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A Framework Based on Blockchain, Artificial Intelligence, and Big Data Analytics to Leverage Supply Chain Resilience considering the COVID-19

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Abstract: In the global supply chains era, firms are more connected, integrated, and interdependent, bringing along a set of benefits and a number of risks. It is clear that the singular COVID-19 epidemic outbreak has led to unparalleled disruptions and considerable challenges for supply chains (SCs). For example, the sluggish economic environment provoked by the COVID-19 has negatively impacted the flow of goods, generating shortages and interruptions through the SCs. At the global level, many markets are enduring the effects of these disruptions. In this challenging context, the firms and their SCs must apply useful and efficient strategies to minimize and adapt their operations during and after these disruptions. In this view, this study aims to propose a novel framework based on Artificial Intelligence, Blockchain, and Big Data Analytics, to bring useful ideas and contribute to overcoming such disruptions. Besides, we propose novel categorizations that can support new insights for scholars and practitioners about the use of cutting-edge technologies during and after severe disruptions.

Keywords: Blockchain; Artificial Intelligence; Data Analytics; Supply Chain; Epidemic; Outbreaks; Resilience; COVID-19

1. INTRODUCTION

The unprecedented and singularity of the Novel Coronavirus (2019-nCoV), simply known as the COVID-19 epidemic outbreak, has challenged the global supply chains (SCs), bringing unparalleled disruptions (Ivanov, 2020; Ivanov and Dolgui, 2020; Queiroz et al., 2020) and thus rendering the decisions and operations of managers more complex, with a significant impact on the entire relationships within SCs.

The ongoing COVID-19 epidemic outbreak has led to devastating disruptions in the SCs (Haren and Simchi-Levi, 2020), thereby seriously affecting the flow of products and resources and creating a shortage in various SC nodes. Furthermore, virtually all SCs worldwide are expected to suffer severe damage during and after the COVID-19 crisis (Fortune, 2020).

In this unheard-of scenario, SC members need to fully grasp the main complexities at stake and generate insights to manage and outperform this crisis. And apart from increasing the SC resilience (Chen, Das and Ivanov, 2019), it is fundamental to develop new skills and capabilities to better prepare for new crises. In this context, this study looks forward to bridging this gap by proposing a novel framework based on Artificial Intelligence (AI) (Fosso Wamba et al., 2021), Blockchain Technology (BCT) (Wamba and Queiroz, 2022), and Big Data Analytics (BDA) (Ivanov et al., 2021) cutting-edge technologies to support and bring insights to SCs.

We identify three main disruptions categories that occur in practical all SCs. To outperform these complexities, we propose a framework considering the following stages continuous monitoring, preparedness, response, and recovery. For each step, we provide insights into the technologies mentioned.

2. THEORETICAL BACKGROUND

2.1 Organizational Resilience Theory

Organizational resilience has been used extensively in different contexts over the years (Horne, 1997; McManus et al., 2008; Duchek, 2019). The concept "organizational resilience" is defined in different ways, including as "a firm's ability to effectively absorb, develop situation-specific responses to, and ultimately engage in transformative activities to capitalize on disruptive surprises that potentially threaten organization survival" (Lengnick-Hall, Beck and Lengnick-Hall, 2011, p. 244). Another widespread definition of organizational resilience takes it as "the incremental capacity of an organization to anticipate and adjust to the environment" (Ortiz-de-Mandojana and Bansal, 2016, p. 1617). These definitions clearly indicate that organizational resilience considers different stages of disruption and the related recovery plan (Duchek, 2019).

In the SC landscape, resilience represents a hot topic (Ivanov, 2018, 2019a; Queiroz et al., 2022), primarily because of the variety of the disruptions that emerged and were amplified from the 2000s (Christopher and Peck, 2004; Craighead et al., 2007; Ponomarov and Holcomb, 2009; Queiroz et al., 2020). The definition of supply chain resilience (SCR) is quite similar to that of organizational resilience. In this regard, the resilience...
We identify a gap by proposing a novel framework based on Artificial Intelligence (AI), Blockchain, and Big Data (Fortune, 2020). Furthermore, virtually all SCs could be visualized; as also with AI, it is possible to run several realistic scenarios of the SCs quickly. Besides, modern supply chains suffer from a lack of visibility and consequently cause complex problems for inventory managers (i.e., where goods are in transit); this issue can be easily improved by using BCT. Moreover, modern supply chains present considerable accountability lack (i.e., many companies have teams of staff dedicated to mitigating this risk of a failure to deliver). In that case, transactions performed by BCT are immutable, and the network’s members can audit the origin node rapidly; consequently, more transparency is brought to the buyer-supplier relationships.

2.3 Epidemic outbreaks on supply chains

The impacts of epidemic outbreaks on logistics and operations and SCs have been frequently discussed in the recent literature (Queiroz et al., 2020; Dasaklis, Rachaniotis and Pappis, 2017). The potentially harmful effects have also been studied, as organizations and their supply chains worldwide have been suffering from these. The literature has highlighted the negative repercussions of different epidemic outbreaks on supply chains. Some of the epidemics that are being studied from this perspective are influenza (Liu and Zhang, 2016), ebola (Büyükahtakin, des-Bordes and Kibis, 2018), cholera (Anparasan and Jejeune, 2017), smallpox (Dasaklis, Rachaniotis and Pappis, 2017), among others. Yet, the impact of the COVID-19 pandemic (Lin et al., 2020) is particular, far-reaching on all aspects of human life and supply chains around the world (Ivanov and Dolgui, 2020; Queiroz et al., 2022).

Though many of such effects are relatively new to the SCs, scholars have managed to shed light on and better understand the resilience issue concerning SCs (Ivanov, 2020; Ivanov and Dolgui, 2020; Queiroz, Fosso Wamba and Branski, 2021) in the COVID-19 context. In this regard, some authors have suggested insightful ideas for predicting and getting prepared for the impacts of epidemic outbreaks on global supply chains (Ivanov, 2020; Ivanov and Dolgui, 2020; Sarkis et al., 2020). For example, simulation techniques can help decision-makers to gain valuable insights and develop strategies at all stages of the disruption process (Ivanov, 2020). Consequently, global supply chains’ resilience could be more responsive. In addition, the COVID-19 forced the SC managers to have an in-depth understanding of the concept of survivability in more sophisticated supply chains/supply chain networks, including intertwined supply networks (Ivanov and Dolgui, 2020).

3. METHODOLOGY DESIGN

We adopted a multi-method approach, considering three main stages. First, we used an adaptation of the Literature-related discovery (LRD) method (Kostoff et al., 2008; Kostoff, 2011; Kostoff and Patel, 2015) to discover potential knowledge (Kostoff et al., 2008), followed by an analysis of papers' references. In the LRD, following Kostoff et al. (2008), we applied the four steps to performing the literature analysis stage – i. recover core literature on the problem; ii. characterization of the core literature; iii. extension of the core literature; and iv. generation of the potential discoveries.
Second, we performed a careful secondary data analysis in different databases (e.g., WEF, WB, Consultancy Reports, FT, among others). We identified public reports on these databases employing a set of keywords related to disruptions, emergency situations and technologies. Finally, we integrated the sources using the best practices in data triangulation (Yin, 2014), with the support of the QDA miner software to the data categorization. Finally, after these steps, we propose a framework. Figure 1 points out the various steps of the process.

4. DISCUSSION

Applying the previous three stages, we identified the main issues reported in Figure 2 as the most recurrent and complicated categories during an epidemic outbreak context. Firstly, we found three basic complexity categories, namely data, relationship, and process (DRP), impacting all epidemic outbreaks stages. These complexities affect the anticipation, coping, and adaptation resilience stages.

The data category refers to all data that one organization acquires, processes, and shares within its SCs. The relationship category is related to the integration level between the organizations and their SCs. Ultimately, the process category refers to the upstream and downstream activities in all stages of the epidemic outbreak.

According to the stage of the disruption and the integration between SCs members, some of the elements can cause more impact (positively or negatively) to promote (or at least try) survivability. The data category emphasizes the supply chain members’ need to adequately manage the different sets of data to enable decisions with robust information from its partners. For example, BDA applications it is likely to monitor supply trends worldwide, integrating a vast of sources, considering dynamically different information from the market, thus, contributing to minimizing the delay and uncertainty of the information (Akter and Fosso Wamba, 2019; Food and Agriculture Organization of the United Nations - FAO, 2020).

Regarding the relationship category, in complex disruptions scenarios, the matters of visibility of the information and the lack of trust between supply chain members gain a devastator amplification. Besides, relationships harmful also impact product traceability in the supply chains and, consequently, increase the shortages in various chain nodes. Furthermore, affecting the integration efforts negatively. With respect to the process category, different complex and lethal problems appear as product shortages and shipments interruption. Thus, contributing negatively to the responsiveness and resilience of the entire supply chain. Furthermore, other complicated issues like different types of delays (e.g., supplier homologation, product reallocation) cause interruptions in the chain. Considering these supply chain disruptions categories in epidemic outbreaks, in the following section, we provide a useful framework to SCs contexts, as also policymakers gain a more in-depth understanding of how AI, BDA, and BCT can leverage the resilience of the supply chains.

5. FRAMEWORK PROPOSAL TO SUPPLY CHAIN RESILIENCE IN EPIDEMIC OUTBREAKS

In response to the complexities reported in Figure 2, based on the literature on resilience and the cutting-edge technologies, we propose a framework (Figure 3) to mitigate or, when possible, outperform the DRP complexities. From this perspective, the framework highlights four main stages i. continuous monitoring; ii. preparedness; iii. response and iv. recovery. In addition, the framework shows the integration of the previous stages with AI, BDA, and BCT technologies and how organizations can use them to face the complexities and some benefits examples. It may be observed that the DRP effects are considered in all stages.

Bearing in mind the Continuous monitoring stage, this is focused on BDA (Akter and Fosso Wamba, 2019) and AI technologies (Dwivedi et al., 2021) to identify abnormal behaviour not only in its supply chains but in other networks that are not necessarily directly connected; thus, signaling insights to the decision-makers anticipate. Moreover, with BCT integrating the SC members in several operations and
transactions (Wamba and Queiroz, 2020), the information's trustworthiness is leveraged, then increasing the quality of the middle and long term planning also the reaction and responsiveness.

The Preparedness stage lays a fundamental influence on the other stages. Our framework posits that with AI techniques (Ivanov, 2020; Sarkis et al., 2020), the resilience of the SCs could be improved significantly. Specifically, AI operating in the DRP enhance the "intelligence" of the information, enabling more reliable relationships between SC members and saving time in all process. Consequently, improving the preparedness stage. Besides, with BCT and BDA supporting this stage, the resources mobilization between the SCs is also raised due to the BCT features' traceability and sharing of information between members. Applying BDA is possible to model in real-time different scenarios impacts and discover the network's weaknesses.

Concerning the Response, this is one of the most time-effort-cost (TEC) consuming stages, mainly because of the chain breaks that come up in various network points. For that reason, the resource allocation dynamically (Savachkin and Uribe, 2012) plays a fundamental role in the response quality. By employing BCT, decision-makers could improve the traceability and visibility in different SC nodes (Dubey et al., 2020). Moreover, with AI and BDA, the dynamics of the patterns could be more understandable, making the resource allocation dynamically possible.

Ultimately, the AI, BCT, and BDA worked together to speed up the network's reconfiguration in the Recovery stage. The reconfiguration plan involves primary the schedule of the material flows in the network (Ivanov et al., 2016) that are influenced by various features like costs, capabilities, network structure, the experience of the SC members in crisis and disruptions, among others (Ivanov and Dolgui, 2019). With AI and BDA, the reconfigurations and the agility of the network could be improved by a critical investigation of the nodes more affected and employing simulation (Araz et al., 2013; Ivanov, 2019b, 2020) to understand the recovery behavior and the capabilities and resources required. Furthermore, with BCT, this process could minimize costs (e.g., transactions, product traceability, information sharing) between the SC members (Wamba and Queiroz, 2020). On the one hand, Recovery, Response, and Preparedness are temporary categories; on the other hand, the Continuous monitoring category does not end.

Regarding implementing this framework, first, the companies should have a digital transformation project to support in a deeper way all the benefits that these cutting-edge technologies could bring to their operations. Accordingly, for better implementation, the companies should present a good digital culture, top management support, and workers with digital and communication skills. Due to the infancy stage of the main cutting-edge technologies, it is important to note that the technology itself cannot minimize the uncertainties through supply chain operations. Furthermore, the cost-effectiveness of the technologies can represent a barrier to the implementation.

5.1 Managerial implications

In this work, we identified critical features in managing the crisis in supply chains. We found that such categories differently affect the various disruption stages, particularly affecting the continuous monitoring, preparedness, response, and recovery. In this regard, Table 1 highlights the main managerial implications. The framework can be applied in companies to support the continuous monitoring of the disruptions and for recovery plans.

### Table 1. Managerial implications considering the DRP (data, relationship, and process)

| Category | Continuous monitoring (AI, BCT, and BDA) | Preparedness (AI, BCT, and BDA) | Response (AI, BCT, and BDA) | Recovering (AI, BCT, and BDA) |
|----------|----------------------------------------|--------------------------------|----------------------------|----------------------------|
| Data     | AI, BCT, and BDA adoption              | Visibility of critical data and information for resources mobilization | Capabilities to examine large database from its SC and other indirect SCs | Data sharing and agility through the network to integrate, reconfigure and restore the SC |
| Relationship | Intertwined supply network (ISN) strategies to integrate more in-depth the members | New levels of trust between SC members to leveraging the network capabilities | Integrated and coordinate actions with high levels of information sharing and transparenc | Closer integration to enable the network balancing |
| Process  | Supply chain digitalization to provide adequate infrastructure to continuous monitoring | Development of the required capabilities and skills for crisis operations and management | Innovation policies to transform the traditional operations into smart operations by Industry 4.0 concepts | Implementatio of the survivability concepts to avoid breakdowns in the SC and to minimize the recovering time |

6. CONCLUSIONS

This study proposed a novel framework considering the integration of Artificial Intelligence, Blockchain Technology, and Big Data Analytics in epidemic outbreaks scenarios on supply chains. This is one of the first studies that integrates insights relating to these three cutting-edge technologies in a useful framework for managers and scholars to understand and enable strategies for other disruptive contexts. The framework was not yet tested; it can be highlighted as the main limitation of this study. Consequently, it can open new directions for future studies empirically test the framework and adapt it to other disruptive situations.

REFERENCES

Akter, S. and Fosso Wamba, S. (2019) “Big data and disaster management: a systematic review and agenda for future research,” *Annals of Operations Research*, 283(1), pp. 939–959. doi:10.1007/s10479-017-2584-2.
Anparasan, A.A. and Lejeune, M. (2017) “Analyzing the response to epidemics: concept of evidence-based Haddon matrix,” Journal of Humanitarian Logistics and Supply Chain Management, 7(3), pp. 266–283. doi:10.1108/JHLSCM-06-2017-0023.

Araz, O.M., Lant, T., Fowler, J. W. and Jehn, M. (2013) “Simulation modeling for pandemic decision making: A case study with bi-criteria analysis on school closures,” Decision Support Systems, 55(2), pp. 564–575. doi:10.1016/j.dss.2012.10.013.

Büyüktahtakın, E., des-Bordes, E. and Kılınç, E.Y. (2018) “A new epidemics–logistics model: Insights into controlling the Ebola virus disease in West Africa,” European Journal of Operational Research, 265(3), pp. 1046–1063. doi:10.1016/j.ejor.2017.08.037.

Chen, H.Y., Das, A. and Ivanov, D. (2019) “Building resilience and managing post-disruption supply chain recovery: Lessons from the information and communication technology industry,” International Journal of Information Management, 49, pp. 330–342. doi:10.1016/j.ijinfomgt.2019.06.002.

Christopher, M. and Peck, H. (2004) “Building the Resilient Supply Chain,” The International Journal of Logistics Management, 15(2), pp. 1–14. doi:10.1108/09574090410700275.

Craighead, C.W., Blackhurst, J., Rungtusanatham, M. J. and Handfield, R. B. (2007) “The severity of supply chain disruptions: Design characteristics and mitigation capabilities,” Decision Sciences, 38(1), pp. 131–156. doi:10.1111/j.1540-5915.2007.00151.x.

Dasaklis, T.K., Rachaniotis, N. and Pappis, C. (2017) “Emergency supply chain management for controlling a smallpox outbreak: the case for regional mass vaccination,” International Journal of Systems Science: Operations and Logistics, 4(1), pp. 27–40. doi:10.1080/23302674.2015.1126379.

Dubey, R., Gunasekaran, A., Bryde, D. J., Dwivedi, Y. K. and Papadopoulos, T. (2020) “Blockchain technology for enhancing swift-trust, collaboration and resilience within a humanitarian supply chain setting,” International Journal of Production Research [Preprint]. doi:10.1080/00207543.2020.1722860.

Duchek, S. (2019) “Organizational resilience: a capability-based conceptualization,” Business Research, 13(1), pp. 215–246. doi:10.1007/s40685-019-0085-7.

Dwivedi, Y.K. et al. (2021) “Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy,” International Journal of Information Management, 57, 101994. doi:10.1016/j.ijinfomgt.2019.08.002.

Food and Agriculture Organization of the United Nations - FAO (2020) About FAO’s Big Data tool on food chains under the COVID-19 pandemic.

Fortune (2020) 94% of the Fortune 1000 are seeing coronavirus supply chain disruptions: Report.

Fosso Wamba, S., Bawack, R. E., Guthrie, C., Queiroz, M. M. and Carillo, K. D. A. (2021) “Are we preparing for a good AI society? A bibliometric review and research agenda,” Technological Forecasting & Social Change, 164, 120482. https://doi.org/10.1016/j.techfore.2020.120482

Fosso Wamba, S., Kala Kamdjoug, J. R., Epie Bawack, R. and Keogh, J. G. (2020) “Bitcoin, Blockchain and Fintech: a systematic review and case studies in the supply chain,” Production Planning and Control, 31(2–3), pp. 115–142. https://doi.org/10.1080/09537238.2019.1631460

Fosso Wamba, S. (2020) “Humanitarian supply chain: a bibliometric analysis and future research directions,” Annals of Operations Research [Preprint]. doi:10.1007/s10479-020-03594-9.

Haren, P. and Simchi-Levi, D. (2020) How Coronavirus Could Impact the Global Supply Chain by Mid-March.

Horne, J.F. (1997) “The coming age of organizational resilience,” Business Forum, 22, pp. 24–29.

Ivanov, D., Pavlov, A., Dolgui, A., Pavlov, D. and Sokolov, B. (2016) “Disruption-driven supply chain (re)-planning and performance impact assessment with consideration of pro-active and recovery policies,” Transportation Research Part E: Logistics and Transportation Review, 90, pp. 7–24. doi:10.1016/j.tre.2015.12.007.

Ivanov, D. (2018) “Revealing interfaces of supply chain resilience and sustainability: a simulation study,” International Journal of Production Research, 56(10), pp. 3507–3523. doi:10.1080/00207543.2017.1343507.

Ivanov, D. (2019a) “‘A blessing in disguise’ or ‘as if it wasn’t hard enough already’: reciprocal and aggravate vulnerabilities in the supply chain,” International Journal of Production Research, pp. 1–11. doi:10.1080/00207543.2019.1634850.

Ivanov, D. (2019b) “Disruption tails and revival policies: A simulation analysis of supply chain design and production-ordering systems in the recovery and post-disruption periods,” Computers and Industrial Engineering, 127, pp. 558–570. doi:10.1016/j.cie.2018.10.043.

Ivanov, D. (2020) “Predicting the impacts of epidemic outbreaks on global supply chains : A simulation-based analysis on the coronavirus outbreak,” Transportation Research Part E, 136(March), p. 101922. doi:10.1016/j.trr.2020.101922.

Ivanov, D., Tang, C. S., Dolgui, A., Battini, D. and Das, A. (2021) “Researchers’ perspectives on Industry 4.0: multi-disciplinary analysis and opportunities for operations management,” International Journal of Production Research, 59(7), pp. 2055–2078. doi:10.1080/00207543.2020.1798035.

Ivanov, D. and Dolgui, A. (2019) “Low-Certainty-Need (LCN) supply chains: a new perspective in managing disruption risks and resilience,” International Journal of Production Research, 57(15–16), pp. 5119–5136. doi:10.1080/00207543.2018.1521025.

Ivanov, D. and Dolgui, A. (2020) “Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak,” International Journal of Production Research, 58(10), pp. 2904–2915. doi:10.1080/00207543.2020.1750727.
Kostoff, R.N., Briggs, M. B., Solka, J. L. and Rushenberg, R. L. (2008) “Literature-related discovery (LRD): Methodology,” Technological Forecasting and Social Change, 75(2), pp. 186–202. doi:10.1016/j.techfore.2007.11.010.

Kostoff, R.N. (2011) “Literature-related discovery: Potential treatments and preventative for SARS,” Technological Forecasting and Social Change, 78(7), pp. 1164–1173. doi:10.1016/j.techfore.2011.03.022.

Kostoff, R.N. and Patel, U. (2015) “Literature-related discovery and innovation: Chronic kidney disease,” Technological Forecasting and Social Change, 91, pp. 341–351. doi:10.1016/j.techfore.2014.09.013.

Lengnick-Hall, C.A., Beck, T.E. and Lengnick-Hall, M.L. (2011) “Developing a capacity for organizational resilience through strategic human resource management,” Human Resource Management Review, 21(3), pp. 243–255. doi:10.1016/j.hrmr.2010.07.001.

Lin, Q., Zhao, S., Gao, D., Lou, Y., Yang, S., Musa, S. S., Wang, M. H., Cai, Y., Wang, W., Yang, L. and He, D. (2020) “A conceptual model for the coronavirus disease 2019 (COVID-19) outbreak in Wuhan, China with individual reaction and governmental action,” International Journal of Infectious Diseases, 93, pp. 211–216. doi:10.1016/j.ijid.2020.02.058.

Liu, M. and Zhang, D. (2016) “A dynamic logistics model for medical resources allocation in an epidemic control with demand forecast updating,” Journal of the Operational Research Society, 67(6), pp. 841–852. doi:10.1057/jors.2015.105.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C. and Hung Byres, A. (2011) Big data: The next frontier for innovation, competition, and productivity, McKinsey Global Institute. doi:10.1080/01443610903114527.

McManus, S., Seville, E., Vargo, J. and Brunsdon, D. (2008) “Facilitated process for improving organizational resilience,” Natural Hazards Review, 9(2), pp. 81–90. doi:10.1061/(ASCE)1527-6988(2008)9:2(81).

Ortiz-de-Mandojana, N. and Bansal, P. (2016) “The long-term benefits of organizational resilience through sustainable business practices,” Strategic Management Journal, 1631(February 2014), pp. 1615–1631. doi:10.1002/smj.20102.

Phillips-Wren, G. and Hoskisson, A. (2015) “An analytical journey towards big data,” Journal of Decision Systems, 24(1), pp. 87–102. doi:10.1080/12460125.2015.994333.

Ponomarov, S.Y. and Holcomb, M.C. (2009) “Understanding the concept of supply chain resilience,” The International Journal of Logistics Management, 20(1), pp. 124–143. doi:10.1108/09574090910954873.

Priya Datta, P., Christopher, M. and Allen, P. (2007) “Agent-based modelling of complex production/distribution systems to improve resilience,” International Journal of Logistics Research and Applications, 10(3), pp. 187–203. doi:10.1080/13675560701467144.

Queiroz, M.M., Ivanov, D., Dolgui, A. and Fosso Wamba, S. (2020) “Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review,” Annals of Operations Research [Preprint]. doi:10.1007/s10479-020-03685-7.

Queiroz, M.M., Fosso Wamba, S., Chiappetta Jabbour, C. J. and Machado, M. C. (2022) “Supply chain resilience in the UK during the coronavirus pandemic: A resource orchestration perspective,” International Journal of Production Economics, 245, 108405. doi:10.1016/j.ijpe.2021.108405.

Queiroz, M.M., Fosso Wamba, S. and Branski, R.M. (2021) “Supply chain resilience during the COVID-19 pandemic for transitioning to sustainable supply and production,” Resources, Conservation and Recycling, 159. doi:10.1016/j.resconrec.2020.104894.

Savachkin, A. and Uribe, A. (2012) “Dynamic redistribution of mitigation resources during influenza pandemics,” Socio-Economic Planning Sciences, 46(1), pp. 33–45. doi:10.1016/j.seps.2011.05.001.

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, 69(January), pp. 135–146. doi:10.1016/j.indmarman.2017.12.019.

Wamba, S.F., Dubey, R., Gunasekaran, A. and Akter, S. (2020) “The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism,” International Journal of Production Economics, 222(September 2019), p. 107498. doi:10.1016/j.ijpe.2019.09.019.

Wamba, S.F. and Queiroz, M.M. (2020) “Blockchain in the operations and supply chain management: Benefits, challenges and future research opportunities,” International Journal of Information Management, p. 102064. doi:10.1016/j.ijinfomgt.2019.102064.

Wamba, S.F. and Queiroz, M.M. (2022) “Industry 4.0 and the supply chain digitalisation: a blockchain diffusion perspective,” Production Planning and Control, 33(2-3), pp. 193–210. doi:10.1080/09537287.2020.1810756.

Yin, R. (2014) Case Study Research: Design and Methods. 5th edn. Thousand Oaks: Sage.

Yong, B., Shen, J., Liu, X., Li, F., Chen, H. and Zhou, Q. (2020) “An intelligent blockchain-based system for safe vaccine supply and supervision,” International Journal of Information Management, 52. doi:10.1016/j.ijinfomgt.2019.10.009.