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Data-driven digital transformation for emergency situations: The case of the UK retail sector

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ABSTRACT

The study explores data-driven Digital Transformation (DT) for emergency situations. By adopting a dynamic capability view, we draw on the predictive practices and Big Data (BD) capabilities applied in the UK retail sector and how such capabilities support and align the supply chain resilience in emergency situations. We explore the views of major stakeholders on the proactive use of BD capabilities of UK grocery retail stores and the associated predictive analytics tools and practices. The contribution lies within the literature streams of data-driven DT by investigating the role of BD capabilities and analytical practices in preparing supply and demand for emergency situations. The study focuses on the predictive way retail firms, such as grocery stores, could proactively prepare for emergency situations (e.g., pandemic crises). The retail industry can adjust the risks of failure to the SC activities and prepare through the insight gained from well-designed predictive data-driven DT strategies. The paper also proposes and ends with future research directions.

1. Introduction

The impacts of emergency situations (e.g., COVID outbreak, Russia-Ukraine war) on society and economy but also operations and Supply Chain (SC) worldwide have recently gained unprecedented interest from both practitioners and academics (Ivanov, 2020; Ivanov and Dolgui, 2021; Queiroz et al., 2020). While past outbreaks can provide useful knowledge about operations (Queiroz et al., 2020), predicting future demand and disruptions can be invaluable in emergency situations (Ivanov, 2020) to secure supply chain responsiveness and resilience. For instance, the severe SC disruptions during the pandemic outbreak of COVID-19 could provide lessons for future research and practice (Ivanov and Dolgui, 2020; Lopes de Sousa Jabbour et al., 2020; Remko, 2020; Sharma et al., 2020). The pandemic situation caused significant disruptions impacting among others logistics providers, as home deliveries of online orders increased dramatically, and in-home consumption of food and beverages (due to lockdown establishments) increased the consumption of goods purchased from the retail sector (e.g., grocery stores) (Forbes, 2022). Furthermore, according to the MIT Centre for Transportation and Logistics, the Russia-Ukraine war has also had a tremendous impact on supply chains globally by creating challenges in energy prices and the flow of goods and commodities such as auto parts, oil, and grain, leading to dramatic cost increases as well as dramatic product and food shortages around the world as it is presented from MIT Centre for Transportation and Logistics (Phadnis et al., 2022).

Research has highlighted the importance of building 'resilience' across the supply chain to ensure adaptability, responsiveness, and risk management. The term 'supply chain resilience (SCR)' has been used in the literature to reflect the ability to recover from disruptions rapidly and effectively at both an organisational (Ambulkar et al., 2015; Parker and Ameen, 2018) and SC levels (Brandon-Jones et al., 2014; Kim et al., 2015; Dubey et al., 2019; Behzadi, O'Sullivan and Olsen, 2020). However, SCR aims mainly to respond and recover from disruptions, a *reactive* approach to risk management. There is literature discussing the risk of disruption, the vulnerability of an enterprise or system to risk, and resilience as a mechanism to return to a state of normality after a

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disruption (e.g. Peck, 2005; Wicaksana et al., 2022) with researchers investigating different risk typologies based on characteristics of risks, location of risks, and/or impact of risks, as well as on sustainable and behavioural supply chain risk management. There are also works suggesting that firms need to develop resilient capabilities and plan for SC continuity. This stream of literature focuses on a holistic management system that *proactively* addresses risk and disruptions by helping to prevent risks, mitigate risks, respond to actual disruptions, and recover from actual disruptions (Azadegan et al., 2020; Um and Han, 2021).

Scholars have underlined the importance of digital technologies, specifically the Digital Transformation (DT) -triggered mainly by the increasing role of data and technology introduction processes (Kache and Seuring, 2017; MacCarthy et al., 2016) in building SCR. Emergent technologies applied through DT can be invaluable in redesigning and transforming conventional operations, especially during epidemic crises and other emergency situations (Queiroz et al., 2020). Furthermore, digital technologies such as SC analytics (SCA) could support the decision-making process and handle SC disruptions (Giannakis and Papadopoulos, 2016; Ivanov and Dolgui, 2021; Papadopoulos et al., 2016; Sheng et al., 2020). SCA is predictive (Kache and Seuring, 2017) and can be used to forecast demand while offering SC visibility and eliminating risks, thereby assisting retailers to be responsive and resilient during SC disruptions (Wamba et al., 2017; Wang et al., 2016).

Nevertheless, there is still a lack of understanding of Predictive Analytics (PA) within retail supply chains, where unpredictive circumstances and crises can easily disrupt demand and supply. The impact of PA on SC resilience and continuity is still not understood, which is needed to provide holistic handling of SC disruptions proactively and reactively. To address this gap, this study focuses on PA as an emergent technology and extends an SC approach as suggested in previous studies on SC disruption, resilience and continuity (Azadegan et al., 2019, 2020; Ivanov and Dolgui, 2021) to develop a measure of the impact of PA in SCM practices in the retail supply chain. We adopt a Dynamic Capabilities perspective (Eckstein et al., 2015; Teece, 2012; Teece et al., 1997; Wamba et al., 2020) to discuss the use of SCA in SCM that entails preparedness and responsiveness of operational processes and consequently enhanced value creation for the retail sector for emergent situations where SCA is applied.

2. Theoretical background

2.1. Supply chain resilience

Nowadays, firms within supply chains operate in a turbulent and uncertain environment and can be susceptible to disruption (Ambulkar et al., 2015; Blome and Schoenherr, 2011). Disruptive events cause turbulence and uncertainty to supply chains (Ambulkar et al., 2015; Sharma et al., 2020). Disruptions appear, among other things, in the form of catastrophic events (Knemeyer et al., 2009; Morrice et al., 2016), transportation and logistics disturbances (Wilson, 2007), and epidemic outbreaks (Ivanov, 2020; Queiroz et al., 2020). According to Craighead et al. (2007), a supply chain disruption is an event that disrupts the flow of goods or services in a supply chain. SC disruptions can be followed by severe negative consequences on firms' financial, market, operational performance (Azadegan et al., 2019; Hendricks and Singhal, 2005a), and reputation (Azadegan et al., 2020; Hendricks and Singhal, 2005a,b; Petersen and Lemke, 2015; Revilla and Saenz, 2017; Rindova et al., 2005; Jacobs and Singhal, 2017; Nunes et al., 2021). As SC disruptions are both harmful and costly (Bode and Wagner, 2015; Hendricks and Singhal, 2003, 2005a,b; Narasimhan and Talluri, 2009), SC stakeholders have to measure and mitigate the risk and negative consequences of such unexpected events (Craighead et al., 2007; Ivanov, 2020; Ivanov and Dolgui, 2021, Ivanov and Dolgui, 2020), and build resilience (Azadegan et al., 2020).

Building SC resilience proactively means dealing with and handling supply chain disruption risks (Hohenstein et al., 2015; Tukamuhabwa et al., 2017). In this study, by resilience, we mean *readiness, effective response to, and recovery from a disruption, including the ability to return to a previous or better level of operational performance* (Ambulkar et al., 2016; Chopra and Sodhi, 2014; Wu et al., 2007). Resilience includes identifying threats (both exogenous and endogenous) and deploying SCR strategies (in terms of operations, relationships, or information management) (Scholten et al., 2014).

The outcomes of these two elements of the SCR strategies (upstream, downstream, and focal) can affect risk mitigation strategies (B. Tukamuhabwa et al., 2017; Zsidisin and Wagner, 2010). Research has also shown that factors such as the resources' deployment and reconfiguration, culture, and the supply network structures and characteristics can contribute to building SCR (Bode et al., 2011; Macdonald et al., 2018; Pettit et al., 2019). To theorise and understand SCR, scholars have drawn upon well-known theories such as resource-based view and dynamic capability theories, information processing theory, and contingency theory (Brandon-Jones et al., 2014; Brusset and Teller, 2017; Chowdhury and Quaddus, 2016; Yu et al., 2019). As SCR is a multi-faceted concept, no unified or integrated theory exists to explain the links to other relevant theories like risk management and SC continuity (Kamalahmadi and Parast, 2016; Linnenluecke, 2017; Scholten et al., 2019). While SC continuity is researched recently through various lenses (Tukamuhabwa et al., 2017; Zsidisin and Wagner, 2010), there are also studies referring to the impact of technology in SC resilience practices that ensure the continuity planning of the firms (Azadegan et al., 2020; Gu et al., 2021).

2.2. Digital transformation and predictive emergency planning

Digital Transformation (DT), triggered mainly by the increasing role of data and technology in the production processes, has been evident in the last decades (Kache and Seuring, 2017; MacCarthy et al., 2016; MacCarthy et al., 2016). Scholars have underlined the importance of emergent technologies in handling disruptions (Giannakis and Papadopoulos, 2016; Ivanov et al., 2017; Ivanov and Dolgui, 2021; Papadopoulos et al., 2016; Queiroz et al., 2020) and enhancing organisational performance (Gawankar et al., 2020; Raman et al., 2018). Big Data Analytics (BDA) is at the heart of these technologies, utilising either predictive or prescriptive data models. Predictive models forecast outcomes that retailers can use or gain *insights* (e.g., future sales), whereas prescriptive models optimise variables and offer *foresight* (e.g. price recommendations to retail managers) (Shankar, 2018). Table 1 provides definitions of concepts used in this research relevant to any type of emergency planning and digital practices and processes, specifically PA.

Big Data Analytics could help SC partners and collaborators have complete visibility and traceability of processes as well as operate a leaner supply chain while eliminating supply risks (Feki et al., 2016; Kache and Seuring, 2017; Wamba et al., 2017; Wang et al., 2016). Hence, BDA could create capabilities that enable intelligent decision-making and efficient and responsive processes to serve better customers (Mikalef et al., 2019) and improve or change the industrial context's operations (Baines et al., 2017), improving performance and achieving competitive advantage (Wamba et al., 2017).

BDA capabilities refer to the orchestration and management of a firm's data-related resources, processes, and tools (Mikalef et al., 2019, 2020; Mikalef and Pateli, 2017). BDA capabilities are dynamic capabilities, as Teece et al. (1997) proposed to explain how firms can gain a competitive advantage in dynamic and changing environments (Teece, 2012; Eckstein et al., 2015; Dubey et al., 2019). A dynamic capability is the "ability to integrate, build, and reconfigure internal and external resources/competencies to address, and possibly shape, rapidly changing business environments" (Teece, 2012, p. 1395).

Hence, we hypothesise as follows:

H1a. Data-driven Digital Transformation has a positive impact on supply chain resilience.

Table 1
Definitions and relevant references.

Definition	Reference
Data-driven Digital Transformation	
A process that aims to improve a firm by triggering significant changes to its capabilities and design through the use of various technologies and data. Digital Transformation implies a redesign of core processes with the reallocation of resources and competencies of the firm.	(Hanelt et al., 2021; Li, 2020; Vial, 2019)
Supply Chain Resilience	
The readiness, effective response to, and recovery from a disruption, including the ability to return to a previous or better level of operational performance	(Brandon-Jones et al., 2014; Hohenstein et al., 2015; Ponomarov and Holcomb, 2009b; Revilla and Saenz, 2017; Scholten et al., 2019)
Big Data Capabilities	
Big Data capabilities refer to the orchestration and management of the data-related resources by the firm Firms can develop strong BD capabilities and utilise them in various operations, which could also include emergency planning functions	(Kache and Seuring, 2017; Mikalef et al., 2019; Mikalef and Pateli, 2017; Wamba et al., 2017; Akter et al., 2016)
Predictive Analytics Practices and Processes	
The information and knowledge sharing practices and coordination are necessary both for upstream suppliers and downstream customers in order to coordinate the supply chain management, as well as respond to the requirements of the market	(Frohlich and Westbrook, 2001; Revilla and Saenz, 2017)
Predictive Analytics Tools	
Integrated data collection technologies that are fully enabling data sharing and real-time communication across all supply chain stages, intelligent decision making, and efficient and responsive processes to serve customers better	(Wang et al., 2016).

H2a. The allocation of BD Capabilities has a positive impact on supply chain resilience.

Regarding risk and disruption, using BDA (PA) tools and processes is useful in modelling different risk scenarios and applying probabilities to provide a decision tree and likelihood of 'emergency situations' affecting retail SCs. Hence, PA tools and processes can constitute dynamic capabilities that help organisations to improve performance (Dubey et al., 2019) and develop disruption mitigation capabilities (Akter et al., 2016; Papadopoulos et al., 2016). Raman et al. (2018) and Singh and Singh (2019) argued that BDA could help organisations increase their resilience in managing supply chain risks and improve recovery attempts, increasing transparency and innovation to improve performance and reduce environmental variability. Although PA can assist organisations in developing risk management capabilities (Dubey et al., 2019), literature is yet to address how PA could help SCR. Furthermore, the literature does not explain how PA moderates the relationships between Data-Driven Digital Transformation and supply chain resilience and between BD Capabilities and supply chain resilience and the strength of these relationships (Akter et al., 2016; Kache and Seuring, 2017). Vidgen et al. (2017) have argued that organisations may struggle in getting value from their business analytics initiatives (and PA), as value depends on how a firm can use the PA capabilities as part of a wider big data and analytics strategy to deliver a valued output -that is, in our case, assess the likelihood of 'emergency situations' affecting retail SCs.

Therefore, we observe the moderating effects of these relationships with the two follow-up hypotheses to our first two hypotheses (H1b and H2b) as:

H1b. PA tools and processes positively moderate the relationship between data-driven Digital Transformation and supply chain resilience.

H2b. PA tools and processes positively moderate the relationship between BD Capabilities and supply chain resilience

Based on the aforementioned hypotheses, our conceptual framework is depicted in Fig. 1.

3. Research methodology

3.1. Pilot study

To further assess the reliability and validity of the constructs in the conceptual framework (Fig. 1) and generate the measurement items for each construct, a pilot study was conducted involving eight senior professionals working in the grocery retail industry for more than ten years. Structured interviews were conducted to ensure that the question items' wording appeals to people working in the grocery retail industry. Minor contextual amendments were made, and any equivocal items were modified or removed. Suggestions were also given regarding the phrasing of the items assuming that supply chain analytics and predictive emergency planning are relatively new topics.

3.2. Sample and data collection

The data for this study was obtained through an online survey hosted by Survey Monkey. Online surveys have been used considerably in previous studies with a similar number of samples (Brandon-Jones and Kauppi, 2018; Oke et al., 2007). They are cost-effective and offer the benefits of getting faster responses and broader reach, and positive environmental impact. The survey was distributed to data analytics and supply chain management professionals employed in ten different grocery retail companies that have been trading in the UK over the past fifteen years (i.e., Aldi UK, Asda Supermarkets, Co-op Food, Lidl GB, Iceland Foods, Wm Morrison Supermarkets, Marks & Spencer Food UK, Sainsbury's Supermarkets, Tesco Supermarkets and Waitrose & Partners). The criterion against the choice of each respondent was the likelihood of being knowledgeable about digital transformation, predictive analytics and resilience in the supply chain operations. Thus, we have included in our survey dichotomous questions in order to guarantee that all respondents have knowledge of the following key meanings (i) Predictive Analytics, (ii) Digital Transformation (iii) Supply Chain Resilience and (iv) Big Data Capabilities.

Our survey methodology follows Dillman's approach as each potential respondent received an email containing the link to the online survey questionnaire and a cover letter stating the study's purpose and assuring the respondents' confidentiality (Dillman, 2007). Each respondent also received a unique password to avert duplicated entries. To avoid potential non-response bias, the survey link was shared for forty-five days, and a friendly reminder was sent by email one week before the survey was removed from the online survey site.

The survey captures causal relationships between constructs and provides generalisable statements on the research setting. Thereby items of measurement are derived from the literature review and survey responses due to the timeliness and the relevance of the overall question of linking SCR and constructs with the digitalisation of SC. Surveys can precisely document the norm, ascertain extreme information, and define connotations between variables in a sample (Gable, 1994). All the constructs in the model were measured using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The survey was administered to 422 potential respondents. We obtained a total of 207 responses; however, only 142 useable survey responses could be considered as 65 respondents were unreachable or filled out incomplete surveys. Table 2 provides the profession of the respondents. Most respondents were Data/Tech analysts/engineers (36.62%) and supply chain analysts/specialists (31.69%).

Using online survey questionnaires as a data collection method, we were concerned with the common method bias and the possible measurement error that could jeopardise the survey results (Churchill, 1979;

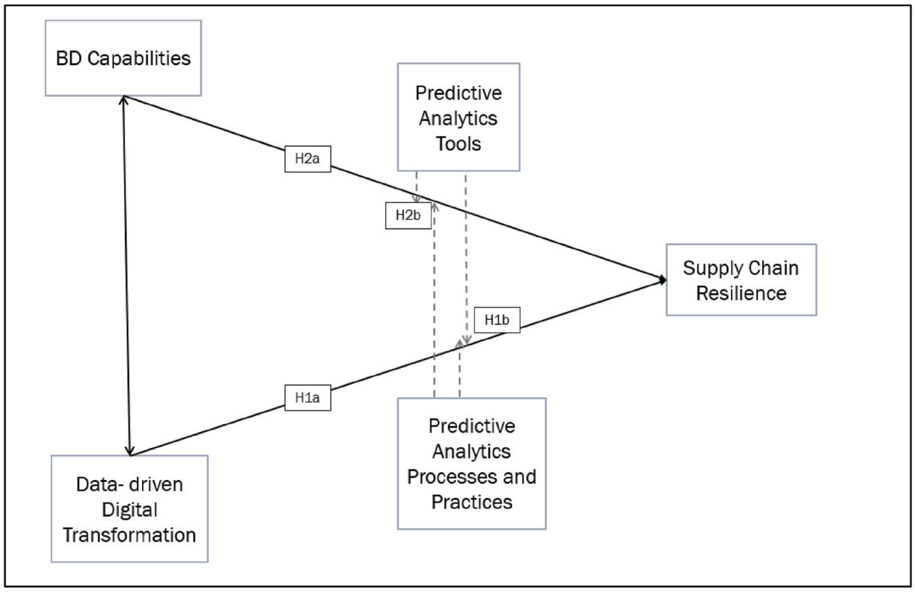

Fig. 1. The conceptual framework.

Table 2
Data for the respondents.

Job Title	Count	Percent
Analyst/Engineer, Data/Tech	52	36.62
Manager/Head, Data Science	12	8.45
Director, Data/Tech Science	5	3.52
Analyst/Specialist, Supply Chain	45	31.69
Manager/Head, Supply Chain/Warehouse	25	17.61
Director, Supply Chain Management	3	2.11
Total:	142	100

Podsakoff et al., 2003). Literature regularly points to Harman's single factor test with regard to testing for common method bias. However, the relevance of the test is at least debatable. Fuller et al. (2016) argue that the test is unable to produce an accurate conclusion, but the authors also state that common method bias is something which should not be presumed automatically. They also claim that their findings, which are based on a simulation technique and an in-depth analysis, even suggest the opposite. Also, for common method bias to be a matter of concern, the authors show that levels of scale reliabilities would even need to be on an untypically high end. Still, we aim to address the possible issue of common method bias more broadly.

Kock et al. (2021) point out additional opportunities in order to mitigate the issues that arise from common method bias. In addition to procedural controls such as a proper survey design and carrying out Harman's single factor test (looking for results in one factor accounting for more than 50% of the variance), Kock et al. (2021) suggest the use of a CFA correlation marker technique running with and without a common latent factor. In this study, Harman's single-factor test was used to assess common method variance, which was of an acceptable standard as the largest variance explained by an individual factor is 36.68% (Podsakoff et al., 2003). Also, the described marker technique comparing the standardised regression weights (with and without a common latent factor) did not point to any common method bias. Exploratory Factor Analysis (EFA) and Structural Equation Modelling (SEM) techniques were applied for the analysis of both the measures and the model. SEM is widely used in social sciences to analyse structure and measurement models (Anderson and Gerbing, 1988; Hair et al., 2014). The proposed research model was examined through IBM SPSS AMOS 23.

4. Results

Statistical analysis was conducted for the large-scale survey to determine the validity and reliability of the instrument constructs. The proposed framework was tested using SEM as the most appropriate method for the assessment of the validity and reliability of scales.

4.1. Exploratory factor analysis (EFA)

Initially, the measurement model was tested based on convergent and discriminant validity to ensure that the measures were representative of the constructs. Consequently, the model was examined for the validity of the developed propositions. Evidence of convergent and discriminant validity was evaluated through exploratory factor analysis (EFA) (Fabrigar et al., 1999; Kline, 2013; Osborne and Costello, 2005). Table 3 presents the values of the average variance extracted (AVE) and composite reliability (CR) for each construct.

Table 4 presents the eigenvalues for the model using principal components analysis with oblique rotation (Osborne, 2015). Eigenvalues associated with each factor equal the variance explained by that particular linear component (SS loadings). Fourteen factors showed eigenvalues above 1.0 (Kaiser's criterion). These factors explain about 67% of the variance. A scree plot that shows eigenvalues against the number of factors confirms the number of factors (Fig. 2).

The average of communities is 0.67, with only four variables below 0.6. We may verify the difference between the reproduced correlation matrix and the correlation matrix in the original data (residuals). If the model was a perfect fit, the reproduced coefficients would equal the original correlation coefficients. The proportion of residuals greater than 0.05 is 18%, which is satisfactory. Also, the measure of fit (sum of squared residuals divided by the sum of squared correlations and also referred to as the fit based upon off-diagonal values) is 0.94.

Finally, Cronbach's alpha is used to determine whether a factor consistently reflects its associated construct. A value above 0.7 is acceptable (Nunnally, 1978; Peterson, 2013). Substantially lower values of Cronbach's alpha indicate an unreliable scale. Also, it is important that at least three items load on one specific factor. We consider items with standardised loadings well above 0.4 (Dunn et al., 1994). After having removed two inconsistent items related to the constructs of *predictive analytics tools* and *supply chain resilience,* respectively, we hold on to the 5 factors (PC1 to PC5), namely: (i) *Predictive Analytics (PA) processes* (α = 0.73), (ii) BD Capabilities (BDC) (α = 0.71), (iii)

Table 3
Factor loadings.

Construct	Items	Loadings (standardised)	AVE	CR
Predictive Analytics (PA) Practices and Processes			0.35	0.73
V62	Applying replenishment planning analytics (e.g., what, when, and where should I ship)	1.000 (0.677)		
V63	Implementing network planning and optimisation (e.g., right networks of manufacturing and/or warehousing facilities)	0.686 (0.566***)		
V64	Employing procurement analytics (e.g., achieve the lowest landed cost and secure long-term, high-quality supplier partners)	0.593 (0.542***)		
V65	Applying inventory optimisation techniques (e.g., maintaining the best stock levels)	0.597 (0.519***)		
V67	Using demand analytics tools (forecast tracking with actual sales, incl. seasonal products).	0.756 (0.636***)		
BD Capabilities (BDC)			0.34	0.71
V31	Allocating resources based on data from previous sales to fulfil customer orders (online and in-store)	1.000 (0.529)		
V32	Identifying flexibility patterns in the data resources to define requirements and adjust supply (including any form of collaboration with partners and transportation).	1.101 (0.527***)		
V20	Adaptation to suppliers' requirements from data resources and the associated information about suppliers' capacity.	1.293 (0.568***)		
V21	The reconfiguring capacity of warehousing and stock levels (incl. RFID data) based on data resources	1.402 (0.741***)		
V59	Sustaining quality and transparency of operations through the extraction of data insight.	1.060 (0.467***)		
Data-driven Digital Transformation (DDT)			0.35	0.78
V30	Allocating through digitalisation a variety of mechanisms to alert for rapid changes in supply and delivery.	1.000 (0.519)		
V29	Allocating through digitalisation a variety of mechanisms to alert for rapid changes in inventory and warehousing levels.	1.085 (0.586***)		
V36	Redesigning the processes integrating digitalisation for maintenance of real-time customer sales fulfilment levels.	.706 (0.425***)		
V35	Redesigning the processes through digitalisation for alertness for rapid changes in customer expectations.	.984 (0.527***)		
V34	Identifying changes in customer profiles and behaviours with the use of digital technology.	1.435 (0.647***)		
V58	Reconfiguring resources and processes in a dynamic environment with the use of digital technology.	1.005 (0.571***)		
V33	Managing IT systems to mitigate supply chain risks and disruptions.	1.671 (0.778***)		
Predictive Analytics Tools (SCI)			0.40	0.67
V22	Attaining information and data integration among different supply chain systems and platforms	1.000 (0.653)		
V39	Coordinating by using real-time data and data analysis methods/tools	1.290 (0.641***)		
V40	Exchanging information and data (e.g., orders, demand forecasting, delivery schedule) with key partners	1.047 (0.606***)		
Supply Chain Resilience (SCR)			0.33	0.66
V43	Measuring proactively the risk of each supply process and planning ahead.	1.000 (0.510)		
V47	Understanding and utilising data from previous supply chain disruptions	1.129 (0.535***)		
V37	Applying mechanisms to restore supply chain status incl. data	2.024 (0.613***)		
V38	Proposing rigorous instruments to recover in times of crisis.	1.806 (0.630***)		

Data-driven Digital Transformation (DDT) (α = 0.78), (iv) Predictive Analytics Tools (SCI) (α = 0.67), and (v) Supply Chain Resilience (SCR) (α = 0.66). Table 4 presents the factor loadings, average variance explained, and the composite reliability of each factor.

4.2. *Confirmatory factor analysis (CFA)*

Next, we follow a confirmatory factor analysis (CFA), followed by

Table 4
Eigenvalues for the first 14 factors (out of 43, the same as the number of variables).

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14
SS loadings	7.61	3.9	2.31	1.9	1.78	1.62	1.5	1.44	1.31	1.26	1.15	1.13	1.06	1.04
Proportion Explained	0.18	0.09	0.05	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02
Cumulative Proportion	0.18	0.27	0.32	0.37	0.41	0.44	0.48	0.51	0.54	0.57	0.6	0.63	0.65	0.67

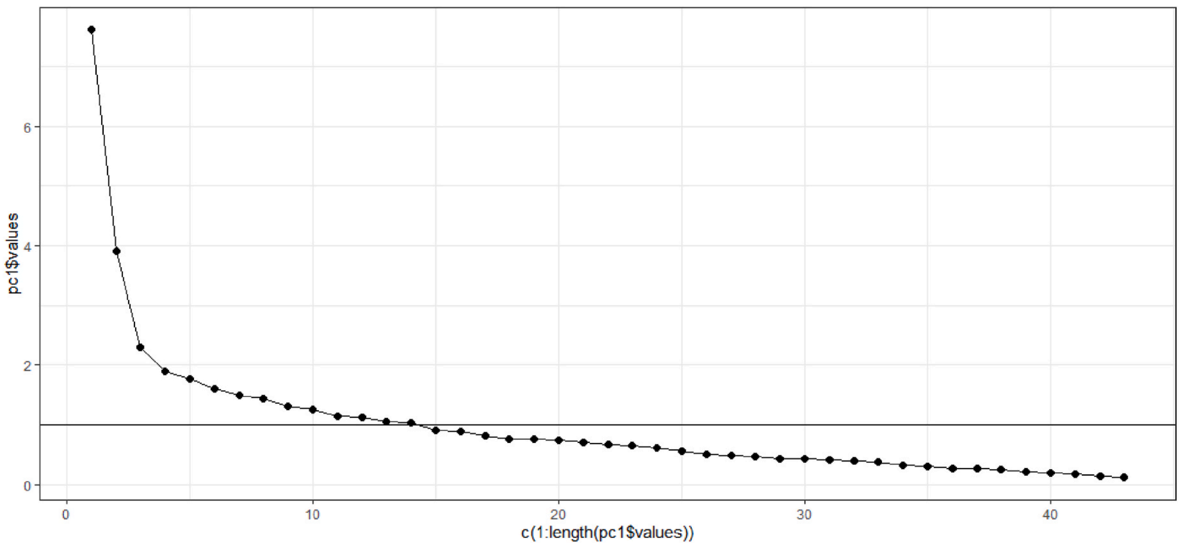

Fig. 2. Eigenvalues.

structural equation modelling (SEM), similarly to Anderson and Gerbing (1988). This step helps to evaluate the scales resulting from the EFA. Eventually, this procedure results in testing the conceptual model depicted in Fig. 1. To summarise, CFA and SEM measure constructs of latent variables by multiple indicator variables. There is only one major difference: CFA suggests correlating all latent variables as covariance is generally assumed between each pairing of latent variables. In contrast, directional relationships between the parings of latent variables are considered in SEM. We first present some descriptive statistics, including Cronbach's alpha (as the previously mentioned measure of internal consistency) in Table 5.

Regarding discriminant validity, correlation coefficients between first-order constructs confirm distinct factors as values range from −0.45 to 0.78 (see Table 6).

Fig. 3 illustrates the final model, including possible modifications. Standardised path coefficients and directional paths are meant to support the reader in identifying the effect size. We prefer the standardised path coefficients because the range from 0 to 1 allows us to compare effect sizes. While developing the SEM, the link between BDC and SCR is not significant at the level expected, and the link between DDT and SCR is positively related. This confirms our assumption that data-driven Digital Transformation can define SC resilience. Here, the path coefficient between DDT and SCR is 0.622, significant with $p < .05$.

Table 5
Descriptive statistics, including Cronbach's alpha.

	PA	BDC	DDT	SCI	SCR
Mean	3.107	4.054	3.915	3.610	3.521
Minimum	2.986	3.655	3.739	3.289	3.239
Maximum	3.261	4.345	4.070	3.979	4.007
Range	0.275	0.690	0.331	0.690	0.768
Maximum/Minimum	1.092	1.189	1.089	1.210	1.237
Variance	0.012	0.065	0.016	0.121	0.127
N of Items	5	5	7	3	4
Cronbach's Alpha	0.730	0.710	0.780	0.670	0.660

Table 6
Discriminant validity (Correlations between first-order constructs).

	BDC	PA	DDT	SCI	SCR
BDC	1.00				
PA	−0.33	1.00			
DDT	0.57	−0.33	1.00		
SCI	0.50	−0.45	0.67	1.00	
SCR	0.52	−0.29	0.70	0.78	1.00

In the next step, we test the moderating effect of supply chain integration and predictive analytics. As presented in Fig. 4, analytics tool integration and predictive analytics proved to be significant moderators between data-driven Digital Transformation and supply chain resilience. As the moderating effect cannot be utilised to test the impact of BD capabilities on SC resilience, this relationship is not significant. If we were to test the moderating effect for analytics tool integration only, the effect would be more substantial (0.37 vs 0.36 at significant at p = .08). Our results indicate that predictive analytics has not been extensively exploited extensively within the grocery retail supply chain. The field requires further exploration of the opportunities arising through data-driven DT.

Table 7 summarises goodness-of-fit indices for the various estimated models utilised by the maximum likelihood (ML) method. We might look at Standardised Root Mean Square Residual (SRMR), the Comparative Fit Index (CFI) and Root Mean Square Error of Approximation (RMSEA). In terms of SRMR, values less than 0.055 would be ideal. Although we do not fulfil the SRMR criteria, all CFI values are greater than 0.80. We also provide confidence intervals for the RMSEA in order to address the sample size issue. The model fit is adequate given that the RMSEA values are between 0.039 and 0.079.

We first examined the parameter estimates to verify whether the links between variables are statistically significant. Factor loadings indicate whether the observed variables contribute to the measurement of the underlying factor. Standardised path coefficients, together with

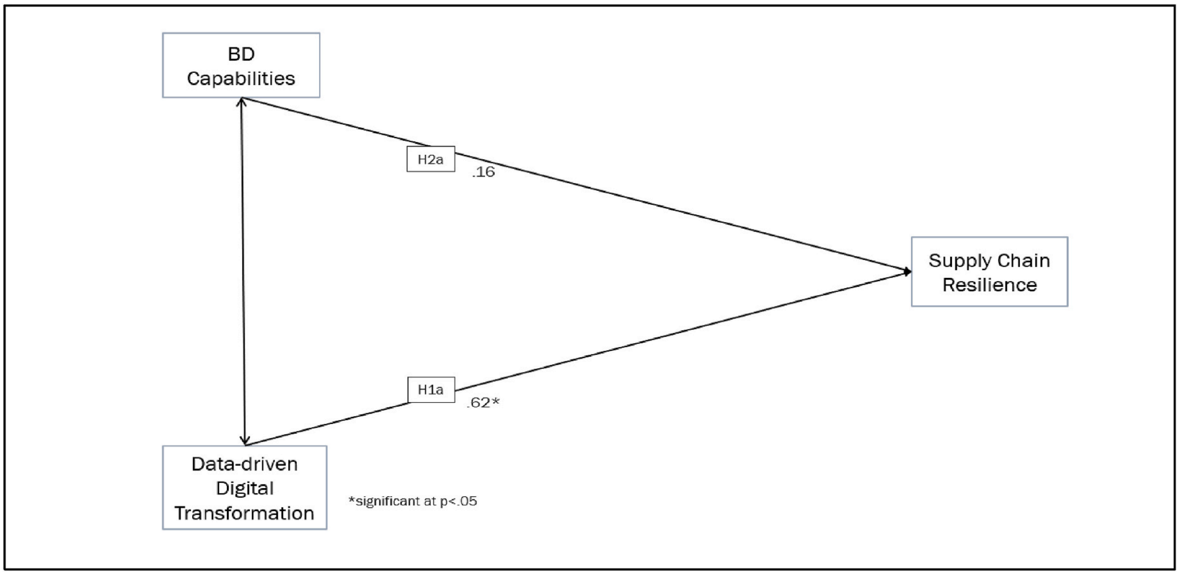

Fig. 3. Sem direct effects model.

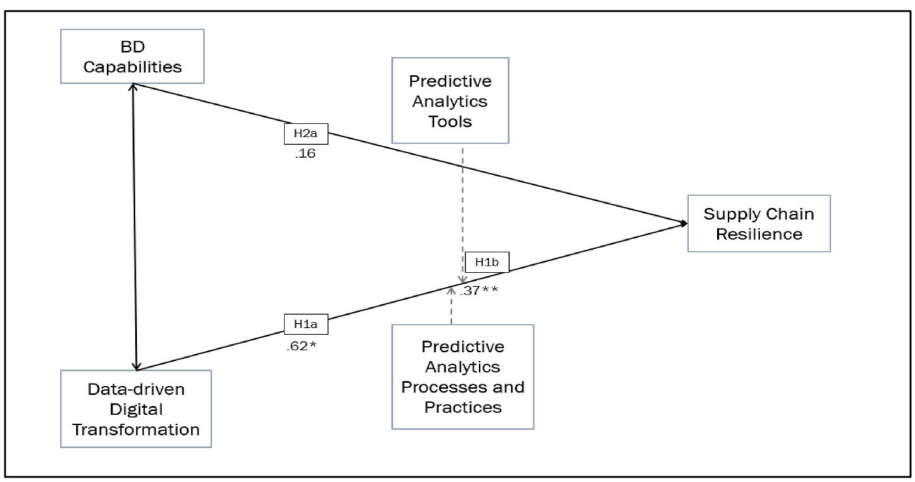

Fig. 4. Final conceptual model relationships.

Table 7
Fit indices.

Model	χ^2	df	$\Delta\chi^2$	Δdf	CFI	SRMR	RMSEA (CI_{90})
Measurement model (revised)	152	101			.884	.069	.060 (.039–.079)
Structural model	182	116	30	15	.873	.075	.064 (.046–.081)

Note: χ^2 = chi-square, *df* = degrees of freedom; *CFI* = Comparative Fit Index; *SRMR* = Standardized Root Mean Square Residual; *RMSEA* = Root Mean Square Error Of Approximation; *RMSEA* (CI_{90}) = *RMSEA* 90% Confidence Intervals.

their respective *p*-values, are presented. Furthermore, the indicator reliability could be calculated by squaring the standardised loadings. As the reliability of most indicators is below the ideal of .390, we look at composite reliability estimates for the latent factors (Cronbach alpha).

Concerning the latent factors, 35% of the variance is captured by our predictive analytics construct, 35% (data-driven Digital Transformation), 34% (BD Capabilities), 38% (PA tools and processes), and 33% (supply chain resilience).

4.2.1. Path analysis

To evaluate the mediating effects of PA and SCI, we proceeded with the analysis of SEM. First, we developed a model that considered the direct impact of DDT and BDC on SCR. Then we looked at our direct effects model to verify how well it fits based on the mentioned goodness-of-fit indices. The values of SRMR = . 075 and RMSE = 0.064 indicate that our direct model is satisfactory. Furthermore, a CFI value of 0.87 is reasonably close to the threshold of 0.9.

Next, we study the significance levels of the paths in the reduced model. The coefficient on the path between DDT and SCR was found .622 with a statistically significant t-value at the 0.001 level. This result supports our proposition H1a that DT in the supply chain positively relates to supply chain resilience (see Table 8). The path between BD capabilities and supply chain resilience has a standardised coefficient of 0.157, which according to a two-tailed *t*-test, is not significant for the context we examine the use of predictive analytics in retail supply chains. Thus, hypothesis H2a is rejected.

Furthermore, we tested for possible indirect effects. To test for a possible mediating effect, we applied the bootstrapping method implemented in IBM SPSS AMOS 23. The indirect effect of data-driven DT on the supply chain and supply chain resilience is tested by assuming that PA tool integration respectively PA processes work as a mediator (H1b).

Table 8
Direct Path tests.

Research Hypotheses (determinants)		Std. estimates (*p*-value)	Supported/not supported
H1a	Data-driven Digital Transformation has a positive impact on supply chain resilience.	.622 (.001)	Supported
H2a	The allocation of BD Capabilities has a positive impact on supply chain resilience.	.157 (.263)	Not supported
H1b	PA tools and processes positively moderate the relationship between data-driven Digital Transformation and supply chain resilience.	.366 (.014)	Supported
H2b	PA tools and processes positively moderate the relationship between BD Capabilities and supply chain resilience	–	Not supported

This indirect effect of PA positively moderating the relationship between data-driven Digital Transformation and supply chain resilience is significant at the .05 level. However, the indirect effect of BD Capabilities and supply chain resilience needs to be rejected.

5. Theoretical and managerial implications

5.1. Theoretical implications

This study investigated how PA tools and practices and Big Data (BD) capabilities can support and align SCR in emergency situations drawing on data from the UK retail sector. The paper addresses an important gap in the literature, that is, on the role of PA in times of disruption. We, therefore, extend studies (Feki et al., 2016; Kache and Seuring, 2017; Wamba et al., 2017; Wang et al., 2016) by illustrating the predictive nature of SCA and its link with SC resilience. We also extend studies focusing on Dynamic Capabilities to discuss the use of SC analytical tools and methods in SCM for value creation for the retail sector for emergent situations.

Our study highlights the importance of data-driven digital transformation in handling disruptions (Giannakis and Papadopoulos, 2016; Ivanov et al., 2017; Ivanov and Dolgui, 2021; Papadopoulos et al., 2016; Queiroz et al., 2020), indicating that data-driven DT is positively related to SC). Companies should be aware of the supply chain environment and ready to reconfigure their resources (Ambulkar et al., 2016). Furthermore, our path analysis results suggest that supply chains reinforced by PA provide companies with a holistic and robust structure that can assist them in deploying risk assessment and disruption management mechanisms. Integrated predictive supply chain tools can help retailers anticipate and quickly respond to supply continuity problems in supply chain disruptions caused by crises like COVID-19. Our findings empirically corroborate studies that utilise PA to cope with the challenges that arise in the face of a supply chain disruption (Ivanov, 2020) as well as those investigating the role of data analytics in predicting supplier disruptions (Brintrup et al., 2020; Ivanov and Dolgui, 2021). Based on empirical evidence, we offer an alternative lens. We argue that grocery retailers consider integrated predictive analytics as an emergent technology to gain visibility and maintain supply chain resilience and continuity.

Our results do not empirically advocate that BD capabilities are vital to strengthening the retail sector's SCR (hypothesis H2a). This contrasts with the literature arguing that PA can help organisations develop disruption mitigation capabilities (Akter et al., 2016; Papadopoulos et al., 2016; Singh and Singh, 2019) and risk management capabilities (Dubey et al., 2019). The reason may be that UK grocery retailers do not still possess the full capacities and relevant skills to respond to extreme circumstances and emergencies. They depend heavily on external suppliers and independent sourcing locations to build resilience to anticipate, adapt and respond to unpredictable events (Ali et al., 2017). However, a firm based on external capabilities can be highly impacted by unpredictable events (el Baz and Ruel, 2021), i.e., in the case of COVID-19. Furthermore, we argue that supply chain resilience is subject to the dependability and efficacy of integration tools and predictive analytics for grocery retailers. With our study, we aim to extend recent literature focusing on the use of IT with suppliers and customers and its significant effects on supplier and customer resilience (Gu et al., 2021).

5.2. Managerial implications

The results of this study suggest managerial insights and implications. First, in emerging situations such as the COVID-19 pandemic, retail grocery managers should recognise the importance of developing and maintaining holistic technology-based management systems, tools, and processes to address risk and disruptions in supply chains. This constitutes a starting point for establishing a robust model that will respond more effectively to changes in customer shopping behaviour, product ranges, and value, model different risk scenarios and apply probabilities to provide a decision tree and likelihood of 'emergency situations' affecting retail SCs. Even in the grocery retail context with a long experience in online deliveries and supplier relationship management, companies in emergent situations should understand the changes in customer behaviours, work more closely with their suppliers, act proactively and ensure supply chain resilience. This study informs managers of the importance of modernising supply chains to prevent and mitigate risks by investing in the data-driven digital transformation of their SC.

Second, grocery retailers should continue bringing forward the aspect of data-driven DT by investing in PA. Data analytics and acquisition technologies enabling data sharing and real-time communication across all supply chain stages have become now essential elements to model risks and investigate the likelihood of emergency situations affecting retail SCs. Furthermore, predicting the outcome of risk scenarios and the increase in home deliveries or sales of products can become very challenging during emerging situations. Therefore, our findings suggest that managers should actively develop intelligent decision-making models to cope with the unprecedented demand levels and elaborate agile supply chains to handle online deliveries in shorter times. The implementation of models beyond the exploration and exploitation of big data and predictive analytics should be part of the overall strategic investment. (big) data and predictive analytics tools. This finding contradicts recent assertions that big data analytics capabilities alone may improve the supply chain performance through enhancement of SC resilience (see indicatively, Bahrami et al., 2022; Park and Singh, 2022).

We believe that companies should also invest on alternative methods to process the large amount of information in supply chains (e.g., investing on simplification of information exchanges and data interoperability) rather than solely focusing on big data capabilities. A simplified business-to-business electronic communication will help companies to determine the inventory levels on high (and less)-demand products by sharing excessive amounts of information with suppliers. Thus, this study suggests that managers should exert efforts to explore multiple facets of data-driven DT through PA beyond BDA to cope with challenges pertinent to supply chain resilience. These may also include cloud-native, low-code application developments and the Internet of Things.

Third, along these lines, this work also highlights the importance of enriching data sets associated with customer interaction with online shopping websites. Our findings suggest that companies should provide high levels of predictive analytics integration during emerging situations by conflating end-to-end supply chain data into a common platform. This will allow predictive analytics to accelerate and optimise supply chain processes leading to better planning, waste minimisation, and a smoother flow of information and products. Hence, the results of this study emphasise that the integration of predictive analytics should be an inextricable part while building supply chain resilience through digital transformation.

Fourth, COVID-19 has exposed the UK's vulnerability to labour shortages in digital skills and knowledge. Our findings demonstrate that grocery retailers should invest in digital skills and training for their employees to establish supply chain resilience efficiently. Our study indicates that managers in critical positions (e.g., fulfilment centres for online orders) should be bound up with people who possess excellent predictive analytics skills to respond effectively to global events, such as pandemics or supply chain disruption. We concur with other studies (Flynn et al., 2010; Knemeyer et al., 2009) that companies should allow their employees to maintain a good awareness of supply chain disruptions. Finally, in line with other recent studies (e.g., Queiroz et al., 2020; Münch and Hartmann, 2022), this work posits that companies should transform the resources (e.g., workforce) into emerging situations with interoperable capabilities.

6. Conclusion

This research explored how PA can assist in dealing with SCR in the retail supply chain (retail grocery stores). We argued that SCR could be interrelated when data-driven DT is applied and strengthened when integrating these analytical practices efficiently. We tested whether the effect of digital transformation and the level of supply chain resilience changes if we considered integrated PA as a mediator. However, we could only determine a minor impact. Our contribution lies in extending previous studies in the field of SCR with PA in the retail sector.

One limitation is that the study was based on a questionnaire for data collection, giving a snapshot time of the phenomenon under investigation. Hence, it may be useful to conduct qualitative and longitudinal studies to see the impact of PA on SC and the framework/dimensions used. Furthermore, it would be useful to examine the role of PA in different types of risk, such as reputational risk. Moreover, it may be useful to investigate the value of SCR's business analytics initiatives (and hence PA tools and processes). Finally, it would be interesting to examine our framework's applicability to industries other than retail. Last but not least, this work may intrigue other researchers or practitioners to examine whether the integration of predictive analytics could moderate the relationship between BD Capabilities and SC resilience.

Data availability

The authors are unable or have chosen not to specify which data has been used.

References

Akter, Wamba, Gunasekaran, Dubey, Childe, 2016. How to improve firm performance using big data analytics capability and business strategy alignment? Int. J. Prod. Econ. 182, 113–131.

Ali, A., Mahfouz, A., Arisha, A., 2017. Analysing supply chain resilience: integrating the constructs in a concept mapping framework via a systematic literature review. Supply Chain Manag. 22 (Issue 1) https://doi.org/10.1108/SCM-06-2016-0197.

Ambulkar, S., Blackhurst, J., Grawe, S., 2015. Firm's resilience to supply chain disruptions: scale development and empirical examination. J. Oper. Manag. 33, 111–122. https://doi.org/10.1016/j.jom.2014.11.002.

Ambulkar, S., Blackhurst, J.V., Cantor, D.E., 2016. Supply chain risk mitigation competency: an individual-level knowledge-based perspective. Int. J. Prod. Res. 54 (5), 1398–1411. https://doi.org/10.1080/00207543.2015.1070972.

Anderson, J.C., Gerbing, D.W., 1988. Structural equation modeling in practice: a review and recommended two-step approach. Psychol. Bull. 103 (3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411.

Azadegan, A., Mellat Parast, M., Lucianetti, L., Nishant, R., Blackhurst, J., 2020. Supply chain disruptions and business continuity: An empirical assessment. Decision Sciences 51 (1), 38–73.

Azadegan, A., Srinivasan, R., Blome, C., Tajeddini, K., 2019. Learning from near-miss events: an organizational learning perspective on supply chain disruption response. Int. J. Prod. Econ. 216, 215–226. https://doi.org/10.1016/j.ijpe.2019.04.021.

Bahrami, M., Shokouhyar, S., Seifian, A., 2022. Big data analytics capability and supply chain performance: the mediating roles of supply chain resilience and innovation. Modern Supply Chain Research and Applications 4 (1), 62–84. https://doi.org/10.1108/MSCRA-11-2021-0021.

Baines, T., Ziaee Bigdeli, A., Bustinza, O.F., Shi, V.G., Baldwin, J., Ridgway, K., 2017. Servitization: revisiting the state-of-the-art and research priorities. Int. J. Oper. Prod. Manag. 37 (2), 256–278. https://doi.org/10.1108/IJOPM-06-2015-0312.

Behzadi, G., O'Sullivan, M.J., Olsen, T.L., 2020. On metrics for supply chain resilience. Eur. J. Oper. Res. 287 (1), 145–158. https://doi.org/10.1016/j.ejor.2020.04.040.

Blome, C., Schoenherr, T., 2011. Supply chain risk management in financial crises - a multiple case-study approach. Int. J. Prod. Econ. 134 (1), 43–57. https://doi.org/10.1016/j.ijpe.2011.01.002.

Bode, C., Wagner, S.M., 2015. Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions. J. Oper. Manag. 36, 215–228. https://doi.org/10.1016/j.jom.2014.12.004.

Bode, Wagner, Petersen, Ellram, 2011. Understanding responses to supply chain disruptions: Insights from information processing and resource dependence perspectives. Acad. Manag. J. 54 (4), 833–856.

Brandon-Jones, A., Kauppi, K., 2018. Examining the antecedents of the technology acceptance model within e-procurement. Int. J. Oper. Prod. Manag. 38 (1), 22–42. https://doi.org/10.1108/IJOPM-06-2015-0346.

Brandon-Jones, E., Squire, B., Autry, C.W., Petersen, K.J., 2014. A contingent resource-based perspective of supply chain resilience and robustness. J. Supply Chain Manag. 50 (3), 55–73. https://doi.org/10.1111/jscm.12050.

Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., McFarlane, D., 2020. Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing. Int. J. Prod. Res. 58 (11) https://doi.org/10.1080/00207543.2019.1685705.

Brusset, X., Teller, C., 2017. Supply chain capabilities, risks, and resilience. Int. J. Prod. Econ. 184, 59–68. https://doi.org/10.1016/j.ijpe.2016.09.008.

Chopra, Sodhi, 2014. Reducing the risk of supply chain disruptions. MIT Sloan Manag. Rev. 55 (3), 72–80.

Chowdhury, M.M.H., Quaddus, M., 2016. Supply chain readiness, response and recovery for resilience. Supply Chain Manag. 21 (6), 709–731. https://doi.org/10.1108/SCM-12-2015-0463.

Churchill Jr., G.A., 1979. Paradigm of for developing constructs measures. J. Market. Res. 16 (1), 64–73.

Craighead, C.W., Blackhurst, J., Rungtusanatham, M.J., Handfield, R.B., 2007. The severity of supply chain disruptions: design characteristics and mitigation capabilities. Decis. Sci. J. 38 (1), 131–156. https://doi.org/10.1111/j.1540-5915.2007.00151.x.

Dillman, D.A., 2007. Mail and internet surveys: the tailored design method. In: Mail and Internet Surveys: the Tailored Design Method, second ed. 2nd ed.

Dubey, R., Gunasekaran, A., Childe, S.J., Fosso Wamba, S., Roubaud, D., Foropon, C., 2019. Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. Int. J. Prod. Res. 59 (1), 110–128. https://doi.org/10.1080/00207543.2019.1582820.

Dunn, S.C., Seaker, R.F., Waller, M.A., 1994. Latent variables in business logistics research: scale development and validation. J. Bus. Logist. 15 (2), 145.

Eckstein, D., Goellner, M., Blome, C., Henke, M., 2015. The performance impact of supply chain agility and supply chain adaptability: the moderating effect of product complexity. Int. J. Prod. Res. 53 (10) https://doi.org/10.1080/00207543.2014.970707.

el Baz, J., Ruel, S., 2021. Can supply chain risk management practices mitigate the disruption impacts on supply chains' resilience and robustness? Evidence from an empirical survey in a COVID-19 outbreak era. Int. J. Prod. Econ. 233 https://doi.org/10.1016/j.ijpe.2020.107972.

Fabrigar, L.R., Fabrigar, L.R., Wegener, D.T., Wegener, D.T., MacCallum, R.C., MacCallum, R.C., Strahan, E.J., Strahan, E.J., 1999. Evaluating the use of exploratory factor analysis in psychological research. Psychol. Methods 4 (3), 272–299. https://doi.org/10.1037/1082-989X.4.3.272.

Feki, M., Boughzala, I., Wamba, S.F., 2016. Big data analytics-enabled supply chain transformation: a literature review. In: Proceedings of the 2016 49th Hawaii International Conference on System Sciences (HICSS), pp. 1123–1132.

Flynn, B.B., Huo, B., Zhao, X., 2010. The impact of supply chain integration on performance: a contingency and configuration approach. J. Oper. Manag. 28 (1), 58–71.

Frohlich, M.T., Westbrook, R., 2001. Arcs of integration: an international study of supply chain strategies. J. Oper. Manag. 19 (2), 185–200.

Forbes, 2022. MANUFACTURING: Supply Chain and Logistics: Things to Watch in 2022 accessed on 10 August 2022 from: https://www.forbes.com/sites/willyshih/2021/12/22/supply-chain-and-logistics-things-to-watch-in-2022/.

Fuller, C.M., Simmering, M.J., Atinc, G., Atinc, Y., Babin, B.J., 2016. Common methods variance detection in business research. J. Bus. Res. 69 (8), 3192–3198.

Gable, 1994. Integrating case study and survey research methods: an example in information systems. Eur. J. Inf. Syst. 3 (2), 112–126.

Gawankar, S.A., Gunasekaran, A., Kamble, S., 2020. A study on investments in the big data-driven supply chain, performance measures and organisational performance in Indian retail 4.0 context. Int. J. Prod. Res. 58 (5), 1574–1593. https://doi.org/10.1080/00207543.2019.1668070.

Giannakis, M., Papadopoulos, T., 2016. Supply chain sustainability: a risk management approach. Int. J. Prod. Econ. 171, 455–470. https://doi.org/10.1016/j.ijpe.2015.06.032.

Gu, M., Yang, L., Huo, B., 2021. The impact of information technology usage on supply chain resilience and performance: an ambidexterous view. Int. J. Prod. Econ. 232 https://doi.org/10.1016/j.ijpe.2020.107956.

Hair Jr., J.F., Hult, G.T.M., Ringle, C., Sarstedt, M., 2014. A primer on partial least squares structural equation modeling (PLS-SEM). In: Long Range Planning, vol. 46. https://doi.org/10.1016/j.lrp.2013.01.002. Issues 1–2).

Hanelt, Bohnsack, Antunes Marante, 2021. A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. J. Manag. Stud. 58 (5), 1159–1197.

Hendricks, K.B., Singhal, V.R., 2003. The effect of supply chain glitches on shareholder wealth. J. Oper. Manag. 21 (5), 501–522. https://doi.org/10.1016/j.jom.2003.02.003.

Hendricks, Singhal, 2005b. Association Between Supply Chain Glitches and Operating Performance. Manag. Sci. 51 (5), 695. https://doi.org/10.1287/mnsc.1040.0353.

Hendricks, Singhal, 2005a. An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. Prod. Oper. Manag. 14 (1), 35–52. https://doi.org/10.1111/j.1937-5956.2005.tb00008.x.

Hohenstein, N.O., Feise, E., Hartmann, E., Giunipero, L., 2015. Research on the phenomenon of supply chain resilience: a systematic review and paths for further investigation. Int. J. Phys. Distrib. Logist. Manag. 45 (1/2), 90. https://doi.org/10.1108/IJPDLM-05-2013-0128.

Ivanov, D., 2020. Predicting the impacts of epidemic outbreaks on global supply chains: a simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transport. Res. E Logist. Transport. Rev. 136 https://doi.org/10.1016/j.tre.2020.101922.

Ivanov, Dolgui, 2020. Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. Int. J. Prod. Res. 58 (10), 2904–2915.

Ivanov, Dolgui, 2021. A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Prod. Plan. Control 32 (9), 775–788.

Ivanov, D., Dolgui, A., Sokolov, B., Ivanova, M., 2017. Literature review on disruption recovery in the supply chain. Int. J. Prod. Res. 55 (20), 6158–6174. https://doi.org/10.1080/00207543.2017.1330572.

Jacobs, B.W., Singhal, V.R., 2017. The effect of the Rana Plaza disaster on shareholder wealth of retailers: implications for sourcing strategies and supply chain governance. J. Oper. Manag. 49, 52–66.

Kache, F., Seuring, S., 2017. Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. Int Jrnl of Op & Prod Mnagemnt 37 (1), 10–36. https://doi.org/10.1108/IJOPM-02-2015-0078.

Kamalahmadi, M., Parast, M.M., 2016. A review of the literature on the principles of enterprise and supply chain resilience: major findings and directions for future research. Int. J. Prod. Econ. 171, 116–133. https://doi.org/10.1016/j.ijpe.2015.10.023.

Kim, Y., Chen, Y.S., Linderman, K., 2015. Supply network disruption and resilience: a network structural perspective. J. Oper. Manag. 33, 43–59. https://doi.org/10.1016/j.jom.2014.10.006.

Kline, R.B., 2013. Exploratory and confirmatory factor Analysis. In: Applied Quantitative Analysis in Education and the Social Sciences, pp. 169–207.

Knemeyer, A.M., Zinn, W., Eroglu, C., 2009. Proactive planning for catastrophic events in supply chains. J. Oper. Manag. 27 (2), 141–153. https://doi.org/10.1016/j.jom.2008.06.002.

Kock, F., Berbekova, A., Assaf, A.G., 2021. Understanding and managing the threat of common method bias: detection, prevention and control. Tourism Manag. 86, 104330.

Li, 2020. Leading Digital Transformation: Three Emerging Approaches for Managing the Transition. Int. J. Oper. Prod. Manag. 40 (6), 809–817.

Linnenluecke, M.K., 2017. Resilience in business and management research: a review of influential publications and a research agenda. Int. J. Manag. Rev. https://doi.org/10.1111/ijmr.12076.

Lopes de Sousa Jabbour, A.B., Chiappetta Jabbour, C.J., Hingley, M., Vilalta-Perdomo, E. L., Ramsden, G., Twigg, D., 2020. Sustainability of supply chains in the wake of the coronavirus (COVID-19/SARS-CoV-2) pandemic: lessons and trends. Modern Supply Chain Research and Applications 2 (3), 117–122. https://doi.org/10.1108/mscra-05-2020-0011.

MacCarthy, B.L., Blome, C., Olhager, J., Srai, J.S., Zhao, X., 2016. Supply chain evolution – theory, concepts and science. Int. J. Oper. Prod. Manag. 36 (12), 1696–1718. https://doi.org/10.1108/IJOPM-02-2016-0080.

Macdonald, J.R., Zobel, C.W., Melnyk, S.A., Griffis, S.E., 2018. Supply chain risk and resilience: theory building through structured experiments and simulation. Int. J. Prod. Res. 56 (12), 4337–4355. https://doi.org/10.1080/00207543.2017.1421787.

Mikalef, P., Boura, M., Lekakos, G., Krogstie, J., 2019. Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. Br. J. Manag. 30 (2), 272–298. https://doi.org/10.1111/1467-8551.12343.

Mikalef, Pappas, Krogstie, Pavlou, 2020. Big data and business analytics: A research agenda for realizing business value. Inf. Manag. 57 (1), 103237.

Mikalef, P., Pateli, A., 2017. Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: findings from PLS-SEM and fsQCA. J. Bus. Res. 70, 1–16. https://doi.org/10.1016/j.jbusres.2016.09.004.

Morrice, D.J., Cronin, P., Tanrisever, F., Butler, J.C., 2016. Supporting hurricane inventory management decisions with consumer demand estimates. J. Oper. Manag. 45, 86–100. https://doi.org/10.1016/j.jom.2016.05.006.

Münch, Hartmann, 2022. Transforming resilience in the context of a pandemic: results from a cross-industry case study exploring supply chain viability. Int. J. Prod. Res. ahead-of-print, 1–19.

Narasimhan, R., Talluri, S., 2009. Perspectives on risk management in supply chains. J. Oper. Manag. 27 (2), 114–118. https://doi.org/10.1016/j.jom.2009.02.001.

Nunes, M.F., Park, C.L., Paiva, E., 2021. Keeping key suppliers alive during the COVID-19 pandemic: artificial supply chain resilience and supplier crisis response strategies. Continuity & Resilience Review 3 (3), 282–299.

Nunnally, J., 1978. Psychometric Theory. McGraw-Hill, New York. https://doi.org/10.1037/018882.

Oke, Burke, Myers, 2007. Innovation types and performance in growing UK SMEs. Int. J. Oper. Prod. Manag. 27 (7), 735–753.

Osborne, J.W., 2015. What is rotating in exploratory factor Analysis? Practical Assess. Res. Eval. 20 (2), 1–7. https://doi.org/10.1037/e558952014-001.

Osborne, J.W., Costello, A.B., 2005. Best practices in exploratory factor Analysis : four recommendations for getting the most from your analysis. Practical Assess. Res. Eval. 10 (7), 1–9.

Papadopoulos, T., Gunasekaran, A., Dubey, R., Altay, N., Childe, S.J., Fosso-Wamba, S., 2016. The role of Big Data in explaining disaster resilience in supply chains for sustainability. J. Clean. Prod. 142, 1108–1118. https://doi.org/10.1016/j.jclepro.2016.03.059.

Park, M., Singh, N.P., 2022. Predicting supply chain risks through big data analytics: role of risk alert tool in mitigating business disruption. Benchmark Int. J. https://doi.org/10.1108/BIJ-03-2022-0169 (ahead-of-print).

Parker, H., Ameen, K., 2018. The role of resilience capabilities in shaping how firms respond to disruptions. J. Bus. Res. 88, 535–541. https://doi.org/10.1016/j.jbusres.2017.12.022.

Peck, H., 2005. Drivers of supply chain vulnerability: an integrated framework. Int. J. Phys. Distrib. Logist. Manag. 35 (4), 210–232.

Petersen, H.L., Lemke, F., 2015. Mitigating reputational risks in supply chains. Supply Chain Manag. 20 (5), 495.

Peterson, R.A., 2013. A Meta-analysis of alpha Cronbach ' s coefficient. J. Consum. Res. 21 (2), 381–391.

Pettit, T.J., Croxton, K.L., Fiksel, J., 2019. The evolution of resilience in supply chain management: a retrospective on ensuring supply chain resilience. J. Bus. Logist. 40 (1), 56–65. https://doi.org/10.1111/jbl.12202.

Phadnis, S.S., Sheffi, Y., Caplice, C., 2022. Strategic Planning for Dynamic Supply Chains: Preparing for Uncertainty Using Scenarios. Springer Nature.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88 (5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879.

Ponomarov, S.Y., Holcomb, M.C., 2009. Understanding the concept of supply chain resilience. Int. J. Logist. Manag. 20 (1), 124–143. https://doi.org/10.1108/09574090910954873.

Queiroz, M.M., Ivanov, D., Dolgui, A., 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. Ann. Oper. Res. 1–38. https://doi.org/10.1007/s10479-020-03685-7.

Raman, S., Patwa, N., Niranjan, I., Ranjan, U., Moorthy, K., Mehta, A., 2018. Impact of big data on supply chain management. Int. J. Logist. Res. Appl. 21 (6), 579–596. https://doi.org/10.1080/13675567.2018.1459523.

Remko, van H., 2020. Research opportunities for a more resilient post-COVID-19 supply chain – closing the gap between research findings and industry practice. Int. J. Oper. Prod. Manag. 40 (2), 341–355.

Revilla, E., Saenz, M.J., 2017. The impact of risk management on the frequency of supply chain disruptions: a configurational approach. Int. J. Oper. Prod. Manag. 37 (5), 557–576. https://doi.org/10.1108/IJOPM-03-2016-0129.

Rindova, Williamson, Petkova, Sever, 2005. Being good or being known: An empirical examination of the dimensions, antecedents, and consequences of organizational reputation. Acad. Manag. J. 48 (6), 1033–1049.

Scholten, K., Scott, P.S., Fynes, B., 2014. Mitigation processes - antecedents for building supply chain resilience. Supply Chain Manag. 19 (2), 211–228. https://doi.org/10.1108/SCM-06-2013-0191.

Scholten, Stevenson, van Donk, 2019. Dealing With the Unpredictable: Supply Chain Resilience. Int. J. Oper. Prod. Manag. 40 (1), 1–10.

Shankar, V., 2018. How artificial intelligence (AI) is reshaping retailing. J. Retailing 97 (1), 28–41. https://doi.org/10.1016/s0022-4359(18)30076-9.

Sharma, A., Adhikary, A., Borah, S.B., 2020. Covid-19′s impact on supply chain decisions: strategic insights from NASDAQ 100 firms using Twitter data. J. Bus. Res. 117, 443–449. https://doi.org/10.1016/j.jbusres.2020.05.035.

Sheng, J., Amankwah-Amoah, J., Khan, Z., Wang, X., 2020. COVID-19 pandemic in the new era of big data analytics: methodological innovations and future research directions. Br. J. Manag. 32 (4), 1164–1183.

Singh, Singh, 2019. Interplay of organizational justice, psychological empowerment, organizational citizenship behavior, and job satisfaction in the context of circular economy. Manag. Decis. 57 (4), 937–952.

Teece, D.J., 2012. Dynamic capabilities: routines versus entrepreneurial action. J. Manag. Stud. 49 (Issue 8) https://doi.org/10.1111/j.1467-6486.2012.01080.x.

Teece, D.J., Pisano, G., Shuen, A., 1997. Dynamic capabilities and strategic management. Strat. Manag. J. 18 (7) https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z.

Tukamuhabwa, B., Stevenson, M., Busby, J., 2017. Supply chain resilience in a developing country context: a case study on the interconnectedness of threats, strategies and outcomes. Supply Chain Manag. 22 (6), 486–505. https://doi.org/10.1108/SCM-02-2017-0059.

Um, Han, 2021. Understanding the relationships between global supply chain risk and supply chain resilience: The role of mitigating strategies. Supply Chain Manag. 26 (2), 240–255.

Vial, 2019. Understanding digital transformation: A review and a research agenda. J. Strat. Inf. Syst. 28 (2), 118–144.

Vidgen, Shaw, Grant, 2017. Management challenges in creating value from business analytics. Eur. J. Oper. Res. 261 (2), 626–639.

Wamba, S.F., Dubey, R., Gunasekaran, A., Akter, S., 2020. The performance effects of big data analytics and supply chain ambidexterity: the moderating effect of environmental dynamism. Int. J. Prod. Econ. 222 https://doi.org/10.1016/j.ijpe.2019.09.019.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J., Dubey, R., Childe, S.J., 2017. Big data analytics and firm performance: effects of dynamic capabilities. J. Bus. Res. 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009.

Wang, G., Gunasekaran, A., Ngai, E.W.T., Papadopoulos, T., 2016. Big data analytics in logistics and supply chain management: certain investigations for research and applications. Int. J. Prod. Econ. 176, 98–110. https://doi.org/10.1016/j.ijpe.2016.03.014.

Wicaksana, A., Ho, W., Talluri, S., Dolgui, A., 2022. A decade of progress in supply chain risk management: risk typology, emerging topics, and research collaborators. Int. J. Prod. Res. 1–23.

Wilson, M.C., 2007. The impact of transportation disruptions on supply chain performance. Transport. Res. E Logist. Transport. Rev. 43 (4), 295–320. https://doi.org/10.1016/j.tre.2005.09.008.

Wu, T., Blackhurst, J., O'Grady, P., 2007. Methodology for supply chain disruption analysis. Int. J. Prod. Res. 45 (7), 1665–1682. https://doi.org/10.1080/00207540500362138.

Yu, W., Jacobs, M.A., Chavez, R., Yang, J., 2019. Dynamism, disruption orientation, and resilience in the supply chain and the impacts on financial performance: a dynamic capabilities perspective. Int. J. Prod. Econ. 218, 352–362. https://doi.org/10.1016/j.ijpe.2019.07.013.

Zsidisin, G.A., Wagner, S.M., 2010. DO perceptions become reality? The moderating role of supply chain resiliency on disruption occurrence. J. Bus. Logist. 31 (2), 1–20. https://doi.org/10.1002/j.2158-1592.2010.tb00140.x.