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Does the world need to change its vaccine distribution strategy for COVID-19?

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ABSTRACT

During an emergency, there are many activities in a pharmaceutical supply chain (PSC) which are rendered ineffective. This study aims to propose a holistic approach for Big Data Driven Pharmaceuticals Supply Chain (BDDPSC) during medical emergencies. During unprecedented situations, the quality of healthcare services by using traditional supply chain becomes a challenge. The current study aims to generate a model wherein multiple entities will be the part of data entries like hospitals, clinical trials, medical practitioners, and drug manufacturing companies during COVID-19. The study has considered certified medical practitioners as the experts and based their responses for proposing a theoretical framework deploying E-Delphi–Qualitative Data Analysis approach. By critically examining experts' responses and comments, the study formulated four major themes and ten sub-themes for smooth functioning of BDDPSCs during an emergency. The E-Delphi was conducted in two rounds to reach final consensus and to find a balance for PSC in terms of efficiency and quality. This research is novel wherein big data enabled PSC theoretical model has been formulated using a qualitative approach for handling COVID-19. The proposed framework provides an enriched way to capture data from the important link viz. "health officials" of PSCs.

1. Introduction

Over the last two decades, nations across the globe have paid much attention towards enhancing the efficiency of healthcare operations (Chen et al., 2013; Diwas Singh et al., 2020). Safeguarding healthy lives and promoting community wellbeing is essential to sustainable development (SDG 2019). All countries are doing their best to ensure the delivery of quality healthcare services with enhanced operational efficiency and reduced costs (Dixit et al., 2019; Nayal et al., 2022). However, due to global climate change patterns and unprecedented human activities, pandemics and epidemics have increased their frequency and intensity, most recently with COVID-19. These bio and epidemiologic disasters are often chaotic and catastrophic, and are characterized by their low probability, high intensity, and high complexity (World Health Organization, 2020).

Previous studies (Aksin-Sivrikaya and Bhattacharya, 2017; Wamba et al., 2020) find that, to leverage the operational efficiency of the healthcare sector, current healthcare Supply Chain Management (SCM) practices need to be digitalized because of new Information and Communications Technology (ICT) disruptions and increased outsourcing (Dixit et al., 2019; Sapci and Sapci, 2019). There is a tremendous amount of data generated across all phases of healthcare operations due to the advancement in ICTs, driving a need for healthcare organizations to move away from traditional supply chains (SCs) toward Big Data-Driven Pharmaceuticals Supply Chains (BDDPSCs) to handle unexpected situations like COVID-19 (Chakraborty and Paul, 2022). The COVID 19 pandemic has provided an opportunity for the healthcare practitioners to forecast future events such as drug supply and demand, and patient load effectively in such situations (Gordon-Wilson, 2022, Kursan- Milakovic, 2021).

ICTs in healthcare operations are increasingly tackling critical issues such as increased service complexity, the need for upgrading healthcare outcomes, and better integration of healthcare systems (Moghaddasi and Sheikhtaheri, 2010; Turan and Palvia, 2014; Spatar et al., 2019). ICT's investment in healthcare is the motivating factor for continuous business process improvement, reducing soaring costs, and enhancing

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quality of services particularly in developing economies (Dey et al., 2007; Abujamra and Randall, 2019). Novel technology usage in clinician decisions and healthcare operations has shown considerable improvements recently by improving safety standards and efficiency through the creation of timely, cost-effective, and patient-centered care (Sittig et al., 2018; Pamplin et al., 2020). Digitalization leads to quality healthcare practices with reduced costs (Archenaa and Anita, 2015; Galetsi and Katsaliaki, 2019).

1.1. Gap identification and research questions

Despite the huge potential of ICTs in automating healthcare operations and clinical decision-making processes, the rate of adoption of ICTs in Pharmaceuticals Supply Chains (PSCs) has remained low (Hennington and Janz, 2007; Nayak et al., 2019). Additionally, the frequent lack of planning along the PSCs during crises (such as pandemics and epidemics) (Gostin and Friedman, 2015; Kamradt-Scott, 2016) often impacts the efficacy of healthcare operations. In the recent Coronavirus pandemic (COVID-19), many gaps in the current healthcare systems have emerged: the lack of successful vaccine testing and the challenges of launching a vaccine; failure of healthcare agencies to forecast and pre-plan stocks, provide timely availability of testing kits, screening facilities, and improvised testing capabilities; information asymmetry, weak inter-organizational alliances, and poor information management systems; all of which have hampered efforts to control COVID-19 (Page and McKay, 2020). Recent studies (Cobianchi et al., 2020) have highlighted the transition healthcare sector needs i.e., from a resilient strategy to an *anti-fragile one.* This scenario reflects a dearth of research (both theoretical and empirical) on BDDPSCs.

Accessibility to technical, financial, and timely healthcare information has a critical role in improving the lifestyles of people in developing economies. ICTs are the principal enablers in supplementing accessibility to healthcare information and enhancing data-driven medical decision-making (Begoli et al., 2019; Galetsi et al., 2019). From a thorough understanding the key ICT challenges, healthcare practitioners and other stakeholders (government, research institutions, pharmaceuticals manufacturers, hospitals, testing agencies, retailers and distributors) along the PSC can make better decisions related to ICT investments in healthcare operations. In addition, the BDDPSCs can assist government in defining effective strategies and policies for their healthcare operations, especially during an epidemic situation like COVID-19. Moreover, BDDPSCs provide digital solutions that can help in adopting *anti-fragile* strategies in healthcare operations (Baudier et al., 2022). Thus, this research study explores the path towards BDDPSCs to transform the current healthcare operations and aims to address the following Research Questions (RQs):

RQ1: What are the shortcomings in current pharmaceutical supply chains and how can BDDPSCs overcome them?

RQ2: How can IT resources be leveraged to effectively tackle emergency situations like COVID-19?

We begin this paper by providing context for big data-driven supply chains using the theoretical lens of the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT) to highlight their benefits for healthcare operations. The RBV of the organization and use of DCT provide a theoretical rationale for the above argument, as they provide a cogent framework for evaluating the strategic value of ICT resources (Haddad et al., 2016; Van de Wetering et al., 2018) and help determine an organization's abilities to renew their competencies in response to a dynamic business environment (Uner et al., 2020). During this article's genesis, the COVID-19 outbreak has had a devastating impact across all sectors. Globally, as of 21 July 2020, there have been 170,812,850 confirmed cases of COVID-19, including 3,557,586 deaths, reported to WHO (World Health Organization, 2020).[1] In response, we conducted an electronic-Delphi on doctors and paramedical experts to identify the critical issues in times of pandemic/epidemic situations and whether BDDPSCs can bolster precautionary actions.

The current study contributes in two ways. First, the research presents a new framework for big

Data-driven pharma supply chains (BDDPSCs) to overcome the multiple challenges of the basic.

PSCs during pandemics and epidemics. Second, we posited that BDDPC

can be used for the smooth functioning of a more balanced, efficient, transparent, and cost-effective system during crises like COVID-19. During unprecedented situations, an effective system based on the potential requirement and the smooth flow of information from different stakeholder is required. In such cases, BDDPSC can be implemented to eliminate the shortage of supply of medicine and various information bottlenecks for government healthcare bodies. Through a basic understanding of different epidemic or pandemic situations, the paper has devised the BDDPSC framework. To understand the information input points and the functioning of the system, multiple stakeholders' inputs were recorded. The outcome of the study can be used by government decision-makers and medical practitioners to predict the requirements of medical supplies long before their actual need, with positive possible impacts for pandemic or epidemic PSC planning.

The remainder of the paper is organized as follows. Section two presents the literature review, which explains the theoretical foundation of the research and proposes the BDDPSC Framework. Research methods are described in section three. The results are presented in section four. Section five presents a discussion of the findings including practical implications and unique contributions. Concluding remarks are then given with the limitations and future scope of the present work.

2. Literature review and theoretical foundation

The following section highlights the previous literature on BDDPSCs and elaborates on the theoretical underpinnings of previous research.

2.1. Big data driven solutions

Big data-driven solutions provide deep insights from big data by using different analytical tools for sustainability, business performance and to develop strategic advantage (Wamba et al., 2017). The role of big data in SCM is typically motivated by its ability to improve and automate various processes across different phases (Brinch, 2018). Notably, as business processes become increasingly data driven, insights derived from data can be seen as pivotal instruments in improving SC performance and visibility. Further, the concepts of big data and business analytics offer effective decision-making practices for improving organizational performance (Ramanathan et al., 2017).

Organizations that have deployed mature SC practices—i.e., improved big data analytics capabilities—can minimize their costs more quickly and achieve higher profit margins as compared to their less mature peers (Zhan and Tan, 2020). Moreover, organizations deploying higher levels of SC integration through effective communication and information sharing have an enhanced competitive advantage and improved SC performance (Sanders, 2016). Therefore, in the current scenario, the SCs are referred to as big data-driven supply chains (BDDSCs), which have an enormous volume of data availability (Chen et al., 2015; Ghasemaghaei, 2018). The performance of BDDSCs is highly dependent on big data analytics such as data management, infrastructure (technology), and talent (personnel) capabilities (Kiron et al., 2014).

With disruptive ICTs (such as Blockchain, fog computing, and mist computing to name a few) arriving on the horizon, traditional PSCs are becoming obsolete. Conventional SC models have many complexities that hamper their efficacy. There is a lack of visibility caused by traditional technology as it restricts the end-to-end visibility of SCs at the

[1] https://covid19.who.int/.

product, order, and shipment points (Papert et al., 2016). As most of the tasks are function oriented, the lack of cross-functional skillsets hinders financial and operational decisions (Kumar et al., 2015; Kache and Seuring, 2017).

To overcome the issues emanating from the traditional PSCs, most organizations have been forced to explore the avenue of digitalization to increase their competency. The advent of industry 4.0 technologies such as big data analytics, Internet of Things (IoT), and Internet of Services (IoS) has had a profound impact on every sector. To improve information processing capabilities across the SCs, academicians, practitioners, and policymakers called for a digital transformation of organizations, according to the guiding principles of Industry 4.0 or the fourth industrial revolution (Kagermann et al., 2013; Deloitte, 2015; Theorin et al., 2017). The adoption of specific enabling technologies (e.g., enhanced ICT systems and big data analytics) is necessary to accomplish this digital transformation of the PSCs (Ardito et al., 2019).

2.2. Big data, supply chains, and COVID-19

The current pandemic situation has exposed the fragility of global SCs. The ripple effect had led to performance deterioration for revenue and service, plus productivity losses (Ivanov, 2020). The pandemic is also testing the resilience of global PSCs due to simultaneous disruptions of logistics, supply, infrastructure, and physical demand. Papadopoulos et al. (2017) report that big data can enhance SC risk management and disaster-resistance. Further, big data analytics can be utilized to enhance resilience of SC operations by making use of the organization's database. Large volumes of data can be analyzed to predict and model risks and assess the vulnerability and risk mitigation capacity of SCs (Choi and Lambert, 2017; Choi et al., 2016). Ivanov et al. (2018) investigate how big data analytics can be effectively used during the SC planning stages to identify potential supplier risk exposures, which will further help to monitor and identify disruptions proactively. As SC operations are influenced by big data, they are also affected by disruption risks; therefore, it is logical to link BDDSCs and SC disruption risk management (Ivanov et al., 2018).

Big data holds immense potential for optimizing recovery strategies in the SC networks (Papadopoulos et al., 2017). Past studies have highlighted the capabilities of big data for improving productivity, efficiency, and competitiveness by aiding decision-making with respect to optimization, enhanced product and service delivery, and operational risk reduction (Song et al., 2018; Wamba et al., 2015). Further, big data can help in disaster recovery and to enhance the adaptive capability in preparing for future catastrophes (Redman, 2014). Integrating big data with IoT can provide real-time solutions for tackling emergencies (Akter and Wamba, 2019) and enhance the receptivity and responsiveness of the BDDPSCs. Based on prior research, utilization and deployment of IT in pre- and post-disaster risk management can be segregated into early warning systems (Kara et al., 2020; Wong et al., 2020), visualization and simulation systems (Fischer-Preßler et al., 2020; Helo and Shamsuzzoha, 2020), and real-time event detection systems (Ivanov et al., 2018; Araz et al., 2020). Information acquisition and sharing of real-time information are critical components in SC recovery planning exercises (Alicke et al., 2020; Ivanov, 2020). Generally, practitioners deploy tracking and traceability systems (such as RFIDs, blockchain, and IoT) along different SC phases to detect potential sources of disruption. These sources are then analyzed, and requisite control mechanisms are engaged to address these without affecting the SC operations. A combination of blockchain and IoT can lead to sharing of real-time information, which will enhance the scalability of the traceability systems along the SC, thereby improving process visibility. For global medical emergencies such as COVID-19, the real-time connectivity of the BDDPSCs can enhance system resilience and effectively mitigate risks. Blockchain technology integration in the BDDPSC framework allows for real-time risk traceability, improved data management, and enhances proactive planning throughout the PSCs (Cerchione et al., 2022; Massaro, 2021; Spanò et al., 2021). The connectivity across the BDDPSCs can strengthen the PSC's capabilities through collaboration which will further enhance the integrated PSC risk management practices and flexibility in healthcare operations.

2.3. Theoretical underpinnings

The RBV highlights that a firm's ability to implement strategies effectively depends on its capability to operate and build resources successfully in the dynamic environment as compared to its competitors (Mirza and Ahsan, 2020). The dynamic capabilities paradigm postulates that, over time, firms can create, complement, and reshape their internal and external abilities for addressing the environmental volatility to gain new forms of competitive advantage (Bilir and Morales, 2020). These abilities are dynamic and make the firm capable of acquiring, combining, and transforming resources differently to gain strategically important values (Teece, 1977). The below sub-sections describe the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT) for realizing BDDPSCs.

2.3.1. Resource-based view

The Resource-Based View (RBV) is a widely renowned theory that has been extensively used in the last three decades in strategic management, IT related capabilities and business value research, and innovation. The RBV provides efficient ways for enhancing information systems (IS) research on how IT creates business value and acknowledges its contribution to organizational performance (Wade and Hulland, 2004). Barney (2001) reports on how the RBV helps organizations to achieve and sustain a competitive advantage based on the resources owned and controlled. Two distinct components central to the RBV are the processes of resource-picking and capacity building (Makadok, 2001). Amit and Schoemaker (1993) highlighted that an organization's resources are tradable and are non-specific organizational assets, with capabilities defined as non-tradable organization specific abilities for integrating, deploying, and utilizing the resources within the organization. Therefore, the resources are an input to the production processes and the capabilities are the organization's capacity to effectively deploy these resources (particularly IT resources) to enhance productivity.

The RBV has been used widely in the IS context encompassing topics such as single IT resources, IT resource sets, and IT capabilities (Yu et al., 2018; Wang et al., 2012). Recent studies (see Schniederjans et al., 2020; Shafiq et al., 2020; Waschull et al., 2020) have highlighted the process of deploying and leveraging IT resources in combination with other organizational resources in business value creation and to gain competitive advantage. Dierickx and Cool (1989) report that organizations can achieve a competitive advantage with the help of their internal resources that cannot be obtained from external markets. Therefore, the deployment of resources and capabilities are critical for acquiring and maintaining an edge over the competitors. Barney (1986) contends that resources form the sources for competitive advantage for organizations and that these resources are Valuable (V), Rare (R), Imperfectly imitable (I) ones which are appropriately Non-substitutable (N) (Barney, 2001; Gunasekaran et al., 2017). Organizational resources can be classified into '*human capital*,' '*physical capital*,' '*technological capital*,' and '*reputational capital*.' Resources can be further categorized into 'tangible' (such as machinery, buildings) or 'intangible' (such as patents, trademarks) (Mahoney and Pandian, 1992; Gunasekaran et al., 2017).

The current study adopts RBV and highlights organizational resources in the form of BDDPSC. Previous studies (Zhu et al., 2020; Kamble and Gunasekaran, 2020; Rajaguru and Matanda, 2019; Hazen et al., 2014) highlight that information and knowledge from various SC phases can be considered as resources that enable SC analytics processes. Further, as Manyika et al. (2011) suggest, when applied to SC processes, big data analytics leads to the creation of new competitive advantages via enhanced operational effectiveness. Put simply, IT-enabled excellence at the operational level acts as a catalyst for enhancing resource productivity and thereby, competitive advantage, in alignment with the foundations of the RBV (Amit and Schoemaker, 1993). Therefore, as per the literature review and the RBV, the current study highlights the organization capabilities in the form of robust IT capabilities (Bharadwaj, 2000). Finally, as suggested by Davenport et al. (2012), the evolution of big data and related IT resources will continuously enhance real-time information sharing, optimize decision-making processes, and generate new insights for businesses and influence organizational performance. Organizations that leverage their capabilities (such as IT, logistics and physical distribution, and communication technologies) can reap the benefits of enhanced productivity, servitization, and operational performance (Partanen et al., 2020; Yusuf et al., 2020; Zhan and Tan, 2020). Accordingly, we use the RBV as a theoretical lens (Amundson, 1998) for developing a framework that proposes BDDPSC as an important organizational resource that facilitates real-time information sharing, which drives PSC business performance in the form of visibility, transparency, and responsiveness.

2.3.2. Dynamic capabilities theory

First introduced by Teece et al. (1997), DCT is aimed at explaining the phenomena of competitive advantage and performance. Dynamic capabilities (DCs) are defined as “the ability of an organization to integrate, build and reconfigure their internal and external competences for rapidly addressing the key challenges in dynamic business environments” (Teece et al., 1997; Braganza et al., 2017). The ability of an organization to accomplish new forms of competitive advantage through the renovation of resources and competences highlights the DCs approach. The DCT is a complement to the RBV. The important characteristics of DCs is that it has no heterogeneity as compared to RBV and DCs lead to the generation of new heterogeneities and VRIN resources, and in turn, superior profitability. Ambrosini and Bowman (2009) assert that DCs allow an organization to continually have competitive advantage and avoid core rigidities. The overall goal of deploying DCs is to create a new bundle of VRIN resources for BDDPSCs.

2.4. Proposed BDDPSC framework

BDDPSCs promise many advantages in terms of flexibility and efficiency to drive the enterprise forward. Fig. 1 depicts the framework for realizing BDDPSCs. It highlights how the BDDPSCs will be deployed across the healthcare SCs to enhance transparency and handle an emergency like COVID-19. This would further enhance the operational efficiency of the healthcare SCs while overcoming the existing lacunae.

Fig. 2. Word cloud analysis.

The day-to-day activities in a PSC generate tremendous amounts of data, but most organizations do not have the requisite analytical capabilities to fully integrate and analyze data from multiple systems across all PSC phases. A transition of the healthcare organizations from traditional PSCs to the BDDPSCs is thus required. The data can be used as a fuel for the advanced predictive, prescriptive, and descriptive algorithms. The outputs can be simulated to predict and respond to PSC disruptions. Moreover, inefficiencies in the information and material flows can be detected and improved.

The initial step in realizing this framework is digitization of data across all PSC phases. As shown in the figure, the PSC is a complex entity

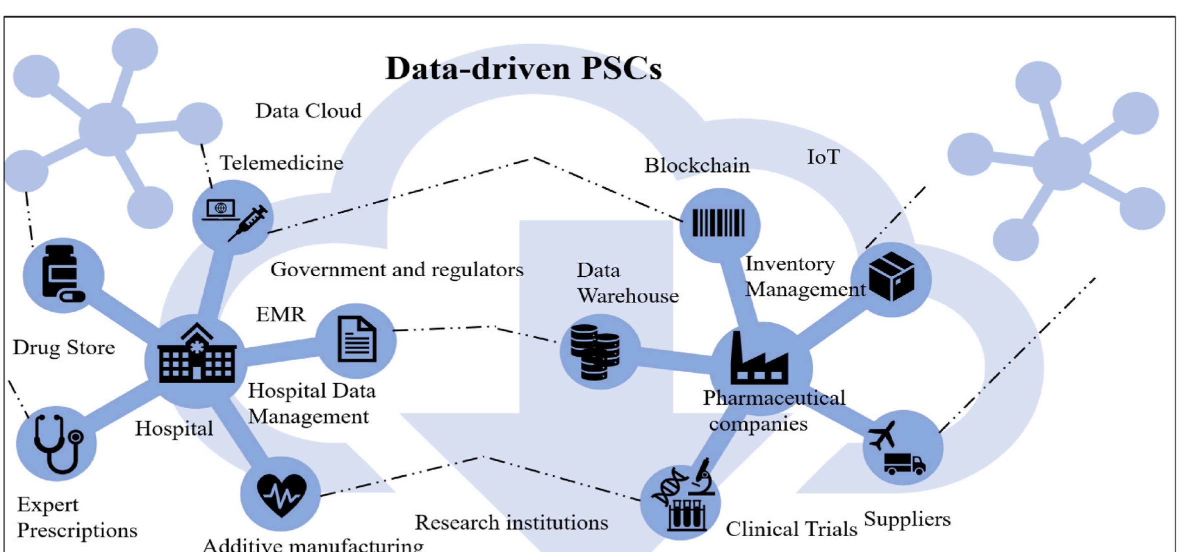

Fig. 1. Proposed BDDPSC framework.

involving numerous stakeholders (such as hospitals, research institutions, suppliers, manufacturers, etc.). Therefore, the visibility and traceability of the critical processes is hampered. The EU Blockchain consortium has devised a Blockchain enabled healthcare system, PharmaLedger, with a consortium of twelve pharmaceutical organizations and seventeen other entities including technology companies, academic institutions (universities), research firms, healthcare service providers, hospitals, and patient firms. PharmaLedger aimed to develop an innovative healthcare solution by using data from different stakeholders (Morris, 2020).

Information asymmetry leads to fluctuations in demand and supply of medicines in situations like COVID-19. Emerging technologies such as Blockchain, additive manufacturing, based on the internet of things (IoT), and internet of services (IoS) platforms continuously drive disruptive innovation of processes which leads to the transformation of the BDDPSCs. PSCs generate extensive data; thus, the digitalization of the PSCs is fundamental to enhance efficiency and quality (van Velthoven et al., 2019).

As per the proposed framework, the data generated across all the phases of the BDDPSC is stored in the cloud where it is accessible in real-time. Sensors and actuators across all BDDPSC phases generate, store, and transfer the data to cloud data warehouses. Government and regulators form an essential part of this framework. Blockchain technology can be used as a service interface as it enables two parties to store transaction details in a secure, transparent, and un-tampered digital format. Blockchain allows a free flow of interaction between individuals and organizations, redefining the way businesses operate (Iansiti and Lakhani, 2017). Due to the non-involvement of a third party and the anonymity of nodes in Blockchain, the system is highly secure, immutable, robust, and transparent (Yli-Huumo et al., 2016). The stakeholders in BDDPSCs can focus on the hybrid type of blockchains (the other types being public, private, and consortium based) as it offers stringent data security mechanisms, reduces transaction costs, and offers more scope (Spanò et al., 2022). The governance mechanism or the consensus algorithm can be based on proof of stake (PoS) as it is more decentralized and consumes lesser amount of energy as compared to the proof of work (PoW) consensus algorithm though PoW offers the highest reliability and fairness (Wendl et al., 2023). Recent research shows that Blockchain is penetrating the healthcare sector (Mettler, 2016), in applications ranging from maintaining Electronic Health Records (EHRs), enhancing drug traceability, and safeguarding clinical trial processes to ensuring smooth claims processing (Angraal et al., 2017). The framework also allows various stakeholders to share and exchange information, which further strengthens the BDDPSC upstream and downstream. A recent example is the collaboration of research institutions and startups during COVID-19 for making testing kits, indigenous masks, ventilators, and other safety equipment for the healthcare workers and practitioners. Real-time information exchange across the BDDPSC can enable an effective risk mitigation mechanism and make the system robust through data-driven decision-making capabilities. Additionally, end-to-end visibility helps in achieving the organization's SC goals regarding service, capital, agility, and cost. Addressing these will help in meeting the vision of such organizations for their transformed SC (Gezgin et al., 2017). Moreover, BDDPSCs are driven by technologies for leveraging the operational capabilities.

3. Research design

We conducted a two-round e-Delphi study between March and May 2020 with the final consensus of twenty-five paramedical senior staff and doctors. The current study adopted an online mode for conducting the Delphi study (Aengenheyster et al., 2017) due to COVID-19 and has therefore been called an e-Delphi method (Hasson and Keeney, 2011). Various studies have highlighted the importance of big data in healthcare (Khanra et al., 2020; Galetsi et al., 2020), while most of the studies have explored the significance only theoretically through structured literature review only, though missed it empirically. This study is a step towards the ground testing with intent of "leaving no stone unturned", with given a fair share of challenges. Delphi method is considered to be highly legitimate research method especially for limited knowledge areas among researchers (Lund, 2020). The significance of Delphi method is recognized among social group studies to eliminate the disparity in responses and conversations during group discussions (Woudenberg, 1991). The e-Delphi study was conducted in May 2020. A Focus Group Discussion (FGD) was also carried out comprising of 106 experts from hospitals and seven medical regulatory agencies (Gossler et al., 2019) for validation of the final consensus of expert responses through the e-Delphi method (Creswell and Poth, 2016; Karampatakis et al., 2019). Due to the unprecedented situation of COVID-19 and the unavailability of medical practitioners physically, the e-Delphi method was adopted rather than the traditional Delphi method. All variants of the Delphi method have only one objective: to reach consensus (Turoff, 1970). Our study makes a contribution to RBV and DCT in the context of vaccine distribution and adds a fresh dimension to understand how big data can help by adopting the e-Delphi research design. The primary objective of e-Delphi is to find the practical solution for a potential method and to reveal the stated argument (Gossler et al., 2019). Therefore, the study design has been structured according to the e-Delphi method.

3.1. Study design

Due to the qualitative and post-positivist nature of the study, the e-Delphi method has been applied to achieve consensus pertaining to the use of BDDPSCs in an epidemic situation (Hasson and Keeney, 2011). Registered medical practitioners were consulted to gather opinions on the data-driven PSCs (Rådestad et al., 2013). The e-Delphi method consists of a repetitive process whereby the items are sent to the respondents for assessment until a final consensus is reached (Hasson and Keeney, 2011); there is no set number of rounds required to achieve consensus (Hsu and Sandford, 2007a). Thereby, it is always advised to include either a homogenous set of groups or heterogeneous with few differences (Hsu and Sandford, 2007b). The current e-Delphi study was performed in two rounds using ontology and epistemology assumptions, where credibility, transferability, dependability, and conformability are applicable when compared to validity, reliability, and objectivity (Alarabiat and Ramos, 2019). The adoption of big data in the healthcare industry is highly talked terminology in literature and brought various medical organizations also in consideration. Although most of the published research talks about the success and resistance factors of big data adoption in healthcare but ignored the critical importance of other crucial factors to study including timely availability of testing kits, screening facilities, and improvised testing capabilities, information asymmetry, weak inter-organizational alliances, and poor information management systems.

The objective of e-Delphi is to find and assess solutions for the issues under consideration and to explore arguments for and against each (Linstone and Turoff, 1975). This approach is more qualitative in nature, but quantitative questions can be applied to evaluate alternatives.

3.2. Instrument development

In the first round of the e-Delphi method, personal and group interviews were conducted to generate questions for next round (Rådestad et al., 2013). An open questionnaire was used in the first round as part of the modified e-Delphi method (Kenney et al., 2017). Thereafter, the open questionnaire was sent to record the responses and then transcribed using NVIVO12 software. Later, the open answers were evaluated using a content analysis method based on the Atlas.ti software (Neuendorf, 2002). Finally, after eliminating six themes, five major theme-based questions were selected. In the second round, a modified questionnaire pertaining to data-driven PSC (Pharma Supply Chain)— i.

e., the PSC Assessment Questionnaire (PSCAQ) including five items—was circulated to the experts to achieve the final consensus. In the questionnaire, respondents were given the freedom to comment on each item. All the responses were coded analytically based on lexicon and emergent codes, which were then finalized after multiple reviews.

3.3. e-Delphi rounds

In the first round of the e-Delphi method, a total of 200 formal invitations were sent to the medical practitioners, containing the detail of the study method, objective, confidentiality, and instructions to the experts. In the first round, the questionnaire objective was to assess the efficacy of PSCs in pandemics and 113 responses were collected. Further, the experts were encouraged to provide additional comments. In the second round, their recommendations were implemented, and the modified questionnaire was sent to 40 experts to attain the final consensus. Finally, 25 responses were collected in the second round and consensus was reached.

3.3.1. Expert panel

The experts were selected from the medical field based on their role in handling emergency cases like COVID-19 and daily medical practices. Heterogeneity among the selected experts has been regarded highly positive due to their medical domain, including area of specialization, practicing location and experience handling emergency cases (McKenna, 1994). Further, the experts were divided into homogenous groups within their specialization (Hasson et al., 2000). The primary method of selection was based on their current employment in a hospital or private OPD. The majority of the medical experts were from general medicine; further details are provided in the results section (see Table 1).

3.3.1.1. Round 1. The process for investigation was as follows. Details on all of the selected experts considered for the first round of the online survey are provided in Table 1. The questionnaire was verified with the selected practitioners before administering it to the panel. The survey encompasses three parts and the details are attached in Appendix 1. First, the panellists were asked to describe a situation related to the issue—if they had experiences with it. They were later asked about their opinions regarding similar situations in the future. This helped in stimulating the link to the panellist's experiences (Froschauer and Lueger, 2003). Secondly, they were asked to list all related factors (write your objective). Third, they were prompted to provide specific recommendations with respect to the areas of provider selection, contract negotiation, performance evaluation, and supplier management, etc. The data obtained from the first survey was analyzed based on the principles of content analysis in Atlas.ti. The actual data analysis was carried out manually and the Atlas.ti tool for Qualitative Data Analysis (QDA) was then used to organize, store, and retrieve the data. Subsequently, conceptual labels were assigned based on the coding process (Fereday and Muir-Cochrane, 2006). Using the responses of the experts, an inductive coding (data-driven coding) method was also used where the experts' suggestions could not be referenced to existing literature. In these cases, labels were assigned by the data itself. This coding process is an iterative procedure to cope with inter-observer variability.

Table 1
Profiles of participants in E-Delphi round 1.

City	Number of hospitals	Number of Respondents	Participation (e-E-Delphi/ Focused GD)
Bengaluru	6	27	E-Delphi/FGD
Bhubaneswar	4	12	E-Delphi/FGD
Chennai	5	15	E-Delphi/FGD
Delhi	9	27	E-Delphi/FGD
Mumbai	9	23	E-Delphi/FGD
Pathankot	4	12	E-Delphi/FGD
Pune	6	13	E-Delphi/FGD

3.3.1.2. Round 2. To validate the obtained results, the analysis was formulated and shared with the experts (see Appendix 1 for details), with this combination of qualitative and quantitative methods being a contribution to the methodological rigor of the study in the first round. The questionnaire was pretested before administering it to the expert panel. In total, 25 experts completed the survey (62.5% return rate). We confined the questions to one page to manage the participants' responses carefully. The experts provided their rating on certain parameters as well as provided details with open comments (Singer and Couper, 2017).

A high level of consensus was observed among the experts; however, some panellists expressed controversial views too. This created a dilemma for the third round regarding whether or not to remove the controversies (Woudenberg, 1991), while considering that participant fatigue had reached a very high level (Hasson et al., 2000). Hence, it was decided to restrict the study to the second round of the e-Delphi method (Delbecq et al., 1975). Thus, additional platforms like Skype, Google Hangouts, Zoom, and WhatsApp (Video calling) for face-to-face focus group were used further.

3.3.2. Focus group discussion (FGD)

The purpose of a FGD is to check the views of participants and to validate the same for the e-Delphi method (Creswell and Poth, 2016). Lincoln and Guba (1985) stated that selection of experts is a crucial task when gathering trustworthy and credible findings. Therefore, it can be considered as a different source of responses (Silverman, 2013). We created groups of a limited number of participants for the focus group discussions. Each group had one representative for discussion among all the experts. The recruited participants' focus groups were formed using opportunity sampling (Patton, 2002).

Firstly, all the experts were invited for the second round based on their presence in the first round. Thereafter, due to unavailability of medical practitioners, we requested the existing panellists to provide a list of prospective experts with equal qualification and hands-on experience. The seating arrangement was structured based on the registration sequence. To have non-biased responses (Okoli and Pawlowski, 2004), the process was carefully monitored to remove potential bias by using purposive sampling (Patton, 2002). Overall, we formulated a group of highly experienced medical practitioners for the FGDs (see Table 1).

3.4. Data analysis

After reaching the consensus level for the study, data analysis was performed using Atlas.ti. The responses were analyzed to measure the mean and for content analysis. While conducting the study, all the experts were informed about certain parameters related to the aim and objective of the study. The confidentiality and anonymity of the experts and their responses were maintained with full diligence. To perform the data analysis, under the e-Delphi technique, E-DLH-QDA) we used open-ended questions by semi-anonymity (investigator knows the participants, but participants do not know each other), a-synchronicity (participants can choose response time based on availability), and iterative questionnaires (the collection of expert responses occurred in two rounds) (Hasson and Keeney, 2011). The e-Delphi method has been used widely across different domains, like higher education (Chen and Yang, 2004); learning (Mamaqi et al., 2010) and logistics (Gossler et al., 2019), to anticipate practical issues and find solutions to address the issues with appropriate data based on expert judgments towards the situation (Rowe and Wright, 1999).

Robustness is a fundamental function of any technical and scientific research, especially empirical research (Hamermesh, 2007). There is a high possibility that errors can arise in such studies, and it is important to reduce such errors (Clemens, 2017). An anonymous medical practitioners' referee was appointed for this study to eliminate all the influential observations, as a truncated sample of an area cannot completely describe and represents the whole population (Clemens, 2017). Another predefined method, of selecting respondents from multiple regions, was taken into very close consideration to avoid the possibility of errors.

3.4.1. Credibility

All the interviews were performed using the online medium with very credible medical practitioners according to the e-Delphi method (Wallendorf and Belk, 1989; Alarabiat and Ramos, 2019). A double check was conducted before finalizing the experts and refining the results.

3.4.2. Transferability

The heterogeneous expert panel was selected with few differences, though the formation of groups was done subsequently. The purposive sampling method assists in transferability to create a better result output (Wallendorf and Belk, 1989; Alarabiat and Ramos, 2019).

3.4.3. Dependability

The selection of the expert panel was performed with full checks and the appropriate measures; still, there would be no conformity in the results if the same process was replicated in another study with the same conditions (Wallendorf and Belk, 1989).

3.4.4. Confirmability

In the e-Delphi method, to attain the highest level of confirmability, the data audits performed on the collected data and interpretation are conducted post-data collection (Skulmoski et al., 2007). NVIVO12 was used to transcribe all the interviews and FGDs, and Atlast it was used to perform content analysis using the coding process.

4. Results

In the first round of the e-Delphi method, 113 interview responses were collected from medical practitioner experts deployed in COVID-19-related jobs. Table 1 provides the detail on the medical practitioner profiles. Further, their responses were presented for evaluation and were used after scrutiny to inform the second round.

Based on the responses from round 1 of the e-Delphi method, the questionnaire was modified, and the responses were collected from 25 experts thereafter. The modified questionnaire was shared among all the participants of round two and the responses were presented for further evaluation to reach the final consensus. Table 2 represents the profile of participants in e-Delphi round 2 and the complete detail of their profile pertaining to various parameters like area of specialization, professional experience, and consultation experience.

Under E-DLH – QDA, content analysis has been performed to find the thematic network based on the frequency of the words given in the expert responses. Table 3 represents the frequency of the words based on the weighted percentage and only the themes above 1% weighted percentage have been taken into consideration.

Based on the content analysis, a thematic network model emerged from the expert responses (see Fig. 3). From the structural thematic network model, four major themes (Disease outbreak, Infestation – Epidemic, Precautionary measures, Health Guidelines) and ten major sub-themes (disease, epidemic, control, effective, health, particular region, community, infectious, medical, and situation) were extracted through content analysis.

Noticing the four major themes and ten sub-themes, we ascertain a level of uniformity in analysis of this study with the published literature (Wu et al., 2020; Lv et al., 2021). Previous studies have highlighted the key challenges including resource limitation (Lv et al., 2021), regulatory challenges, operational challenges (Lv et al., 2021), data on epidemic prevention, consumer data (Wu et al., 2020), conducting clinical trials, data tracking, and controlling (Haleem et al., 2020) for global health system during COVID19. Given the large reference to literature, this study provides the results in line with previous research by providing more deep insights on major challenges and will likely to lead to open paths for future research in healthcare domain. The detail on the themes and sub-themes are provided below with the complete verbatim of the expert responses for further analysis.

Table 2
Profiles of participants in E-Delphi round 2.

ID (Experts)	Area of Specialization	Professional Experience (Years)	Consultation Experience (Hospital/ Clinic)	Participation (e-E-Delphi)
E1	Pediatrics	18	Hospitals	E-Delphi
E2	General physician	11	Hospitals	E-Delphi
E3	Dermatology	10	Hospitals	E-Delphi
E4	Marine medicine	26	Others	E-Delphi
E5	Dentistry	10	Private Clinics/ OP	E-Delphi
E6	Medicine and Clinical cardiology	15	Hospitals	E-Delphi
E7	Psychiatry	39	Private Clinics/ OP	E-Delphi
E8	Marine medicine	19	Hospitals	E-Delphi
E9	Pediatrics	35	Hospitals	E-Delphi
E10	General physician	10	Hospitals	E-Delphi
E11	General physician	2	Hospitals	E-Delphi
E12	General physician	18	Hospitals	E-Delphi
E13	Pathologist	40	Private Clinics/ OP	E-Delphi
E14	Cardiologist	33	Hospitals	E-Delphi
E15	Physician executive	38	Others	E-Delphi
E16	Pediatrics	15	Hospitals	E-Delphi
E17	Dermatologist	18	Hospitals	E-Delphi
E18	General physician	23	Hospitals	E-Delphi
E19	ENT specialist	12	Hospitals	E-Delphi
E20	Physician executive	31	Hospitals	E-Delphi
E21	Obstetrician	3	Hospitals	E-Delphi
E22	Radiologist	17	Hospitals	E-Delphi
E23	General physician	38	Hospitals	E-Delphi
E24	General physician	33	Hospitals	E-Delphi
E25	General physician	37	Hospitals	E-Delphi

Table 3
Word frequency – Participants Reponses based.

Word	Length	Count	Weighted Percentage (%)
Disease	7	30	4.64
Epidemic	8	11	1.70
Control	7	7	1.08
Effective	9	7	1.08
Health conditions	6	7	1.08
Particular region	10	7	1.08
Community	9	6	0.93
Infectious	10	6	0.93
Medical	7	6	0.93
Situation	9	6	0.93

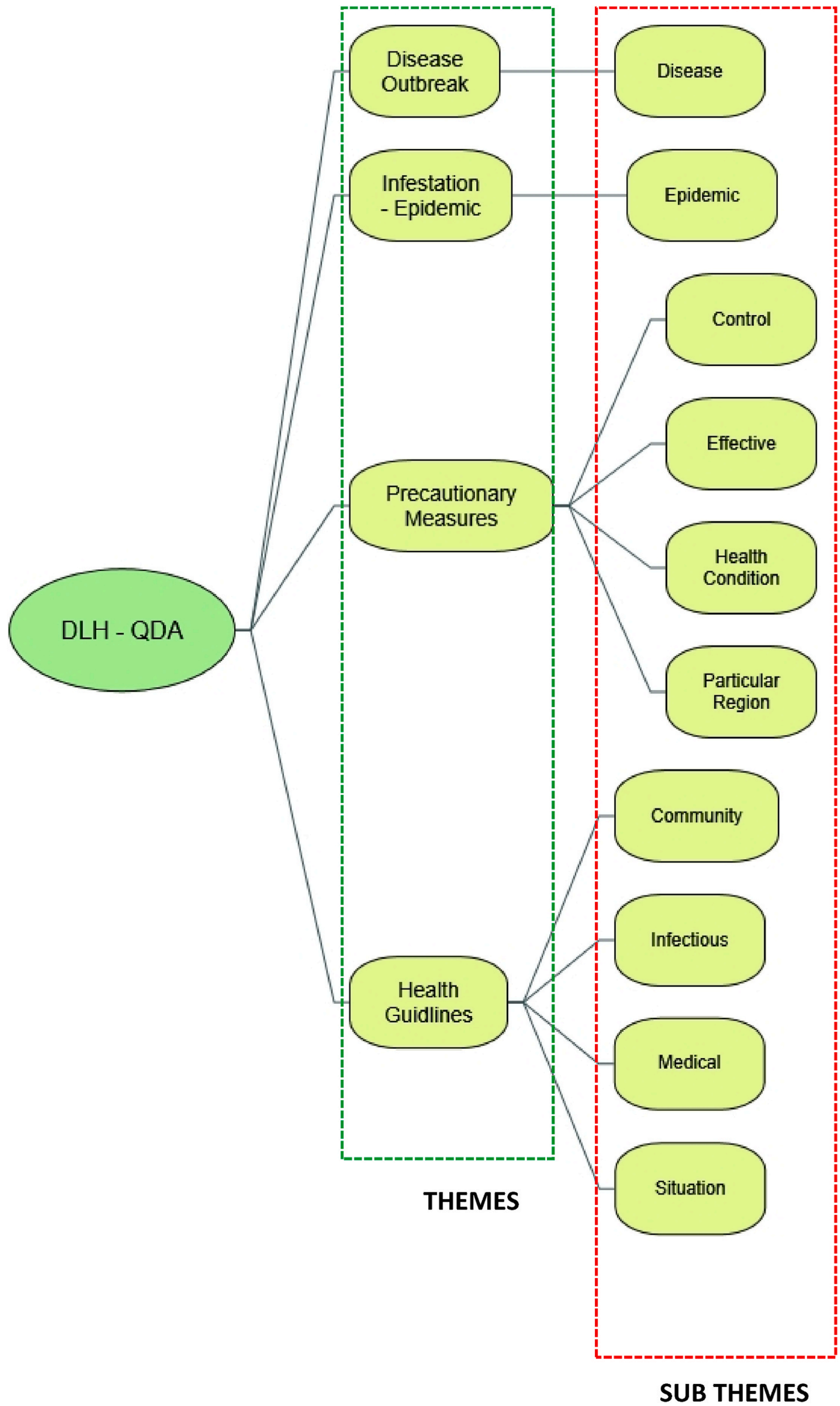

Fig. 3. Thematic network model – DLH-QDA.

4.1. *Theme 1: disease outbreak*

Disease is the most important trigger point or may be the reason that results in the declaration of the pandemic or epidemic situation. There are two major situations that often lead to a major disease crisis. An outbreak gets declared as a pandemic or an epidemic based on "when a disease is in excess of normalcy" (E2) or the "widespread occurrence of an infectious disease and the type of disease" (E4). There are instances that an epidemic situation is declared when there is a "disease which is spreading fast from person to person and, lack of knowledge, lack of awareness" (E6) and it becomes difficult to diagnose. There may be a sudden increase in the "number of patients suffering from same disease increase" (E7) and a situation may come where "the disease becomes widespread among the whole community" (E8). In such situations, it is very important to understand the "Patient load for particular disease, mode of spreading of disease, and understand about the disease" (E11).

So, when a “disease is communicable in nature” (E16), “Spread across community” (E17) and there is “Rapid spread in region” (E19); it becomes difficult to handle. Respondents observed that the patients suffering from same disease were “requiring the same prescription of medicine” (E21). So, there is a need of a centralized system to “Report from disease monitoring systems” (E17). A word tree has been generated in Fig. 4 to depict the disease theme based on the analysis.

4.2. Theme 2: infestation – epidemic

According to experts, an outbreak is named as an epidemic when there emerges “an infectious disease affecting higher number of publics is an epidemic situation” (E15). There are multiple ways to treat infectious people and “Drug replenishment is a part to treat patient but removal or control of the factors causing infection will be right direction to bring epidemic control” (E15). There may be other factors too that can “control the infection in a right direction to bring epidemic control along with the strengthening of human resource and medical infrastructure” (E16). It is very important to prepare “data based on authentic scientific testing for the disease” and gather “Data regarding the area, locality, type of individuals affected” (E6). The delay in active intervention and primary requisite can lead to a more drastic situation. There are possible solutions but “the supply of essential drugs will affect the efficiency of medical services provided and attenuate the hazard of epidemic” (E2).

Fig. 5 represents a detailed word tree analysis to provide the verbatim details.

4.3. Theme 3: precautionary measures

Experts emphasized precautionary measures, under which multiple sub-themes are contained such as control the epidemic, effective strategy, a good healthcare system, and particular region. The primary important factor related to precautionary measures is to “Overcome the crisis situation” (E6), therefore, it’s very important to take “effective measures for control” (E11). During a control situation, an important aspect is taking the “Right direction to bring epidemic control along with the strengthening of human resource and medical infrastructure” (E15).

In addition to taking right steps for control, experts highlighted the importance of effective treatment like “Quick screening and Effective treatment, increase awareness among people” (E2). Therefore, taking “effective measures for control” (E11) may be helpful to handle an epidemic scenario. So, there are multiple possible solutions to handle this challenging scenario and “Effective containment strategy along with the contact tracing and smart testing” (E14) could be some of them. Another probable solution to handle such situations could be to “increase awareness among people” (E3).

Further, a healthcare system is even more important for the smooth functioning of the whole system, therefore, “building a strong primary health system at village and district level is a must” and there must be “tertiary care centers with enough Medical, paramedics and devices” (E6). There should be a standardized set of “Health guidelines shared by the CMO of a particular region” (E16) and also “Various health agencies guidelines” (E18). To understand the criticality of the situation and how widespread the disease is among whole community, there should be some trigger points in the system like “similar health problems in many people across the city/state” (E8).

Therefore, the final important control measure should be handling the situation in a particular region and it should be defined based on certain parameters like “disease is in excess of normalcy in a particular area” (E2), “Patients suffering from same disease increase too much in particular area” (E7), and “Sudden outburst of very highly virulent disease with particular time in a particular region of country” (E14). So, control measures should be complemented by an appropriate data system and healthcare monitoring system with standardized tools guidelines for better PSC. For deep understanding of expert response, Fig. 6 represents the corresponding word tree analysis.

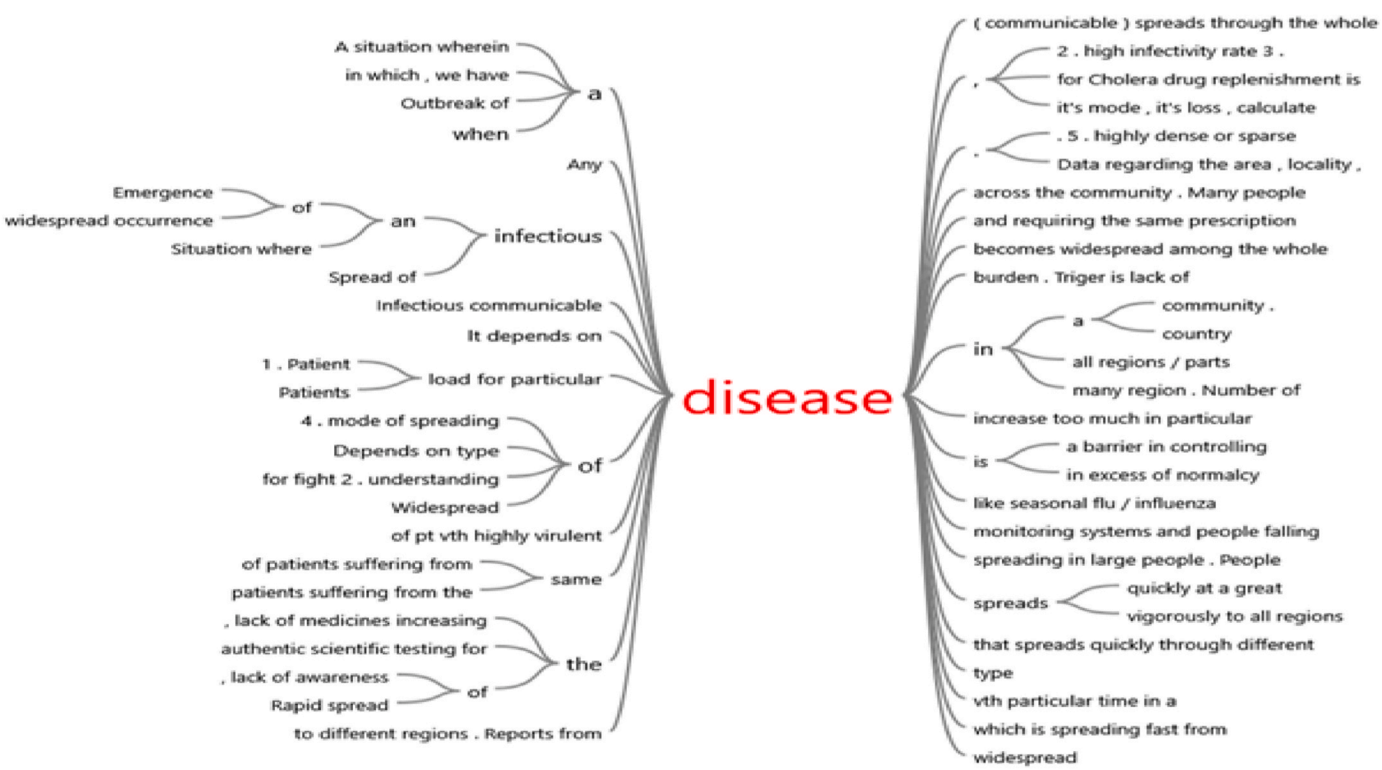

Fig. 4. Word tree – Disease theme.

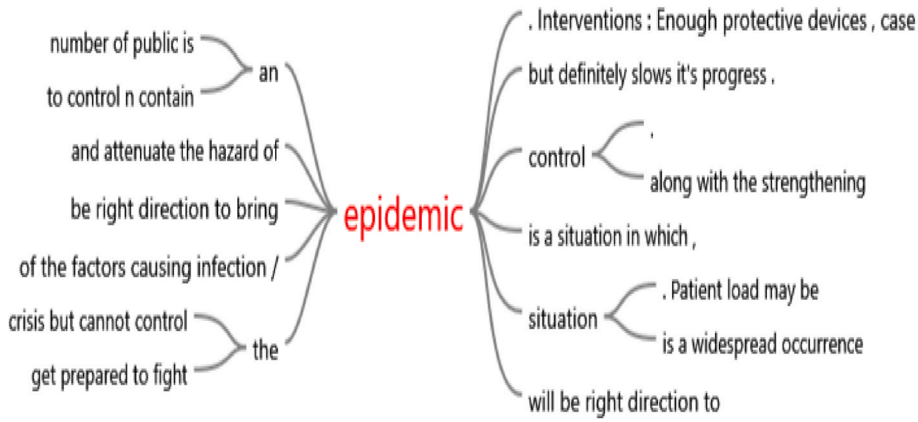

Fig. 5. Word tree – Epidemic theme.

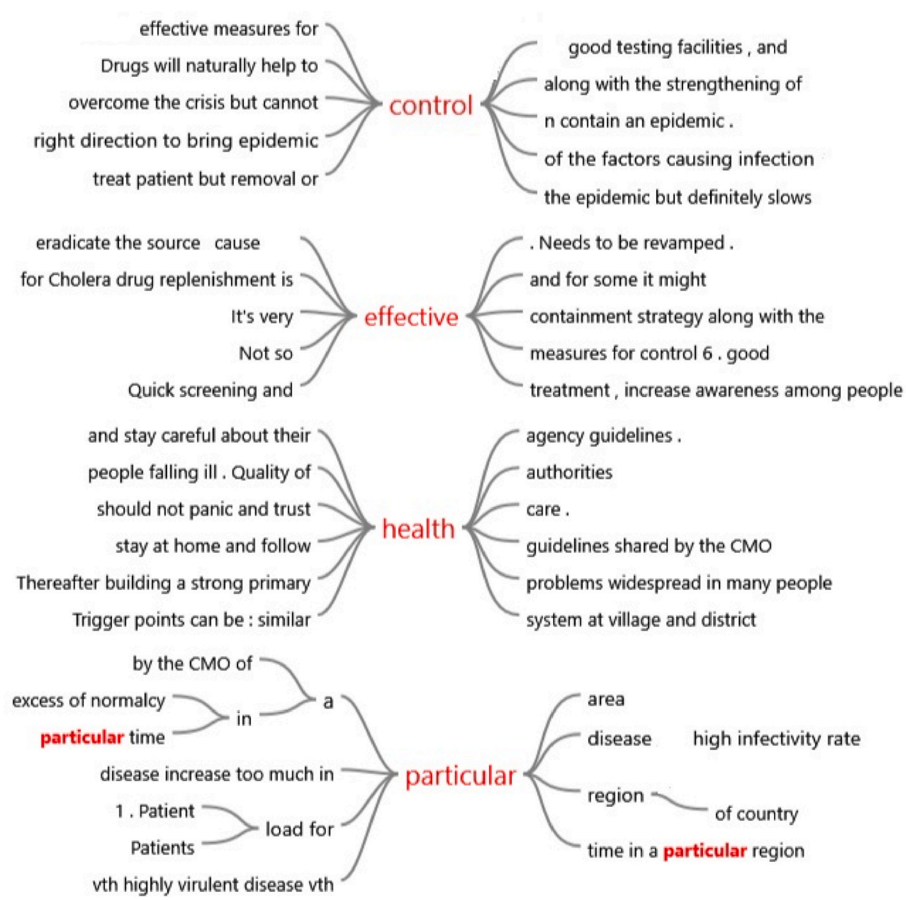

Fig. 6. Word tree – Precautionary measures.

4.4. Theme 4: health guidelines

Besides having streamlined precautionary measures, there is a strong requirement of defined health guidelines and specific guidelines. The set standard of guidelines allows authorities to use the information in an efficient way, such as "Isolation and treatment guidelines for the infected population and making the entire community aware of the ways to prevent the spread" (E5). A situation becomes more difficult when the "Infectious communicable disease spreading in large people" and "People experience common problems/symptoms" (E18). There are instances where the "Situation of an infectious disease spreads quickly at a great rate to different regions" (E20) and "Patient load may be the decisive factor" (E15) in such cases.

So, the importance of "data based on authentic scientific testing for the disease" (E6) becomes the crucial factor in the smooth functioning of the system. It is highly required to "understand the intensity of such situations" (E11) and commit to "strengthening of human resource and medical infrastructure" (E15). So, "Figuring out the initial causes and taking steps accordingly to medical guidelines (or WHO) that are to be followed in case of epidemics" (E24) and "Directives from CMO and medical/healthcare authorities" (E20) are highly recommended. A "strategic approach keeping in mind the over populous situation of India" (E25) was recommended. Fig. 7 provides a detailed overview of the expert responses pertaining to the Health Guidelines theme.

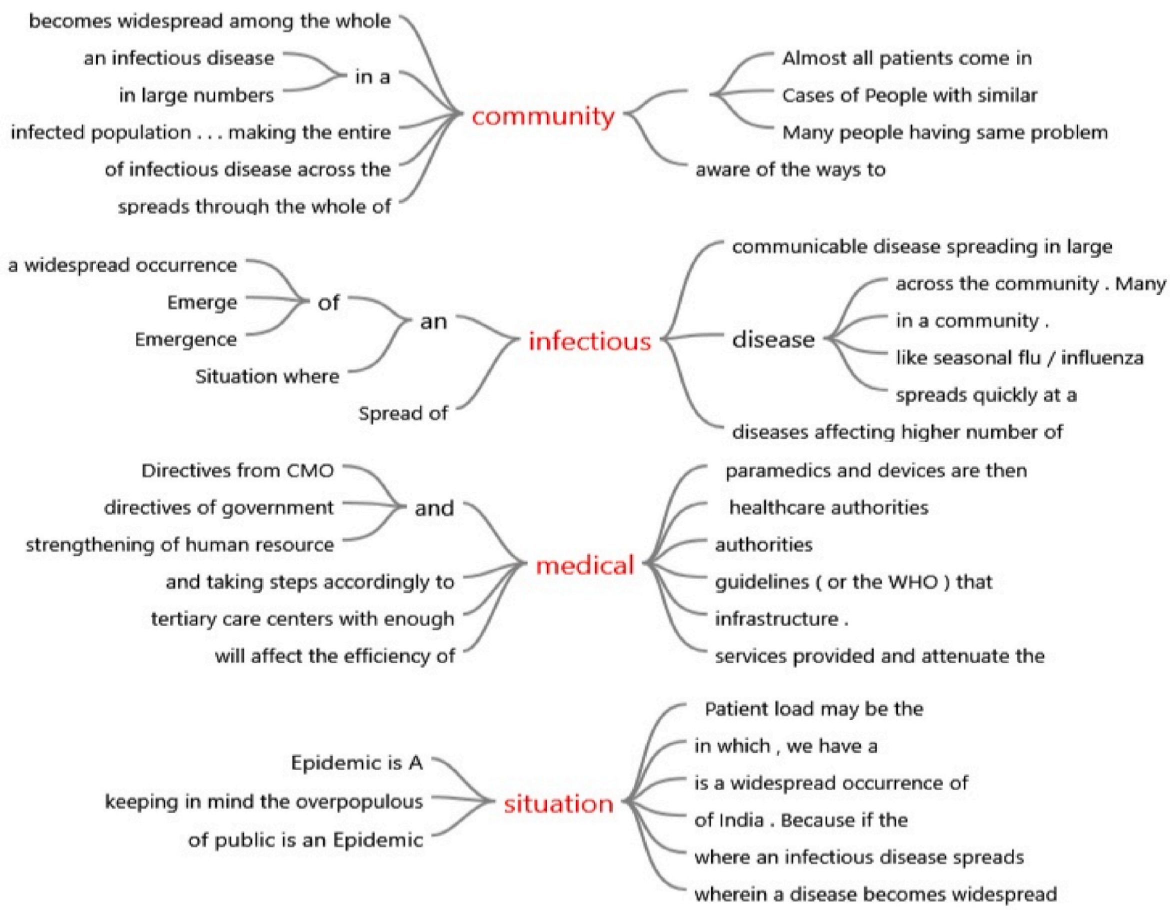

Fig. 7. Word tree – Health guidelines.

5. Discussion of findings

The global health SC is vast and intrinsically complex. It includes numerous varied stakeholders such as hospitals, pharmacists, doctors, patients, insurance companies, government, drug manufacturers, distributors, suppliers, research organizations, etc. (Kapoor et al., 2018). Each of these stakeholders face different challenges and have unique requirements. COVID-19 exposed the fragile nature of the health SC in handling emergencies. It is critical for the system to anticipate unprecedented events and handle an emergency in a well-coordinated manner. Strategic thinking coupled with seamless coordination among various stakeholders is a way forward (Clauson et al., 2018).

The researchers propose BDDPSCs (see Fig. 1) to overcome the challenges faced by the health care industry. In this way, the current study formulates a robust PSC during an emergency that will surely open new areas of research pertaining to COVID-19 regarding PSCs. A number of technologies such as blockchain, IoT, IoS, sensors, and artificial intelligence with big data analytics will render the proposed BDDPSC well equipped to deal with pandemics or other medical emergencies efficiently (PharmaLedger, 2020). While the researchers planned to carry out the study for all stakeholders as entities of BDDPSC, due to the paucity of resources, only patient health care practitioners were considered for the present study.

Medicine takes a complex journey that begins with researchers followed by manufacturers then traces a long path of distribution and warehousing before it reaches the patient (Kapoor et al., 2018). Health care practitioners are the most important link in the system. They are the first source to detect a health emergency and ways to counter it (Sweiti et al., 2019). Technology-driven platforms like BDDPSC will assist health officials to be ahead of the curve and manage it effectively. As part of BDDPSC, health officials would generate enormous amount of data that, in turn, would become the reference point for the remaining entities in the SC.

Using RBT (Gunasekaran et al., 2017) and DCT (Teece et al., 1997; Braganza et al., 2017) as a base, the researchers conducted an extensive study using an online survey, focus group discussions, and e-Delphi (Tables 1–3) (Hasson and Keeney, 2011; Aengenheyster et al., 2017). Text analytics was performed to understand the nature of crucial trigger points that can be provided by health officials. The word cloud analysis (Fig. 2) indicates some prominent themes that emerged from the expert responses.

Regarding our first objective, the analysis of the e-Delphi reveals the gaps in current PSCs during an emergency like COVID-19. The thematic network model DLH-QDA (Fig. 3) specifies four major themes: disease outbreak, infestation epidemic, precautionary measures, and health guidelines. The disease outbreak (Fig. 4) and its widespread scale (Fig. 5) are captured at the health practitioners' level. This serves as a trigger in the proposed BDDPSC model. This posits the possible initial challenge during an emergency in relation to the existing literature (Mettler, 2016). The theme "precautionary measures" has four subthemes: control, effective, health, and particular region. The word tree results indicate that there is a strong requirement for a centralized healthcare system (Angraal et al., 2017).

Regarding the second objective, the verbatim detail and word tree indicate the required IT resources to effectively tackle emergency situations like COVID-19. Further, Fig. 6 on the theme "precautionary measures" offers contextual information. It highlights that health officials provide significant information on factors that cause infection and hence recommendations regarding how to make precautionary measures effective through increasing awareness (VanVactor, 2017), quick screening etc.; how to stay healthy; and lastly region-specific information (Lippi et al., 2017). Such information is crucial in managing a pandemic efficiently as information helps organizations to build new strategies and transform SCs (Gezgin et al., 2017). The last theme, "health guidelines" (Fig. 7), reveals that health officials are also an important source for framing guidelines for a community that has witnessed widespread occurrences of a disease, in addition to important clues on infrastructure (Lippi et al., 2017), paramedics, devices (Cole et al., 2018), and human resource requirements (Aviso et al., 2018) that are essential in dealing with pandemics. The resultant sub-themes under "health guidelines" provide detail on the required functions pertaining to healthcare system solutions by using various technologies mentioned under Fig. 7 (Jayaraman et al., 2019).

The current study will help the market practitioners, especially logistics operations and SC managers, to understand the natural complexity of the PSC, where an additional adjustment may be difficult to manage and less effective as well. However, BDDPSCs will provide a solution to managers to understand the real-time problems and technical aspects with the potential benefits of scalability and effectiveness. The BDDPSC model is a dynamic data model specifically driven by information from multiple stakeholders and various sources of entry points. From the operations perspective, BDDPSCs will meet the real-time requirements of pharma supplies from multiple data entries and also assist to predict the impact of pandemics or epidemics.

5.1. Implications for practice

The study aims to enable innovations in BDDPSCs and contributes incrementally towards the complete digital transformation of the healthcare sector and the pharmaceutical value chain. The goal of BDDPSCs is to ensure that government and other agencies associated with pharmaceutical industry can prepare themselves to handle pandemic situations such as COVID-19 by using data driven approach (Basile et al., 2022). The pharma SC must ensure the supplies of essential medication to mitigate pandemic disasters and the research demonstrates the significance of BDDPSCs in handling pandemics or medical emergencies. Yet, as Hazen et al. (2014) point out, there are gaps in SCs in terms of how data is produced.

The study will considerably improve the data quality and, subsequently, performance. BDDPSCs involve response and quick action from all the stakeholders during medical emergencies. Since the pharmaceutical industry is an integral part of a healthcare system (Chen et al., 2019), BDDPSCs integrate health practitioners and health officials in the SC and positively impact information asymmetry in supply and demand. Health officials can collaborate with pharmaceutical suppliers and manufacturers and provide actionable insights based on real-time inputs (Drago et al., 2021). The proposed framework addresses the challenges associated with planning in a technological environment. The framework would assist pharmaceutical manufacturers, suppliers, health officials, and government agencies in demand administration and capacity forecasting. As organizations world over are scrambling to create vaccines for COVID-19, a BDDPSC is expected to play an integral role in equitable vaccine distribution. In support of the current practices of using a BDDPSC in the healthcare sector, the distribution of a COVID-19 vaccine will require the largest ever healthcare SC capacities and capabilities. Like the current study, StaTwig[2] (UNICEF Innovation Fund and Gavi Infuse portfolio startup) is in the prototype stages of building and testing a vaccine SCM platform that integrates stakeholders along the PSC, thereby ensuring vaccine traceability and visibility across the PSC. For ensuring wide acceptance of blockchains in the PSCs, the practitioners can focus on improving the scalability, sustainability, reducing the operational costs, and finding alternate ways of compensating the miners (Schinckus, 2020).

[2] https://statwig.com/.

Empirically, the research proposes a convincing case for dealing with pandemics by employing BDDPSCs. The proposed approach underlines how BDDPSCs can be helpful in handling medical emergencies. The research also provides a valuable methodological insight on how the e-Delphi method with a case-based approach can be useful in collecting insights from BDDPSC stakeholders from the healthcare operations management purview.

A BDDPSC would enable government, policy makers, and other regulating agencies to assess the extent of a pandemic disaster and the risks associated with it at the outset to effectively plan and take measures to mitigate the disaster through data-driven decision-making. The research has established common ground for all the stakeholders of BDDPSCs to invest in capability building. Big data analytics can generate valuable insights from the data captured from varied sources (Wang and Hajli, 2017). The predictive nature of BDDPSC exercises evidence-based medicine and, when applied to the health care decision support system, reduces errors. Past research on big data analytics suggests that BDDPSC will reduce health care costs by reducing inefficiencies (Wang et al., 2018) and digitally transform the present healthcare ecosystem (Raimo et al., 2022; Garcia-Perez et al., 2022).

5.2. Theoretical implications

The present study is the first attempt in the field to create a blockchain-enabled SC using insights from an e-Delphi method. The term BDDPSCs has been coined in the current paper to examine the application of data driven SCs during unprecedented human activities, pandemics, epidemics, and the climate change scenario. In this study, using one contributor as a trigger point in the whole PSC, expert responses have been taken into consideration to discover the best practices through two major theoretical frameworks, RBV and DCT. Our research found ten sub-themes and four main themes by using PSCAQ instrument and DLH–QDA analysis technique. All the themes provide the detail on the areas while developing an effective data-driven PSC for an unprecedented scenario. The current findings will support future quantitative research in defining antecedents while testing the adoption of BDDSCs.

The study employs dynamic capability theory and the Resource-Based View as a foundation for BDDPSCs. This study makes a significant theoretical contribution to research that relates big data driven supply chain practices specifically to capture the changes during unprecedented situations.

The major contribution of this study is the identification of the themes which are critical for the functioning of BDDPSCs in a complex pharmaceutical supply chain. The result indicates that in order to implement big data technology, the understanding of processes, existing practices and changing business process is critical.

This research presents insights in terms of the role of medical practitioners and responsibilities of other stakeholders in smooth functioning of BDDPSCs. Another contribution is the fact that there are no studies that have carried out qualitative study that emphasizes the role of various stakeholders in BDDPSCs. Hence, this research contributes to the literature by illuminating the representation of medical experts in the data driven supply chain.

Operations decisions in any organization are dependent on gauging and using information, which is not easy in case of big data. Effective theoretical framework for managing the data helps firms to leverage big data analytics capabilities in pharmaceutical industry.

5.3. Directions for future research

The COVID-19 pandemic has resulted in structural changes in many areas of business (Gordon-Wilson, 2022; Rayburn et al., 2021: Kursan Milaković, 2021; Nayal et al., 2022; Paul and Bhukya, 2021; Sharma et al., 2021; Chopdar et al., 2022). For example, online transactions, Artificial intelligence, mobile Apps and blockchain technologies have become part of people's life in many sectors including healthcare, food delivery etc (Paul et al., 2023; Arya et al., 2022; Chakraborty and Paul, 2022; Purohit et al., 2022; Chopdar et al., 2022). As an outcome, we need new theories, methods, and paradigms to carry research studies in the post-pandemic era to analyze the new phenomenon, processes, patterns, and problems (Paul et al., 2023; Dash and Paul, 2021).

6. Conclusion

Medical experts have previously highlighted the major issues pertaining to traditional SC to some extent and have also confirmed the possible issues and challenges related to the existing available literature (Sabouhi et al., 2018). Similarly, experts have called for a Centralized Disease Monitoring System (C-DMS) and Data Enabled Scientific Testing System (DESES) as the part of PSC to increase efficiency and transparency (van Velthoven et al., 2019). Some studies have argued for the use of different technologies in the SC like enhanced ICT and integrated IoT (Ardito et al., 2019; Shi et al., 2019), while others consider data-driven PSC as more relevant (Gezgin et al., 2017; Angraal et al., 2017).

In light of this, the current study aimed to provide a comprehensive approach and advances the literature highlighting possible solutions to various challenges and issues of existing PSCs by deploying BDDPSCs. This research has identified major four themes for the smooth functioning of BDDPSCs with a complete balance of improved efficiency, transparency, and better cost during pandemic situations like COVID-19.

The limitations of the study offer possibilities for future research. The present study refers to the context of the role of health officials in BDDPSCs in efficiently handling a pandemic, but future studies may consider other stakeholders of the system. This will offer insights on requirements, contributions, and challenges they face. It would be immensely valuable if future studies can infuse IoT, IoS, AI, and other relevant areas with BDDPSCs to expand the scope of the subject (see Gupta et al., 2022; Aloini et al., 2022). There are several technological, organizational, and environmental challenges with the associated technologies (blockchains as they are in nascent stages) in BDDPSCs which need to be overcome such as regulatory issues, high cost of implementation, high energy consumption, and difficulties in integrating them into legacy systems (Kamble et al., 2020). Therefore, the implementation of blockchains in the healthcare system and PSCs is limited because of the associated operational costs (such as development cost, implementation cost, and compensation to miners) (Schinckus, 2022). While understanding the first data entry point of BDDPSCs was the intended focus of the current study, in future, other studies may determine other data entry points. Moreover, due to the limitation of resources during this unprecedented situation, we were unable to measure the dependency of SHC's (State Health Center's)/PHC's (Private Healthcare Center's)/UPHCs (Urban Primary Healthcare Center's), and HWCs (Health and Wellness Center's)) data on medical practitioners, which may cause problems in cases supply shortages of medicine; this is another area of potential research.

Future studies can explore accessibility, affordability, and sustainability related issues in developing and implementing BDDPSCs and its associated technologies. Social and cultural perspectives in developing and implementing BDDPSCs can also be studied (Li and Lin, 2006). BDDPSCs may face challenges in convincing all stakeholders in the system, a) to share their information on a single system and b) to believe that by sharing information will benefit them in long run.

The vast potential benefit of the proposed BDDPSC remains an undelivered assurance. Hence there is a need to invest in research and evaluate proposed solutions to ensure BDDPSCs bring these potential benefits to the health care (Clauson et al., 2018). While possible medical dependencies could not be addressed in this study due to certain limitations, the analysis provided of this study can still be integrated with an adequate research method in the future to complete our understanding of BDDPSCs.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.technovation.2023.102819.

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