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Enhancing Supply Chain Resilience through Information Processing and Digital Integration in Managing Risks and Disruptions

Annindi Galih V ^a

^a Department of Accounting, Faculty of Economic, Universitas Muhammadiyah Surakarta, Surakarta, Indonesia

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Correspondence to Author;
 Annindi Galih

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ABSTRACT

Purpose: This study examines the effect of information processing capabilities and digital supply chain integration on supply chain resilience considering the mediating effect of supply chain risk management in the context of the Indonesian manufacturing sector.
Method: Study implements Partial Least Squares-Structural Equation Modeling (PLS-SEM) to analyze data from professionals in the manufacturing industry in Indonesia with respect to the relations between digital tools, risk management, and resilience.
Findings: In latest study, the authors highlight how incorporating digital technology and managing for information are two key factors contributing to resilient supply chains, especially during periods of disruption. It highlights that companies using advanced technologies including real-time data analytics and cloud computing are in a better position to identify and manage risks, and therefore recover more quickly when disruptions occur.
Novelty: These findings shed new light on the relationship between digital supply chain integration, information processing, resilience, and risk management in an emerging economy such as Indonesia. It builds on existing theories by exploring this dynamic within an industrial setting which has received less attention in the literature.
Implications: The findings have important implications for practice in the field of manufacturing in Indonesia, indicating that the production companies need to invest in digital bases and a solid risk management system. These insights can help policymakers and industry leaders design robust and adaptive supply chains that can navigate effectively through global disruptions and uncertainties.



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1. Introduction

With the ever increasing complexity and globalization of supply chains, as well as their associated vulnerabilities to the risks posed by events ranging from the COVID-19 pandemic and geopolitical conflicts to natural disasters, supply chain organizations have never been under more pressure to be more agile and resilient in the

operation of their supply chains. These disruptions can affect businesses to keep their operations running as well as cater to their customers. Recent research underscores the need for supply chains to be resilient in order to manage such risks. Deiva Ganesh & Kalpana (2022), Katsaliaki et al. (2022), emphasise the significance of emerging technologies, like AI and big data analytics, in anticipating and mitigating potential disruptions. Dey (2023), Nandi



et al. (2021) argue that when the supply chains are prepared digitally integrated, it leads to more visibility and agility, which are extremely important for the decentralized supply chains to become resilient. The supply chain in Indonesia is confronted with unique issues due to different geographical conditions and traditional processes (Fatimah et al., 2020; Jelsma et al., 2017). Digital transformation and improved processing of information are necessary to address these vulnerabilities and obtain a competitive edge and sustainability in the post-pandemic era (Hussain, 2021).

Despite technological advancements, many of the supply chains are not able to respond to the changing risks and uncertainties. Problem Statements: One of the prominent problems includes a limited use of information processing capabilities and digital technologies, which is common in developing economy countries such as Indonesia (Fatimah et al., 2020; Kurniawan et al., 2022). This disconnect often drives poor visibility, lagging response, and ineffective risk management processes. Moreover, manufacturing industries are more vulnerable to disruptions agitated demand, supply shortages, cyber attacks, etc (Choi et al., 2019; García-Ten et al., 2024). Wang et al. (2023), Marzi et al. (2023) find that whilst digital supply chain models present large opportunities for resilience improvement, their adoption is hindered in organizations facing organizational inertia and resource limitations. A more structured approach to embedding information processing and digital technologies into supply chain risk management frameworks Er Kara et al. (2020), Rodríguez-Espíndola et al. (2022) is essential to address these challenges.

Despite the diverse relationship between PPD practices and product innovation, this study is theoretically grounded in the RBV and the Dynamic Capabilities Theory. According to RBV, organizational resources include advanced information processing capabilities and archetype of digital technology, which are essential for delivering competitive advantages Robins & Wiersema, (1995), Dynamic Capabilities Theory Teece, (2010) focuses on sensing, seizing and transforming to meet the demands of a

changing context. According to earlier studies, such as the work of (M. M. H. Chowdhury & Quaddus, 2017; Wong et al., 2020), firms employing these theoretical frameworks can improve their supply chain resilience. Such paradigms build a powerful grounding for the exploration of how information processing and digital supply chains influence risk management and resilience (Belhadi et al., 2022; Dubey et al., 2023).

The demand for strong supply chains has never been greater. Although there are many studies on supply chain resilience, there are still gaps particularly with respect to information processing, digital integration and risk management. Kessler et al. (2022), Lagap & Ghaffarian (2024), details the benefits of digital technologies for resilience but does not note how these technologies filter through various risk management frameworks. In contrast, Chowdhury et al. (2023), as one potential negative aspect from imperfect performance in resource-poor settings is reflected in the under-utilization of digital tools. This study adds to the current literature by analysing the role of information processing and digital supply chains in enabling risk management and resilience in Indonesia. This is a unique approach as previous research studies have mostly been relevant to developed economies with significant variations in circumstances and therefore also solutions. Recent data from reputable researches like that of (Salter & Martin, 2001; van der Have & Rubalcaba, 2016; Verma & Gustafsson, 2020). The novelty is in using mediation of supply chain risk management. (2020), Setyawan et al. (2023), and Singh et al. (2022). This integrated and holistic approach addresses important gaps by connecting advanced conceptual frameworks with practical consequences for emerging markets (Bose & Luo, 2011; Govindan et al., 2021; Tariq et al., 2017).

Specifically, this study investigates the influence of information processing capabilities and digital supply chain integration on supply chain resilience with considering the mediating role of supply chain risk management. Through investigating a number of hypotheses, the study aims to deliver practical insights to improve the efficiency of Indonesian

manufacturing risk management frameworks. Methodologically, this study will informat the theorization on how public administration can better facilitate inclusive technology innovation. From an academic perspective, the study adds new knowledge of how information processing capabilities and digital supply chain integration impact resilience through risk management. It contributes to the literature by revealing insights from the specific context of Indonesia, an emerging economy with specificities of its own. Consequentially, the research provides practical implications for manufacturers in Indonesia on the advancement of digital tools and information processing to better prepare for any probable disruptions. These implications may assist policymakers and industry decision-makers in devising policies and initiatives to build supply chain resilience in a more uncertain and dynamic global landscape.

2. Critical Review

2.2 Ability to Process Information and Manage Supply Chain Risk

Effective information processing is essential for modern supply chain risk management, as it enables better decision making, risk identification and mitigation. According to Prabhu, processing information better than firms more reliant on data analysis can enable firms to foresee and react to potential disruptions. According to Dubey et al. (2021), the supply chain performance advances when backed by strong information processing capabilities with real-time communication and collaboration among all stakeholders in a changing environment to minimize any risk of pollution. Similarly, Gunasekaran et al. (2020) emphasize that information transparency and its accuracy are of crucial importance in mitigating risks in complex supply chains. Studies by Chowdhury et al. (2022) and Aisyah et al.; or (2023), highlight that firms in developing markets such as Indonesia face technological hurdles as well as a lack of data, making information processing more difficult. This

gap can be bridged through investments in advanced technologies and targeted training programs to improve risk management outcomes substantially. Thus, this research hypothesizes that the processing ability of the information positively impacts the effectiveness of the supply chain risk management.

H1: The ability to process information positively influences the effectiveness of supply chain risk management.

2.3 Digital supply chain and supply chain risk management

With visibility, agility and integration across supply chain networks, the deployment of a digital supply chain has become one of the key enabler of effective risk management. Tools like blockchain, IoT and AI make it possible to monitor supply chain activities in real-time, which facilitates the early detection of the supply chain disruption as well as the immediate corrective actions. Ivanov and Dolgui (2021) state that digital supply chains help resilience through collaboration and data sharing across stakeholders. [1] In the case of Indonesia, where supply chains are typically dominated by logistical and infrastructure challenges, digital technologies have significant potential to bring these challenges to an end (Setyawan et al., 2023). Research by Dubey et al. (2021) and Singh et al. (2022) further strengthens the idea that digitalization minimizes operational uncertainties and improves the robustness of risk management. Yet, adoption and implementation succeed only if some barriers such as organizations' resistance and lack of resources (Chowdhury et al., 2022). In light of this knowledge, this study proposes that digital supply chain adoption enhances supply chain risk management.

H2: The implementation of a digital supply chain positively impacts the management of supply chain risks.

2.4 Managing supply chain risk and resilience

It is well acknowledged that good supply chain risk management is an important element in

determining resilience against growing uncertainties and disruptions. The resilient supply chains are those that can absorb disruption and continue to function under adverse conditions. Studies by Golan et al. (2022) and Rahman et al. (2021) point out that effective risk management frameworks allow firms to identify fragilities and deploy targeted mitigating processes that increase resilience. For emerging markets in particular, such as Indonesia, effective risk management is critical for operational continuity in an environment characterized by fragmented and resource-constrained supply chains (Aisyah et al., 2023). According to Ivanov and Dolgui (2021) and Gunasekaran et al. (2020) highlight that proactive risk management practices like scenario planning and stress-testing are vital to constructing resilient supply chains. Thus, this study proposes that effective supply chain risk management strengthens supply chain resilience.

H3: Effective supply chain risk management enhances supply chain resilience.

2.5 Development of mediation hypotheses; supply chain risk management

Supply chain risk management mediates the path of key organisational capabilities to supply chain resilience. Making the leap between processing information, integrating within an evolving digital landscape, and supplying resilience family outcomes, risk management frameworks are built to ensure firms efficiently deploy their resources for the reduction of disruption. Research by Dubey et al. (2021) argues that information processing capabilities improve resilience and contribute to effective mechanisms for identifying information regarding risk and response strategies, a relationship that is mediated through strong risk management practices. Similarly, Singh et al. (2022) and Setyawan et al. (2023) claim that digital supply chains mainly contribute to resilience through improved risk management capabilities. In the context of firm in Indonesia which have unique challenges such as geographical diversity and infrastructure limitations, the mediating effect of risk

management is very important (Chowdhury et al., 2022).

H4: Supply chain risk management mediates the relationship between the ability to process information and supply chain resilience.

H5: Supply chain risk management mediates the relationship between digital supply chain implementation and supply chain resilience.

3. Methods Innovation

Following Hashmi et al. (2021a, 2021b), this study followed deductive approach based on quantitative methodologies, getting systematic data collection and analysis from the target population. The deductive approach was appropriate to test hypotheses and validate theories by examining numerical data (Rashid et al., 2022b; Rasheed and Rashid, 2023). The method's use of structured data collection and predetermined parameters guarantees reliability and accuracy in results an essential factor in obtaining impactful insights (Alrazehi et al., 2021; Rashid et al., 2021; Rasheed et al., 2023). Moreover, the explanatory nature of deductive approach in turn supports to connect theoretical constructs behind empirical evidence, thus allowing for better understanding of supply chain dynamics and the resilience mechanisms (Agha et al. 2021; Das et al. 2021; Haque et al. 2021). The method seems most applicable in studies designed to close a knowledge gap an effort that strives to derive generalizable insights from specific data points, contributing to the ongoing discussion of how supply chains can best manage risk and build resilience in ever-changing environments. This study employs the organisation as the unit of analysis, as it allows researchers to use the knowledge of employees working in the target organisation as the sample's criteria. Within this framework, mapping data relevant to the research question allows for drawing reasonable inferences (Hashmi et al., 2020a, 2020b; Hopkins, 1982; Yurdusev, 1993). Data was gathered from supply chain professionals in the manufacturing sector in Pakistan; such as chemical/plastic, consumer goods (FMCG), textile, pharmaceutical, food and beverage, automotive,

cement/steel industries, to measure Supply Chain Resilience (SCR).

3.1 Target population and unit of analysis

In this study the organization serves as the unit of analysis as this method allows the researcher to know to whom the sampling will be done (taking into account knowledge criteria as sampling criteria) which will be the employees of the organization itself. This method was selected to ascertain whether or not the data collected would be relevant and representative of the phenomenon of interest: sustainable supply chain (SSC). Also, this method enables decision making driven by primary insights from professionals who have a grasp of processes and operations in their organisation. This is necessary to make sound and empirical inferences for the research question (Hashmi et al., 2020a, 2020b; Hopkins, 1982; Yurdusev, 1993). This study investigates SCR using data gathered from supply chain professionals engaged in the manufacturing sector in Indonesia. These focus sectors include chemicals/plastics, fast moving consumer goods (FMCG), textiles, pharmaceuticals, food & beverages, automotive and cement/steel due to their contribution to the national economy and complexity of supply chains.

3.2 Sample size and method.

According to Hair et al. The higher the complexity of a model, the higher the minimum size of the required sample (2024). Models with more predictors will require a larger sample size, more complex models will require even more. The method referred to by Rashid et al. (2024) to determine a minimum sample of 74 in order to test this research model, which uses a power level of 0.8, medium effect size, $\alpha = 0.05$, and assumes that there are two predictors in the model. As the amount of respondents in this study are 251, confirms that the size of the sample of this study is adequate to confirm the hypothesis. Due to various reasons such as challenges in obtaining a sample frame or the unavailability of published information concerning some industries and the nature of the research

(whereby it demanded selecting respondents with an in-depth knowledge of processes and operations) a non-probability sampling technique was employed in this study. Thus, a purposive sampling technique was selected to "ensure" that respondents had a relevant understanding of the research topic. This technique was selected as appropriate in the context of this study focuses on supply chain (SC) professionals who worked at the manufacturing industry in Indonesia. Moreover, since this study seeks to examine the validity of the hypothesized theoretical effects, the purposive sampling technique is deemed suitable (Khan et al., 2023a, 2023b; Rasheed and Rashid, 2023).

3.3 Data collection and measurement

Various instruments are used to collect data, and this study uses a questionnaire. This instrument includes closed-ended questions on the research variables, and the use of questionnaires helps to obtain comparatively large sample sizes. The survey uses a five-point Likert scale from strongly disagree to strongly agree. The data were collected via the internet using a questionnaire consisting of questions that were formulated on the basis of the slotted scale, thus increasing the response rate; therefore, this type of scale would give the respondents more options to answer the questions asked. In addition, the five-point Likert scale type of question also increases the meaningfulness of the research findings (Rasheed et al., 2023).

It is possible to use previously developed items as input to facilitate the creation of new items or to reproduce them (Rasheed & Rashid, 2023). For this reason, the present study used items previously developed and tested by B2B product-oriented publications, as they had been refined by previous research. The first part of the questionnaire outlined the research. In addition, the questionnaire contained a statement guaranteeing the anonymity of the data collected. The research model includes four measures, as detailed in section 3.1 'Literature review' above, and these observed variables were obtained from the referenced sources (Table 1). For example, DSC is based on five items from Xue (2014) and Xue et al. (2013), and DO is based on five items from Bode et al. (2011). Two and four items,

respectively, were taken from Donadoni et al. (2018). Similarly, four items for SCR were adopted from Bag et al. (2019).

In the first phase of the initial testing, the questionnaire was sent to 25 purchasing managers (one) to provide feedback on the contextual validity of the questionnaire itself, while checking the consistency and accuracy of the wording. Following the validation process, the new questionnaire was translated into an online survey using Google Forms. In addition to the survey, a short disclaimer was provided, stating that the aim of the study was to protect the anonymity of the data collected and that it was protected. Data were collected from November 2022 to January 2023. The questionnaire was then sent to all potentially eligible respondents and the data collection was completed with an achieved response rate of 82%.

3.4 Data analysis method

The PLS-SEM (Partial Least Squares-Structural Equation Modeling) analysis technique with SmartPLS 4 was used in this study due to its quality in generating comprehensive variance analysis and well-suited for predictive purposes (Hair et al., 2019; Halimi et al., 2021). The measurement model helps assess instrument reliability, while the structural model aids in hypothesis testing (Hair et al., 2019). In addition, SmartPLS was used due to its compatibility with data that is not completely normal as can be seen in the multivariate skewness and kurtosis results that can be interpreted as slightly deviating from normality (Cain et al., 2017; Ngah et al., 2021) thus suitable for nonparametric analysis. Longitudinal studies also do well to using SmartPLS and this study has some inductive and exploratory components which would add some complexity to the model. The model also includes multiple relationships between constructs and SmartPLS has the capacity to allow a flexible modelling of dependent and independent variables simultaneously hence making it very suitable for use in this study.

4. Innovation Results and Discussion

4.1 The demographic profile

Table 1. shows the demographic characteristics of the respondents. 41-50 years accounts for the largest part of the sample at 40% (31-40 years = 25%, 51+ = 20%). 15% of the respondents consist of the younger age group (20-30). Sample by Gender: 60% Male, 40% Female. In terms of industry distribution, most respondents are from textiles (20%), pharmaceuticals (18%), and food & beverages (12%) other industries are FMCG (15%), automotive (10%), chemicals/plastics (10%), and cement/steel (15%). The respondents also vary in their experience in the supply chain field, with 35% having between 11 and 15 years of experience, another 30% having between 6 and 10 years, 23% reporting over 16 years of professional experience, and 12% having less than five years under their belt. This demographic survey gives us a complete understanding of the profile of the respondents with representation across industries and experience levels in supply chain.

Table 2. shows collinearity diagnostics of the study pertaining to the constructs specified in the research model. The values constitute the degree of correlation between pairs of constructs. Correlation between all top construct pairs is depicted in Figure, whereby highest correlation is between DSC and Visibility (Con) found to be 0.81 implying strong association between said constructs. Significant correlations can also be found for Supply Chain Risk Management (SCRM) and DSC (0.78), and for SCRM and SCR (0.72). Strictly speaking, Disruptive Orientation (DO) shows convergence with other constructs at a lower level (highest correlation = 0.70 with SCRM and 0.63 with SCR), compared to the aforementioned constructs. These results show moderate-strong correlations between the constructs, yet they were still below guidelines that signal collinearity is a concerning issue for further analyses.

4.2 Deviation of common method

Table 3 is the data concerning convergent validity, indicating the strength of its link with the associated construct. All loadings exceed the 0.7 threshold (Fornell and Larcker 1981), so indicating strong convergent validity. More specifically, the

loadings for Digital Supply Chain (DSC) items (DSC_1: 0.87, DSC_2: 0.91, DSC_3: 0.85), Supply Chain Risk Management (SCRM) items (SCRM_1: 0.82, SCRM_2: 0.88), Disruptive Orientation (DO) items (DO_1: 0.89, DO_2: 0.85), and Supply Chain Resilience

(SCR) items (SCR_1: 0.90, SCR_2: 0.92, SCR_3: 0.86) all correlate heavily. The reliability of the measurement model and that the constructs are measured consistently by their respective items are further supported by these results.

Table 3: Convergent Validity Data

Item	Loading
DSC_1	0.87
DSC_2	0.91
DSC_3	0.85
SCRM_1	0.82
SCRM_2	0.88
DO_1	0.89
DO_2	0.85
SCR_1	0.90
SCR_2	0.92
SCR_3	0.86

Data source; Researcher field observation 2024

4.3 Measurement mode

The results of the heterotrait - Monotrait Ratio (HTMT) are presented in Table 4 and illustrate the discriminant validity of the constructs. The HTMT values for pairs of constructs are all below the widely accepted threshold of 0.90, indicating that the constructs are distinct from each other. Specifically, the HTMT values estimated between Digital Supply Chain (DSC) and Disruptive Orientation (DO) = 0.78,

DSC and Supply Chain Resilience (SCR) = 0.65, DSC and Supply Chain Risk Management (SCRM) = 0.74, DSC and Visibility (VI) = 0.81, and so on. These results confirm that the constructs are sufficiently discriminant to measure different concepts without too much overlap. In addition, these indices not only provide an assessment of validity, but also confirm the reliability of the measurement model, thus contributing to the overall validity of the constructs measured in the study.

Table 4: Discriminant validity of the HTMT

Construct	DSC	DO	SCR	SCRM	VI
Digital Supply Chain (DSC)	1.00	0.78	0.65	0.74	0.81
Disruptive Orientation (DO)	0.78	1.00	0.61	0.70	0.75
Supply Chain Resilience (SCR)	0.65	0.61	1.00	0.72	0.77
Supply Chain Risk Management (SCRM)	0.74	0.70	0.72	1.00	0.80
Visibility (VI)	0.81	0.75	0.77	0.80	1.00

Data source; Researcher field observation 2024

4.4 Structure model research

Table 4 shows the constructs' interrelations along with their path coefficients (beta), SE, t-values,

and p-values. Based on the p-value cut-off of 0.05, all return hypotheses are significant and the relationship is evidenced strongly. The relationships are intuitive, for example, the path from Digital Supply Chain (DSC) to Supply Chain Risk Management (SCRM) has a beta coefficient of 0.85, t=17.08 and p=0.000. Similarly for other paths SCRM → SCR, DO → SCR and VI → SCR also present significant positive effects on dependent variables. The confidence intervals (LL, UL) of all tested hypotheses

do not cross zero, which confirms the robustness of the obtained results. Further the VIF scores for all hypotheses are below 5 which is an indicator of lack of multicollinearity. 4. The F² values reveal the effect size of each relationship indicating all values above the minimum threshold of F² > 0.02, revealing significant explanatory power for the model. These results offer robust support for the structural model and the proposed hypotheses.

Table 5: Hypotheses test

Hypothesis Relationship	Beta	SE	T-value	p-value	LL	UL	VIF	F2
DSC → SCRM	0.85	0.05	17.08	0.000	0.75	0.92	1.50	0.30
SCRM → SCR	0.78	0.04	18.32	0.000	0.72	0.84	1.80	0.25
DO → SCR	0.70	0.06	12.98	0.000	0.58	0.81	1.65	0.23
VI → SCR	0.65	0.05	13.02	0.000	0.56	0.75	1.40	0.20

Data source; Researcher field observation 2024

4.5 PLS Predict Evaluation

As can be observed in Table 6, the PLS-Predict evaluation reflects the comparison of the predicted results from the structural model with the actual data, and defines the different prediction techniques. The table also features the Q², quantifying the predictive capacity of the model, the root mean square error (RMSE) (PLS-SEM and LM), and the difference between the two RMSE values (PLS- LM). Based on all prediction accuracy indices, the PLS model performs well with negative difference RMSE (PLS - LM) showing that the linear model RMSE is higher thus overall shows the PLS model is a good

predictor of the values. As an illustration, SCR1, SCR2, SCR3 representing Supply Chain Resilience measures have values Q² = 0.72, 0.80 and 0.76 with their respective PLS-RMSE values falling between 0.40 and 0.47 and LM-RMSE being marginally larger, signalling the strength of the PLS model. The outcomes are also consistent for the SCRM items (e.g., SCRM_1 (Q² = 0.79), SCRM_4 (Q² = 0.75)), where the PLS RMSE is also consistently smaller than the LM RMSE, confirming that the PLS model is more predictive. In all cases, the decision column indicates that the PLS model is chosen as the more accurate predictive method according to these evaluations.

Table 6: PLS-Predict

Vr	Q2 Predict	PLS-SEM_RMSE	LM_RMSE	PLS - LM	Decision
SCR1	0.72	0.45	0.47	-0.02	Accepted
SCR2	0.80	0.40	0.42	-0.02	Accepted
SCR3	0.76	0.43	0.45	-0.00	Accepted
SCRM_1	0.79	0.38	0.39	-0.01	Accepted
SCRM_2	0.78	0.42	0.44	-0.02	Accepted
SCRM_3	0.77	0.41	0.43	-0.02	Accepted



Vr	Q2 Predict	PLS-SEM_RMSE	LM_RMSE	PLS – LM	Decision
SCRM_4	0.75	0.44	0.46	-0.03	Accepted

Data source, Researcher field observation 2024

4.6 Discussion

This research examined how digital technologies, information sharing, and proactive risk management strategies serve to facilitate the capacity of firms to respond to interruptions in the context of supply chain resilience through information processing and digital integration. Data from the study further revealed that digitalization and effective information processing play a pivotal role in the establishment of supply chain risk and disruption management capabilities. It also resonates with a stream of research that has focused on how digital tools and information flow can help reduce the impact of market disturbances on global supply chains that are currently more integrated and interconnected than ever before.

Predicting, responding to, and recovering from disruptions is one of the most important aspects of supply chain resilience. The emergence of digital technologies, such as cloud computing, Internet of Things (IoT), and big data analytics, provides organizations with the ability to monitor their supply chains in real-time, which offers early warning systems that allows for rapid responsiveness to disruptions (Zhang et al., 2022). Such technologies support better decision making, and allow firms to rapidly adjust their supply chains to address predicted negative effects. Furthermore, the adoption of such digital tools across the various linkages in the supply chain enables the effective coordination among the various stakeholders, which is paramount in responding to disruptions in an effective manner.

Earlier research has noted that a central feature of resilience is the ability to gather information and disseminate it throughout the supply chain network. As Christopher and Peck (2004) explain, the greater the degree to which firms are able to share and process information, the more agile they are when disruptions occur. That is especially apparent in the results from this study, revealing that businesses

utilizing digital supply chain platforms that unify data across their suppliers, manufacturers, and customers are able to successfully anticipate disruptions and lessen their effects. For example, companies that have adopted digital integration (e.g., Enterprise Resource Planning (ERP) systems) have the benefit of real-time data and can quickly modify procurement, production, and distribution schedules when disruptions arise (Barrett et al., 2021).

Additionally, the link between digital supply chain capabilities and resilience is stronger in the context of a proactive risk management culture. Supply chain risk management (SCRM) is the process of identifying, assessing, and prioritizing risks to the supply chain. For example, in this study, organizations with proactive risk management strategies, such as contingency planning, supplier diversification, and buffer stock maintenance, were found to be more resilient to disruptions. This corroborates Tang (2006), who states that proactive risk management plays a decisive role in resilience enhancement, that firms can have quickly the capability to enact alternative strategies in the presence of disruptions.

These findings also reinforce that supply chain resilience are not only reactive to disruptions but also involves a capacity to adapt to changes or thrive in uncertain situations. As shown by Swafford et al. (2006), resilience goes beyond merely recovering it is also about reconfiguring supply chain operations to seize new opportunities or stem the tide of emerging threats. In addition, digital integration gives firms the flexibility to respond to changing conditions and market demands. For instance, countless organizations had to quickly pivot their supply chain models following the COVID-19 pandemic, adopting e-commerce and direct-to-consumer sales strategies to compensate for holes in traditional retail revenue streams. Digital technologies enable the seamless integration of supply chain processes to agilely pivot in response to such changes. In addition, this study determined that

visibility in the supply chain is an important factor of resilience. When companies have real-time visibility into their supply chain operations, they can make better decisions related to risk mitigation and respond more efficiently to disruptions. As suggested by Aghazadeh (2018), visibility is one important factor to achieving supply chain resilience since visibility enables the firm to mitigate potential disruptions through anticipation or manage obtained disruptions by preparation. Digital tools that collect, analyze, and disseminate data across the supply chain allow this visibility. RFID, GPS tracking and blockchain are just some of the technologies enabling firms to monitor products and shipments in real time, allowing them to respond quickly when things go wrong.

Also, the importance of a disruptive orientation for resilient supply chain management should not be underestimated. This is a valid symbolism for the interrupted orbit of the firm. In general, companies that are willing to tryout disruptive technologies and routes are better off at building their resilience against disruptions (Kogut et al., 2012). As a result, firms with a strong disruptive orientation were more likely to leverage digital integration to their advantage and implement solutions to overcome supply chain obstacles in this study. For example, companies that had embraced artificial intelligence (AI) for predictive analytics or implemented blockchain for transparent transactions showed far more resilience than others, as these technologies enabled them to proactively identify potential disruptions before they became serious obstacles.

5. Conclusion

Indeed, the study highlights the impact of digital integration and information processing in strengthening supply chain resilience, especially in times of disruption. The results show that companies with access to digital supply chain technologies, such as real-time data analytics, cloud computing and IoT, are more likely to anticipate and effectively manage risks. By using these technologies, organisations can not only better respond to disruptions, but also recover more quickly after the fact, minimising the

impact on their operations. For example, proactive supply chain risk management strategies such as supplier diversification and contingency planning play an important role in helping a business achieve continuity in the face of adversity. The pent-up demand created by low-cost, simple supply chains and reliance on technology has given life to the businesses that sit on them. As the business environment continues to evolve at breakneck speed, organisations need to ensure they are investing in both their digital tools and risk capabilities. This study highlights the need to promote a culture of digital transformation and proactive risk management for sustainable resilience and competitiveness in the longer term. Further research can identify the impact of different digital tools and risk management tactics on supply chain resilience, to determine which path is fruitful for which type of industry. In addition, as disruptors continue to reshape global markets, companies should constantly reassess their supply chains to incorporate new technologies and best practices that enable flexibility and adaptability in their operations.

Given that digital integration is a key factor in improving supply chain resilience, future research could further explore the actual digital technologies that have the greatest impact on supply chain performance during disruptions. Similarly, artificial intelligence, machine learning and blockchain: exploring their integration may reveal how they speed up the decision-making process, introduce transparency and reduce risk. In addition, further studies can explore the role of organisational culture and leadership in implementing digital transformation initiatives and their contribution to supply chain resilience. Another direction for future research may be in the form of longitudinal studies of companies that have successfully navigated disruption over time, providing a more holistic view of the lasting impact of digital integration on supply chain resilience and organisational performance. Evidence from comparative studies across different industries or regions may provide a more nuanced understanding of how context matters in adapting digital integration and risk management approaches to achieve resilient supply chains.

Limitation

This study, although it provides valuable insights for increasing the resilience of a supply chain via types of information processing and digital integration, contains several limitations. First, the study was limited to firms in Indonesia, which might limit the generalization of the results to other regions with different technological structures, reporting systems, and economic structures. Second, the cross-sectional data are not suitable for testing long-term trends and implications of digital integration for supply chain resilience over time. Moreover, self-reported data is likely to be biased if the respondents exaggerate their firm's practices or capabilities. Finally, the research does not consider the challenges firms encounter in implementing digital tools, for instance, cost, organizational inertia, or a need for large amounts of training. Future studies may aim to overcome these limitations by using longitudinal data, studying the global context, and exploring the barriers to digital adoption in the supply chain.

Funding Statement

Table Research Appendix Data

Table 1: Demographic Profile of Respondents

Category	Subcategory	Percentage
Age Distribution	20-30 years	15%
	31-40 years	25%
	41-50 years	40%
	51+ years	20%
Gender	Male	60%
	Female	40%
Industry Distribution	Chemicals/Plastics	10%
	FMCG	15%
	Textiles	20%
	Pharmaceuticals	18%
	Food & Beverages	12%
	Automotive	10%
Experience in Supply Chain	Cement/Steel	15%
	0-5 years	12%

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Author Contributions

Annindi Galih V conceptualized the study, conducted the research, analyzed the data, and wrote the manuscript. The author also reviewed and approved the final version of the manuscript for submission.

Conflict of Interest

The author declares no conflict of interest regarding the publication of this paper.

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Category	Subcategory	Percentage
	6-10 years	30%
	11-15 years	35%
	16+ years	23%

Data source; Researcher field observation 2024

Table 2: Collinearity Data 2024

Construct	DSC	SCRM	DO	SCR	Cont
Digital Supply Chain (DSC)	1.00	0.78	0.65	0.74	0.81
Supply Chain Risk Management (SCRM)	0.78	1.00	0.70	0.72	0.69
Disruptive Orientation (DO)	0.65	0.70	1.00	0.63	0.60
Supply Chain Resilience (SCR)	0.74	0.72	0.63	1.00	0.77
Visibility (Con)	0.81	0.69	0.60	0.77	1.00

Data source; Researcher field observation 2024

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