp. 137-144.
- Gehrie, E.A. and Booth, G.S. (2017), "The impact of driverless cars on the US blood supply", *Transfusion and Apheresis Science*, Vol. 56 No. 2, p. 233.
- Gervais, A., Karame, G.O., Wüst, K., Glykantzis, V., Ritzdorf, H. and Capkun, S. (2016), "On the security and performance of proof of work blockchains", *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, pp. 3-16.
- Ghashghaee, P. (2016), "Smart manufacturing: role of Internet of Things in process optimization".
- Ghobadian, A., Talavera, I., Bhattacharya, A., Kumar, V., Garza-Reyes, J.A. and O'Regan, N. (2018), "Examining legitimatisation of additive manufacturing in the interplay between innovation, lean manufacturing and sustainability", *International Journal of Production Economics*.
- Grant, G. and Hogan, R. (2015), "Bitcoin: risks and controls", *Journal of Corporate Accounting and Finance*, Vol. 26 No. 5, pp. 29-35.
- Gupta, R.K. and Kumari, R. (2017), "Artificial intelligence in public health: opportunities and challenges", *JK Science*, Vol. 19 No. 4, pp. 191-192.
- Haddud, A., DeSouza, A.R., Khare, A. and Lee, H. (2017), "Examining potential benefits and challenges associated with the Internet of Things integration in supply chains", *Journal of Manufacturing Technology Management*, Vol. 28 No. 8, pp. 1055-1085.
- Ham, A.M. (2018), "Integrated scheduling of m-truck, m-drone, and m-depot constrained by time-window, drop-pickup, and m-visit using constraint programming", *Transportation Research Part C: Emerging Technologies*, Vol. 91, pp. 1-14.
- Hamledari, H., Davari, S., Sajedi, S.O., Zangeneh, P., McCabe, B. and Fischer, M. (2018), "UAV mission planning using swarm intelligence and 4D BIMs in support of vision-based construction progress monitoring and as-built modeling", *Construction Research Congress 2018*, pp. 43-53.
- He, D., Chan, S. and Guizani, M. (2017), "Drone-assisted public safety networks: the security aspect", *IEEE Communications Magazine*, Vol. 55 No. 8, pp. 218-223.
- Herrmann, A., Brenner, W. and Stadler, R. (2018), "Protection and liability, autonomous driving".
- Holmström, J., Liotta, G. and Chaudhuri, A. (2017), "Sustainability outcomes through direct digital manufacturing-based operational practices: a design theory approach", *Journal of Cleaner Production*, Vol. 167, pp. 951-961.
- Hossain, M.M., Fotouhi, M. and Hasan, R. (2015), "Towards an analysis of security issues, challenges, and open problems in the internet of things", *2015 IEEE World Congress on Services*, IEEE, pp. 21-28.
- Hung, P.C. (Ed.) (2016), *Big Data Applications and Use Cases*, Springer.
- Hussain, M.I. (2017), "Internet of Things: challenges and research opportunities", *CSI Transactions on ICT*, Vol. 5 No. 1, pp. 87-95.

- Irizarry, J. and Costa, D.B. (2016), "Exploratory study of potential applications of unmanned aerial systems for construction management tasks", *Journal of Management in Engineering*, Vol. 32 No. 3, 05016001.
- Kamble, S.S., Gunasekaran, A., Parekh, H. and Joshi, S. (2019), "Modeling the internet of things adoption barriers in food retail supply chains", *Journal of Retailing and Consumer Services*, Vol. 48, pp. 154-168.
- Karpowicz, J. (2017), "Transferring big drone data", available at: www.expouav.com/news/latest/transferring-big-drone-data/ (accessed 19 June 2018).
- König, M. and Neumayr, L. (2017), "Users' resistance towards radical innovations: the case of the self-driving car", *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 44, pp. 42-52.
- Krishnamurthy, R. and Desouza, K.C. (2014), "Big data analytics: the case of the social security administration", *Information Polity*, Vol. 19 No. 34, pp. 165-178.
- Kurzban, A.A. and Varaiya, P. (2015), "Traffic management: an outlook", *Economics of Transportation*, Vol. 4 No. 3, pp. 135-146.
- Kyriakidis, M., Happee, R. and de Winter, J.C. (2015), "Public opinion on automated driving: results of an international questionnaire among 5000 respondents", *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 32, pp. 127-140.
- Laosirihongthong, T., Paul, H. and Speece, M.W. (2003), "Evaluation of new manufacturing technology implementation: an empirical study in the Thai automotive industry", *Technovation*, Vol. 23 No. 4, pp. 321-331.
- Lee, I. and Lee, K. (2015), "The internet of things (IoT): applications, investments, and challenges for enterprises", *Business Horizons*, Vol. 58 No. 4, pp. 431-440.
- Li, S., Da Xu, L. and Zhao, S. (2015), "The internet of things: a survey", *Information Systems Frontiers*, Vol. 17 No. 2, pp. 243-259.
- Li, Y. and Liu, C. (2019), "Applications of multirotor drone technologies in construction management", *International Journal of Construction Management*, Vol. 19 No. 5, pp. 401-412.
- Lidynia, C., Philipsen, R. and Ziefle, M. (2017), "The sky's (not) the limit-influence of Expertise and privacy disposition on the use of Multicopters", *International Conference on Applied Human Factors and Ergonomics*, Springer, Cham, pp. 270-281.
- Liu, C., Yang, C., Zhang, X. and Chen, J. (2015), "External integrity verification for outsourced big data in cloud and IoT: a big picture", *Future Generation Computer Systems*, Vol. 49, pp. 58-67.
- Liu, G., Tan, Q., Kou, H., Zhang, L., Wang, J., Lv, W., ... and Xiong, J. (2018), "A flexible temperature sensor based on reduced graphene oxide for robot skin used in internet of things", *Sensors*, Vol. 18 No. 5, p. 1400.
- Luppici, R. and So, A. (2016), "A technoethical review of commercial drone use in the context of governance, ethics, and privacy", *Technology in Society*, Vol. 46, pp. 109-119.
- Luxton, D.D. (2014), "Recommendations for the ethical use and design of artificial intelligent care providers", *Artificial Intelligence in Medicine*, Vol. 62 No. 1, pp. 1-10.
- MacDonald, T.J., Allen, D.W. and Potts, J. (2016), "Blockchains and the boundaries of self-organized economies: predictions for the future of banking", *Banking beyond Banks and Money*, Springer, Cham, pp. 279-296.
- Malaka, I. and Brown, I. (2015), "Challenges to the organizational adoption of big data analytics: a case study in the South African telecommunications industry", *Proceedings of the 2015 Annual Research Conference on South African Institute of Computer Scientists and Information Technologists*, pp. 1-9.
- Mendis, D., Secchi, D. and Reeves, P. (2015), *A Legal and Empirical Study into the Intellectual Property Implications of 3D Printing. Executive Summary*, Intellectual Property Office, pp. 1-11.

- Merritt, S.M., Heimbaugh, H., LaChapell, J. and Lee, D. (2013), "I trust it, but I don't know why: effects of implicit attitudes toward automation on trust in an automated system", *Human Factors*, Vol. 55 No. 3, pp. 520-534.
- Moffitt, K.C. and Vasarhelyi, M.A. (2013), "AIS in an age of big data", *Journal of Information Systems*, Vol. 27 No. 2, pp. 1-19.
- Moktadir, M.A., Ali, S.M., Paul, S.K. and Shukla, N. (2019), "Barriers to big data analytics in manufacturing supply chains: a case study from Bangladesh", *Computers and Industrial Engineering*, Vol. 128, pp. 1063-1075.
- Moore, M.M. and Lu, B. (2011), "Autonomous vehicles for personal transport: a technology assessment", SSRN 1865047.
- Niaki, M.K., Torabi, S.A. and Nonino, F. (2019), "Why manufacturers adopt additive manufacturing technologies: the role of sustainability", *Journal of Cleaner Production*, Vol. 222, pp. 381-392.
- Olaronke, I. and Oluwaseun, O. (2016), "Big data in healthcare: prospects, challenges and resolutions", *2016 Future Technologies Conference (FTC)*, IEEE, pp. 1152-1157.
- Petrick, I.J. and Simpson, T.W. (2013), "3D printing disrupts manufacturing: how economies of one create new rules of competition", *Research-Technology Management*, Vol. 56 No. 6, pp. 12-16.
- Pour, M.A. and Zaroni, S. (2017), "Impact of merging components by additive manufacturing in spare parts management", *Procedia Manufacturing*, Vol. 11, pp. 610-618.
- PwC (2016), "3D Printing comes of age in US industrial manufacturing", available at: <https://www.pwc.com/us/en/industries/industrial-products/library/3d-printing-comes-of-age.html> (accessed 15 January 2022).
- Raghupathi, W. and Raghupathi, V. (2014), "Big data analytics in healthcare: promise and potential", *Health Information Science and Systems*, Vol. 2 No. 1, p. 3.
- Ready, P.J., Gunasekaran, A. and Spalanzani, A. (2015), "Bottom-up approach based on Internet of Things for order fulfillment in a collaborative warehousing environment", *International Journal of Production Economics*, Vol. 159, pp. 29-40.
- Reimer, B. (2014), "Driver assistance systems and the transition to automated vehicles: a path to increase older adult safety and mobility?", *Public Policy and Aging Report*, Vol. 24 No. 1, pp. 27-31.
- Riggins, F.J. and Wamba, S.F. (2015), "Research directions on the adoption, usage, and impact of the internet of things through the use of big data analytics", *2015 48th Hawaii International Conference on System Sciences*, IEEE, pp. 1531-1540.
- Ring, T. (2015), "Connected cars—the next target for hackers", *Network Security*, Vol. 2015 No. 11, pp. 11-16.
- Rose, K., Eldridge, S. and Chapin, L. (2015), *The Internet of Things: an Overview*, The Internet Society (ISOC), p. 80.
- Rosenfeld, M. (2014), "Analysis of hashrate-based double spending", arXiv:1402.2009.
- Ryan, P.J. and Watson, R.B. (2017), "Research challenges for the Internet of Things: what role can OR play?", *Systems*, Vol. 5 No. 1, p. 24.
- Rylands, B., Bohme, T., Gorkin, R.A. III, Fan, J.P. and Birtchnell, T. (2015), "3D Printing-To print or not to print? Aspects to consider before adoption-A supply chain perspective".
- Sapirshstein, A., Sompolinsky, Y. and Zohar, A. (2016), "Optimal selfish mining strategies in bitcoin", *International Conference on Financial Cryptography and Data Security*, Springer, Berlin, Heidelberg, pp. 515-532.
- Sayogo, D.S., Zhang, J., Luna-Reyes, L., Jarman, H., Tayi, G., Andersen, D.L. and Andersen, D.F. (2015), "Challenges and requirements for developing data architecture supporting integration of sustainable supply chains", *Information Technology and Management*, Vol. 16 No. 1, pp. 5-18.

- Schaeffer, C., Booton, L., Halleck, J., Studeny, J. and Coustasse, A. (2017), "Big data management in US hospitals: benefits and barriers", *The Health Care Manager*, Vol. 36 No. 1, pp. 87-95.
- Sebastian, V.J. and Gupta, R. (2018), "Retail ecosystem in India—an overview of the regulatory framework and the emerging paradigm", *Theoretical Economics Letters*, Vol. 8 No. 3, p. 183.
- Siebert, S. and Teizer, J. (2014), "Mobile 3D mapping for surveying earthwork projects using an Unmanned Aerial Vehicle (UAV) system", *Automation in Construction*, Vol. 41, pp. 1-14.
- Solodov, A., Williams, A., Al Hanaei, S. and Goddard, B. (2018), "Analyzing the threat of unmanned aerial vehicles (UAV) to nuclear facilities", *Security Journal*, Vol. 31 No. 1, pp. 305-324.
- Sun, T.Q. and Medaglia, R. (2019), "Mapping the challenges of Artificial Intelligence in the public sector: evidence from public healthcare", *Government Information Quarterly*, Vol. 36 No. 2, pp. 368-383.
- Swan, M. (2015), "Blockchain thinking: the brain as a decentralized autonomous corporation [commentary]", *IEEE Technology and Society Magazine*, Vol. 34 No. 4, pp. 41-52.
- Szalay, Z., Tettamanti, T., Esztergár-Kiss, D., Varga, I. and Bartolini, C. (2018), "Development of a test track for driverless cars: vehicle design, track configuration, and liability considerations", *Periodica Polytechnica Transportation Engineering*, Vol. 46 No. 1, pp. 29-35.
- Tizhoosh, H.R. and Pantanowitz, L. (2018), "Artificial intelligence and digital pathology: challenges and opportunities", *Journal of Pathology Informatics*, Vol. 9.
- Torres, L.G., Nieukirk, S.L., Lemos, L. and Chandler, T.E. (2018), "Drone up! Quantifying whale behavior from a new perspective improves observational capacity", *Frontiers in Marine Science*, Vol. 5, p. 319.
- Van Rijmenam, M. (2014), *Think Bigger: Developing a Successful Big Data Strategy for Your Business*, Amacom.
- Villaronga, E.F., Kieseberg, P. and Li, T. (2018), "Humans forget, machines remember: artificial intelligence and the right to be forgotten", *Computer Law and Security Review*, Vol. 34 No. 2, pp. 304-313.
- Waldrop, M.M. (2015), "No drivers required", *Nature*, Vol. 518 No. 7537, p. 20.
- Wang, H., Zhang, T., Quan, Y. and Dong, R. (2013), "Research on the framework of the environmental internet of things", *International Journal of Sustainable Development and World Ecology*, Vol. 20 No. 3, pp. 199-204.
- Weller, C., Kleer, R. and Piller, F.T. (2015), "Economic implications of 3D printing: market structure models in light of additive manufacturing revisited", *International Journal of Production Economics*, Vol. 164, pp. 43-56.
- Wirtz, B.W., Weyerer, J.C. and Geyer, C. (2019), "Artificial intelligence and the public sector—applications and challenges", *International Journal of Public Administration*, Vol. 42 No. 7, pp. 596-615.
- Wirtz, B.W. and Müller, W.M. (2019), "An integrated artificial intelligence framework for public management", *Public Management Review*, Vol. 21 No. 7, pp. 1076-1100.
- Wong, H.T., Yin, Q., Guo, Y.Q., Murray, K., Zhou, D.H. and Slade, D. (2015), "Big data as a new approach in emergency medicine research", *Journal of Acute Disease*, Vol. 4 No. 3, pp. 178-179.
- Yli-Huuma, J., Ko, D., Choi, S., Park, S. and Smolander, K. (2016), "Where is current research on blockchain technology? —a systematic review", *PLoS One*, Vol. 11 No. 10, e0163477.
- Yoo, W., Yu, E. and Jung, J. (2018), "Drone delivery: factors affecting the public's attitude and intention to adopt", *Telematics and Informatics*, Vol. 35 No. 6, pp. 1687-1700.

Barrier	Disruptive technologies (DT)	Literature sources
B1	Blockchain	Grant and Hogan (2015), Beck <i>et al.</i> (2018)
	Internet of Things	Rose <i>et al.</i> (2015), Sebastian and Gupta (2018)
	Drone/UAVs	Lidynia <i>et al.</i> (2017), Chang <i>et al.</i> (2017)
	Artificial intelligence	Gupta and Kumari (2017), Wirtz <i>et al.</i> (2019)
	Big Data	Moktadir <i>et al.</i> (2019)
	Driverless cars	Szalay <i>et al.</i> (2018), Collingwood (2017), Herrmann <i>et al.</i> (2018)
	3D printing	Mendis <i>et al.</i> (2015), US GAO (2015), Rogers <i>et al.</i> (2016)
B2	Blockchain	Sander <i>et al.</i> (2018), Saberi <i>et al.</i> (2019)
	Internet of Things	Mani and Chouk (2018), Liu <i>et al.</i> (2018)
	Drone/UAVs	Ali <i>et al.</i> (2019)
	Artificial intelligence	Wirtz and Müller (2019)
	Big Data	Olaronke and Oluwaseun (2016), Moffitt and Vasarhelyi (2013)
	Driverless cars	König and Neumayr (2017), Fuller (2016)
	3D printing	Ghobadian <i>et al.</i> (2018), Dwivedi <i>et al.</i> (2017), Weller <i>et al.</i> (2015), Niaki <i>et al.</i> (2019), Mellor <i>et al.</i> (2014)
B3	Blockchain	Croman <i>et al.</i> (2016), MacDonald <i>et al.</i> (2016)
	Internet of Things	Luthra <i>et al.</i> (2018), Li <i>et al.</i> (2015), Haddud <i>et al.</i> (2017)
	Drone/UAVs	Torres <i>et al.</i> (2018), Ham (2018), Kim <i>et al.</i> (2017), Irizarry and Costa (2016)
	Artificial intelligence	Abduljabbar <i>et al.</i> (2019)
	Big Data	Barbierato <i>et al.</i> (2014), Malaka and Brown (2015), Alharthi <i>et al.</i> (2017)
	Driverless cars	Kaur and Rampersad. (2018), Szalay <i>et al.</i> (2018)
	3D printing	Baumers <i>et al.</i> (2016), Holmström <i>et al.</i> (2017) Niaki and Nonino (2017)
B4	Blockchain	Abramova and Böhme (2016), Yli-Huumo <i>et al.</i> (2016), Fairley (2017), Swan (2015)
	Internet of Things	Kamble <i>et al.</i> (2019)
	Drone/UAVs	Karpowicz (2017), Irizarry and Costa (2016), Kim <i>et al.</i> (2017), Hamledari <i>et al.</i> (2018), Ham (2018)
	Artificial intelligence	Abduljabbar <i>et al.</i> (2019), Sun and Medaglia (2019), Tizhoosh and Pantanowitz (2018)
	Big Data	Gandomi and Haider (2015), Malaka and Brown (2015), Liu <i>et al.</i> (2015), Chen <i>et al.</i> (2013), Raghupathi and Raghupathi (2014), Da Xu <i>et al.</i> (2014), Diedrichs <i>et al.</i> (2014)
	Driverless cars	Kaur and Rampersad (2018)
	3D printing	Chan <i>et al.</i> (2018)
B5	Blockchain	Gervais <i>et al.</i> (2016), Rosenfeld (2014), Sapirshtein <i>et al.</i> (2016), Apostolaki <i>et al.</i> (2017)
	Internet of Things	Riggins and Wamba (2015), Da Xu <i>et al.</i> (2014), Ghashghaee (2016), Hussain (2017)
	Drone/UAVs	Clothier <i>et al.</i> (2015), Lidynia <i>et al.</i> (2017), Duffy <i>et al.</i> (2018), Kwon <i>et al.</i> (2017)
	Artificial intelligence	Abduljabbar <i>et al.</i> (2019)
	Big Data	Moktadir <i>et al.</i> (2019), LaVelle <i>et al.</i> (2011), McAfee <i>et al.</i> (2012)
	Driverless cars	Merritt <i>et al.</i> (2013), Kyriakidis <i>et al.</i> (2015), Bansal <i>et al.</i> (2016)
	3D printing	Mellor <i>et al.</i> (2014), Laosirihongthong <i>et al.</i> (2003), Niaki and Nonino (2017)

(continued)

Table A1.
Barriers to the
adoption of DTs in the
logistics sector

Barrier	Disruptive technologies (DT)	Literature sources
B6	Blockchain Internet of Things	Govindan and Hasanagic (2018), Saberi <i>et al.</i> (2019), Fawcett <i>et al.</i> (2006) Haddud <i>et al.</i> (2017), Chen <i>et al.</i> (2013), Lee and Lee (2015), Decker <i>et al.</i> (2008)
	Drone/UAVs	Bamburly (2015)
	Artificial intelligence	Wirtz <i>et al.</i> (2019)
	Big Data	Kim <i>et al.</i> (2014), LaVelle <i>et al.</i> (2011), McAfee <i>et al.</i> (2012)
	Driverless cars	Kurzanskiy and Varaiya (2015); Kaur and Rampersad (2018)
	3D printing	Rylands <i>et al.</i> (2015), Petrick and Simpson (2013), Weller <i>et al.</i> (2015)
B7	Blockchain	Saberi <i>et al.</i> (2019), Mougayar (2016)
	Internet of Things	Hussain (2017), Hung (2016), Ryan and Watson (2017)
	Drone/UAVs	Clarke and Moses (2014), Boucher (2016), Li and Liu (2019), Kim <i>et al.</i> (2017), Siebert and Teizer (2014)
	Artificial intelligence	Abduljabbar <i>et al.</i> (2019)
	Big Data	Schaeffer <i>et al.</i> (2017), Moktadir <i>et al.</i> (2019), Zhong <i>et al.</i> (2016), Malaka and Brown (2015)
	Driverless cars	Gehrie and Booth (2017)
	3D printing	Baumers <i>et al.</i> (2016), PwC (2016), US GAO (2015)
B8	Blockchain	Saberi <i>et al.</i> (2019), Mougayar (2016)
	Internet of Things	Abduljabbar <i>et al.</i> (2019)
	Drone/UAVs	Kellermann <i>et al.</i> (2020), McDonald (2019)
	Artificial intelligence	Wirtz <i>et al.</i> (2019)
	Big Data	Lavelle <i>et al.</i> (2011), McAfee <i>et al.</i> (2012)
	Driverless cars	Waldrop (2015), Fagnant and Kockelman (2015), König and Neumayr (2017)
B9	3D printing	Pour and Zaroni (2017)
	Blockchain	Andrychowicz <i>et al.</i> (2015), Sayogo <i>et al.</i> (2015), Bashir <i>et al.</i> (2016), Krombholz <i>et al.</i> (2016), Mougayar (2016)
	Internet of Things	Hossain <i>et al.</i> (2015), Wang <i>et al.</i> (2013), Lee and Lee (2015), Reaidy <i>et al.</i> (2015), Haddud <i>et al.</i> (2017), Li <i>et al.</i> (2015)
	Drone/UAVs	Luppacini and So (2016), Finn and Wright (2016), Kim <i>et al.</i> (2017), Lidynia <i>et al.</i> (2017), He <i>et al.</i> (2017), Solodov <i>et al.</i> (2018)
	Artificial intelligence	Balthazar <i>et al.</i> (2018), Luxton (2014), Fast and Jago (2020), Abduljabbar <i>et al.</i> (2019)
	Big Data	Alharthi <i>et al.</i> (2017), Malaka and Brown (2015), Wong <i>et al.</i> (2015), Krishnamurthy and Desouza (2014), Van Rijmenam (2014)
	Driverless cars	Fagnant and Kockelman (2015), Collingwood (2017), Ring (2015), Moore and Lu (2011), Reimer (2014), Herrmann <i>et al.</i> (2018)
	3D printing	Chan <i>et al.</i> (2018), Mellor <i>et al.</i> (2014)
B10	Blockchain	Böhme <i>et al.</i> (2015)
	Internet of Things	Li <i>et al.</i> (2015), Haddud <i>et al.</i> (2017)
	Drone/UAVs	Yoo <i>et al.</i> (2018)
	Artificial intelligence	Villaronga <i>et al.</i> (2018), Basnayake <i>et al.</i> (2015), Tizhoosh and Pantanowitz (2018), Baldassarre <i>et al.</i> (2017), Edwards <i>et al.</i> (2018), Sun and Medaglia (2019)
	Big Data	Schaeffer <i>et al.</i> (2017), Moktadir <i>et al.</i> (2019)
	Driverless cars	Fagnant and Kockelman (2015), Waldrop (2015), König and Neumayr (2017)
	3D printing	Niaki and Nonino (2017)

Note(s): B1 = legal and regulatory framework; B2 = resistance to change; B3 = infrastructure; B4 = data management; B5 = lack of trust; B6 = lack of top management support; B7 = lack of adequate resources; B8 = lack of reliability; B9 = privacy and security; B10 = technical issues

Table A1.

The following is a questionnaire on the barriers that could have hindered your company in the adoption of disruptive technologies. Please respond to the questionnaire about the significance level of each adoption barrier, using the following answers: "Very high", "High", "Moderate", "Low", "Very low"

Barrier name	Answer
Legal and regulatory framework	
Resistance to change	
Infrastructure	
Data Management	
Lack of trust	
Lack of communication	
Lack of top management support	
Lack of adequate resources	
Lack of advanced analytics skills	
Lack of reliability	
Privacy and security	
Technical issues	

Table A2.
FDM questionnaire

Codes	Linguistic terms	Corresponding TFN
VH	Very high	(0.7, 0.9, 0.9)
H	High	(0.5, 0.7, 0.9)
M	Moderate	(0.3, 0.5, 0.7)
L	Low	(0.1, 0.3, 0.5)
VL	Very low	(0.1, 0.1, 0.3)

Source(s): Singh and Sarkar (2020)

Table A3.
Description of
linguistic scale

Please answer the questions by filling the appropriate response.

After scrutinising the significant barriers of DTs adoption, the contextual relationships amongst the barriers are developed. To depict these contextual relationships, a SSIM matrix is prepared. The following symbols are used to interpret the direction of relationships between the two significant barriers to the adoption of DTs in logistic sector.

V: Barrier i will influence barrier j ;

A: Barrier j will influence barrier i ;

X: Barrier i and j will influence each other and

O: Barriers i and j are unrelated.

Let us assume barrier $i = 1$, i.e. "Legal and regulatory framework", will influence $j = 2$, i.e. "Resistance to change", then fill the symbol "V". Similarly, if $j = 2$ will influence $i = 1$, then fill symbol "A". If both barriers $i = 1$ and $j = 2$ will influence each other, then insert the symbol "X", and if both barriers $i = 1$ and $j = 2$ are unrelated to each other, then insert the symbols "O"

Please follow the same procedure for all the cells (barriers) shown in the below table:

Table A4.
ISM questionnaire

S.No	Code, <i>i</i> ↓	Barriers, <i>j</i> →	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
1	B1	Legal and regulatory framework										
2	B2	Resistance to change										
3	B3	Infrastructure										
4	B4	Data management										
5	B5	Lack of trust										
6	B6	Lack of top management support										
7	B7	Lack of adequate resources										
8	B8	Lack of reliability										
9	B9	Privacy and security										
10	B10	Technical issues										
Note(s): <i>B1</i> = legal and regulatory framework; <i>B2</i> = resistance to change; <i>B3</i> = infrastructure; <i>B4</i> = data management; <i>B5</i> = lack of trust; <i>B6</i> = lack of top management support; <i>B7</i> = lack of adequate resources; <i>B8</i> = lack of reliability; <i>B9</i> = privacy and security; <i>B10</i> = technical issues												

Table A5.
Level partition of
reachability matrix

Barriers	Reachability set	Antecedent set	Intersection	Level
<i>Iteration I</i>				
B1	1,2,3,4,5,7,8,9,10	1,6	1	I
B2	2,4,5,7,8,9,10	1,2,3,6	2	
B3	2,3,4,5,7,8,9,10	1,3,6	3	
B4	4,5,7,8,9,10	1,2,3,4,6,7,10	4,7,10	
B5	5,8	1,2,3,4,5,6,7, 10	5	
B6	1,2,3,4,5,6,7,8,9,10	6	6	
B7	4,5,7,8,9,10	1,2,3,4,6,7,10	4,7,10	
B8	1	1,2,3,4,5,6,7,8,9,10	1	
B9	8,9	1,2,3,4,6,7,9, 10	9	
B10	4,5,7,8,9,10	1,2,3,4,6,7,10	4,7,10	
<i>Iteration II</i>				
B1	1,2,3,4,5,7,9,10	1,6	1	II
B2	2,4,5,7,9,10	1,2,3,6	2	
B3	2,3,4,5,7,9,10	1,3,6	3	
B4	4,5,7,9,10	1,2,3,4,6,7,10	4, 7,10	
B5	5	1,2,3,4,5,6,7,10	5	
B6	1,2,3,4,5,6,7,9,10	6	6	
B7	4,5,7,9,10	1,2,3,4,6,7,10	4,7,10	
B9	9	1,2,3,4,6,7,9,10	9	
B10	4,5,7,9,10	1,2,3,4,6,7,10	4,7,10	
<i>Iteration III</i>				
B1	1,2,3,4,7,10	1,6	1	III
B2	2,4,7,10	1,2,3,6	2	
B3	2,3,4,7,10	1,3,6	3	
B4	4,7,10	1,2,3,4,6,7,10	4,7,10	
B6	1,2,3,4,6,7,10	6	6	
B7	4,7,10	1,2,3,4,6,7,10	4,7,10	
B10	4,7,10	1,2,3,4,6,7,10	4,7,10	

(continued)

Barriers	Reachability set	Antecedent set	Intersection	Level
<i>Iteration IV</i>				
B1	1,2,3	1,6	1	IV
B2	2	1,2,3,6	2	
B3	2,3	1,3,6	3	
B6	1,2,3,6	6	6	
<i>Iteration V</i>				
B1	1,3	1,6	1	V
B3	3	1,3,6	3	
B6	1,2,6	6	6	
<i>Iteration VI</i>				
B1	1	1,6	1	VI
B6	1,6	6	6	
<i>Iteration VII</i>				
B6	6	6	6	VII

Note(s): B1 = legal and regulatory framework; B2 = resistance to change; B3 = infrastructure; B4 = data management; B5 = lack of trust; B6 = lack of top management support; B7 = lack of adequate resources; B8 = lack of reliability; B9 = privacy and security; B10 = technical issues

Table A5.

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