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A Data-Driven Supply Chain: Marketing Data Sharing, Data Security, and Digital Technology Adoption to Predict Firm's Resilience

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ABSTRACT

Business automation has been driven recently with Technology 4.0 to manage the supply chain process and complexity. The secured data-driven supply chain is critical for business competitiveness. However, not all companies can manage, analyze, and interpret structured and unstructured data wisely. For record-keeping purposes, data are left unprotected and stored. Ideally, it should play a strategic role in decision-making and escalating business performance. The practices are inconsistent with the awareness of data security governance and proper usage of digital technologies. The research aimed to examine the data-driven supply chain that conceptualised marketing data sharing, data security, and digital technology adoption to predict a firm's resilience. The research applied a quantitative approach. The survey was conducted on Malaysian manufacturing firms. The data were collected electronically and analysed using Partial Least Squares-Structural Equation Modeling (PLS-SEM) 4.0. Around 375 companies participated in the survey. The results show the positive path links from predictors (marketing data sharing, digital technology adoption, and data security governance) and criteria. It also finds that data security and marketing data sharing have impacted digital technology adoption, leading to the supply chain's resilience. The research has concluded that the secure sharing of the data-driven supply chain can improve a firm's resilience. Manufacturing companies should make swift focus on data quality and utilize it wisely. The research concludes that empowering data analytics to understand customer preferences is necessary.

Keywords: data-driven supply chain, marketing data sharing, data security, digital technology adoption, firm's resilience

INTRODUCTION

Business expansion and global operation have driven manufacturing firms to digitalise their supply chain activities. The aim is to achieve efficiency and reach global market customers. However, managing the global supply chain is challenging as the vendors, manufacturers, distributors, and end users are located in different places (Fernando et al., 2023). Additionally, the digital transformation of the manufacturing supply chain has dynamic and complex processes and leads to business uncertainty. Global policy, disasters, pandemics, and customer preferences change dynamically. The business must anticipate the change in customer preference and demand and survive in the hyper-competitive market (Liu, 2022).

The competitiveness of the manufacturing industry has impacted the country's attractiveness for foreign technology transfer and know-how. According to Weko and Goldthau (2022), less attention has been paid to capacity-building and knowledge transfer in the public-private partnerships initiative. Moreover, market turbulence and uncertainty have affected the company and its performance. As suggested by Sun, Tekleab, Cheung, and Wu (2022), managers should consider market turbulence and organisational innovativeness to share information and knowledge for performance improvement. The firm has strengthened its competitiveness to gain market share and understand customer needs. It is argued that there is an unclear direction on how competitive intensity stimulates firms to develop new products based on knowledge integration (Lyu et al., 2022).

According to Ghanbarpour and Gustafsson (2022), there is a lack of research to study the long-term impact of customers' perceived business innovation strategy. Customer involvement in the success of supply chain management and practices has not been well explored. The customers' behaviors are primarily discussed in the marketing research field. However, they are not well integrated with the strategic supply chain, which includes the customers as the primary reference to design the business strategy.

The increasing supply chain complexity leads to many factors to improve business performance. The digital transformation initiative and reliance on the systems have put the firm at risk. However, the firm's resilience has enabled it to sustain and maintain its competitive advantage (Heredia, Rubiños, Vega, Heredia, & Flores, 2022). The firm must design the strategy to anticipate uncertain events and adapt its resilience ability (Duchek, 2020).

Nowadays, the increasing proportion of products and the supply chain of ever more complex products consider that measuring production and business performance is increasingly challenging compared to the past. It is critical to study a firm's resilience. Firms have struggled to anticipate the rapidly changing patterns and disruptions to meet the equilibrium point of demand and supply (Beninger & Francis, 2022).

During COVID-19, the industry has been challenged to optimize business activities due to the strict standard operating procedure. The company cannot run business as usual. There is a limited number of workers in the workplace, and only essential sectors are allowed to operate. Moreover, the business is expected to use a digital platform. It benefits the company and changes people's mindsets and attitudes. The Industry 4.0 (IR4.0) technology adoption has replaced human support routine activities and anticipated a major disruption. Digitalization can improve industry competitiveness, and the government has motivated firms to adopt IR4.0 technology (Fernando, Tseng, Nur, Ikhsan, & Lim, 2022). Digital technology has transformed the manufacturing industry into the automation era. It helps to improve the firm's productivity and opens more skilled jobs than in the past.

Economy recovery post-COVID-19 outbreak and IR4.0 technology adoption have given better light at the end of the tunnel. The government has utilized the country's savings to promote more business transactions and increase cash. As a result, strong demand and economic growth have influenced the industry's ability to supply products and services while meeting customer demand (Mezgebe, Gebreslassie, Sibhato, & Bahta, 2023).

Digital technology, such as blockchain technology, artificial intelligence, and Internet of Things, is frequently used to manage various automated jobs. According to Mangla, Kazançoğlu, Yıldızbaşı, Öztürk, and Çalık (2022), digitalization can reduce unnecessary costs, especially involving multiple-layer supply chain networks. Digital technology can eliminate intermediaries. The adoption of digital technology can also assist the company in managing and monitoring raw material flow, manufacturing processes, logistics, and end users in real time. It links the business function, such as sales, marketing, human resource, accounting, and operations, into a single digital platform. Additionally, digital technologies can improve supply chain resilience by accommodating user experiences. In the supply chain disruptions context, digital technology has directly influenced the firm's resilience (Li, Wang, Ye, Chen, & Zhan, 2022). The hypotheses formulated are as follows.

H1: Digital technology adoption has a positive effect on marketing data sharing practices.
H3: Digital technology adoption has a positive effect on data-driven supply chains.
H4: Digital technology adoption has a positive effect on data security governance.

According to Waller and Fawcett (2013), the data-driven supply chain can assist the company in managing, processing, and analysing the data. Digitalization in the supply chain has created more job opportunities and specialisation for data analytics. However, the company needs a data specialist to manage and interpret the data. The outcome of the data-driven supply chain can improve business design, supply chain performance, and competitiveness. In manufacturing, the data-driven supply chain can lead to capability improvement. The data-driven supply chain can improve manufacturing capability (Chavez, Yu, Jacobs, & Feng, 2017). Manufacturing capabilities' outcomes include cost, delivery, quality, and flexibility. It has been found that a data-driven supply chain can improve security and sustainable businesses' resilience (Ivanov, 2020). The data-driven supply chain has also led to cost-competitive resilience and secured supply chain and sustainability (Bechtsis, Tsolakis, Iakovou, & Vlachos, 2022). Hence, the next hypothesis is as follows.

H5: Data-driven supply chains have a positive effect on data security governance.

Next, the customers' behaviors are widely discussed in the marketing literature. The customers' data have been collected, stored, and analyzed to make a business decision. It is the basis for designing the retention and marketing strategy. Typically, the customers' data on perception are collected using social media sites for the company to make a decision (Kane, 2017).

Data sharing strategy among supply chain partners is on how the supply can meet the demand depends on the firm's ability to understand the customers' behaviors. However, it is not much discussed in supply chain studies. Supply chain managers must frequently analyze customer data to improve business performance (Gani, Fernando, Lan, Lim, & Tseng, 2022).

Shared information will assist the company in predicting demand. The recent COVID-19 pandemic and inflation have driven the firm to find an alternative strategy to sustain itself in the market. The firm needs to explore alternative ventures for business survival and development. However, the countless number of transactions, goods, and services that have been shared need system automation. It reduces the number of unskilled labourers and 24/7 systems surveillance. The effectiveness of managing the supply chain can lead to economic improvement at the micro and macro levels. It is not only will benefit the company but also the country (Gani, & Fernando, 2021).

The company gains competitiveness when it can predict what the customer needs. Unfortunately, the missing information and misunderstanding among the supply chain partners on customer data make an inaccurate business decision (Nyadzayo, Casidy, & Mohan, 2022). The company has lost the essence of customers' data and is not able to design the marketing strategy properly. The misunderstanding in the supply chain is usually referred to as the bullwhip effect. Typically, a slight fluctuation in marketing data on customer preference and demand can still be anticipated, but when a huge discrepancy happens, it will impact the company's performance (Fernando, Abideen, & Shaharudin, 2020).

The company's ability to manage marketing data sharing will drive business competitiveness (Fernando et al., 2022). The manufacturing company needs to observe and collect customers' data and share them with supply chain partners. It is the basis before designing and producing new products. The success of the new product in the market depends on the firm's ability to understand its customers. Hence, the hypothesis is formulated as follows.

H2: Marketing data sharing practices have a positive effect on data-driven supply chains.

According to Shen, Zhu, Wu, Wang, and Zhou (2022), the immature stage of personal data protection and data security has led to security issues. Data security means that the right people have utilized data for the proper purposes (Karkošková, 2022). Five areas are needed by data security governance to protect personal information, such as data leakage prevention, cloud access security agents, identity protection management, encryption, data-centric audit, and protection (Shen et al., 2022).

Data security issues have attracted industry and academia to study human-machine interaction. It is relevant when the data are shared, stored, and analyzed in the global context with different purposes. The data security governance should be in the place which guides the multiple companies in the supply chain to standardize the procedure. It helps companies involved in multiple supply chains protect their data as cyber-attacks and scams have recently increased (Gani et al., 2022).

According to Alzahrani, Ahmad, and Ansari (2022), Zero Access and The Zeus Trojan (Zbot) are malware that is considered prevalent fraud. Those steal confidential financial information by clicking the ad on social media. However, most companies are not ready for cyber-attack because they do not practice data security governance.

Data are safe when standards and procedures are well specified. However, data security governance in the supply chain is complex. It requires certain procedures to mitigate the strategy. In addition, the digital business model and IR4.0 technology adoption have put companies at risk. Data security governance is designed to minimize the risk of cyber-attack (Fernando, Tseng, Nur, Ikhsan, & Lim, 2022).

Insecure data sharing has impended the IR4.0 technology adoption in SME manufacturing supply chains (Fernando et al., 2022). On the other hand, from the e-commerce perspective, data sharing has provided better opportunities to all supply chain partners (Niu, Dong, Dai, & Liu, 2022). Concerning integrated strategic marketing and supply chain studies, a socially responsible supply chain has motivated the company to focus on customer satisfaction and retention (Fernando, Halili, Tseng, Tseng, & Lim, 2022).

The customer's data is equally important as other resources. It should be shared among supply chain partners and networks to gain more understanding and decide the decision. Unfortunately, the data sharing activities that drive supply chain strategy have focused less on managing data governance security effectively. In addition, data sharing among cross-companies is not common in Asian countries (Fernando, Ho, Algunaid, & Zailani, 2013). The last hypothesis is as follows.

H6: Data security governance has a positive effect on a firm's resilience.

The research has contributed to fulfilling the research gaps in several ways. First, the digitalization of supply chains has triggered security issues involving global supply chains. Therefore, it is necessary to study how data security governance is managed. Second, the data-driven supply chain has gotten little attention when linked to marketing data sharing, including customers' profiles, behaviors, and preferences. Third, the research has closed the research gaps between strategic digital marketing and supply chain management by examining the relationship. Integrating strategic digital marketing and the supply chain will enable the company to understand customers' requirements and assist the firm in maintaining resilience.

The research aims to investigate the relationship among drivers of a firm's resilience, which is linked to a data-driven supply chain, marketing data sharing, data security, digital technology adoption and resilience. The firm's resilience has indicated the readiness to

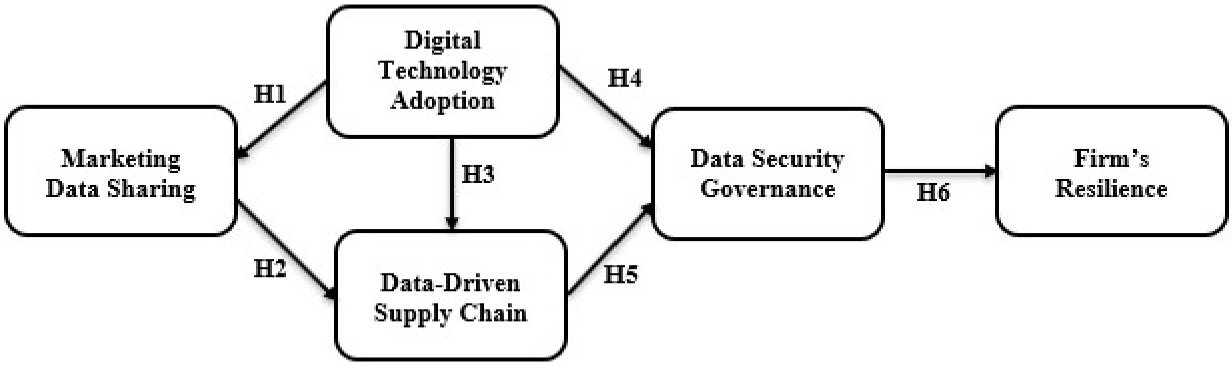

Figure 1 Research Model

anticipate rapid change and market uncertainty. It can be established when the company can optimize the marketing data sharing to lead the data-driven supply chain to leverage the business performance. The manufacturing industry incorporates small and medium vendors in business operations and strategies, so sharing consumer data is worth investigating. Figure 1 shows the research model that links each predictor to the outcomes.

METHODS

The research design applies a quantitative approach to analyse the firm resilience by connecting data-based supply chains, sharing marketing data, digital technology adoption, and data security. The population used is over 3.000 manufacturing companies registered under the Federation of Malaysian Manufacturers. It includes the electrics and electronics, foods and beverages, chemical, textile, plastic, furniture industries, oil and gas, automotive, and other manufacturers.

The entire population is used to identify the research sample. The selection of the sample has utilised several criteria. First, the company has practiced the digitalisation initiative in the supply chain. Second, the company has practiced data sharing and data security governance. All criteria are asked before the respondents respond to the questionnaire. It assists the researchers in getting quality data and obtaining comprehensive results. Third, the unit analysis is the firm and stratified random sampling utilised.

A survey is a research data collection tool to collect the respondents' past experiences and opinions. The measurement items are distributed by sending questionnaires via the company's email. All items in this questionnaire are adapted from previous studies, such as firm's resilience by Ambulkar, Blackhurst, and Grawe (2015), digital technology adoption by Ghobakhloo and Ching (2019), data-driven supply chains by Kumar, Singh, and Modgil (2023), marketing data sharing by Wei, O'Neill, Lee, and Zhou (2013), and data security governance by Flores, Antonsen, and Ekstedt (2014). All question items are measured with a 5-point Likert scale (5 strongly agree to 1 strongly disagree).

The firm's resilience indicators reflect the firm's ability to handle business changes in the industry. In addition, digital technology adoption refers to the firm's practice and experience in utilising digital technological advancement. Then, a data-driven supply chain indicator is conceptualised as how the firm can utilise the data and information from supply chain partners for business decision-making and achieve better performance. Data security governance reflects the firm's ability to manage and secure information sharing according to business needs.

The collected data are tabulated and analysed using a professional version of SmartPLS 4.0 software. Partial Least Squares (PLS) is a component-based structural equation modeling method that can examine constructs with reflective, formative models or both simultaneously (Hair Jr, Hult, Ringle, & Sarstedt, 2021). The measurement of each variable in the model is reflective and first-order in nature. The first stage in testing the model is to examine data bias with common method bias (Kock, 2015). Furthermore, validity and reliability testing are carried out after ensuring that the data is not biased. Validity testing consists of convergent and discriminant validity. Convergent validity testing refers to the Factor Loading (FL) value in the Confirmatory Factor Analysis (CFA) and Average Variance Extracted (AVE) tests. Recommended values are $\geq$ 0,7 for FL and > 0,5 for AVE. Furthermore, the discriminant validity test uses the Heterotrait-Monotrait Ratio of Correlations (HTMT) method with the condition that the correlation value between variables is less than 0,9 (Henseler, Ringle, & Sarstedt, 2015). Next, the reliability test uses Composite Reliability (CR) with the condition that the CR value is > 0,7 and does not exceed 0,95 (Hair Jr et al., 2021).

The next step is testing the structural model. First, it examines the significance of the relationship between variables. Second, it assesses the contribution level of exogenous variables to endogenous (R^2). Third, it checks the value of the effect size (F^2). Finally, it ensures the level of goodness of model predictions with PLSpredict. PLSpredict measurement gives effect to predictive power outside the study sample at the item level of measurement (Hair Jr, 2021; Shmueli et al., 2019)

RESULTS AND DISCUSSIONS

Out of 3.000 sets of questionnaires that are distributed electronically, 375 feedbacks from companies are collected successfully. Therefore, all participating companies have met the sampling criteria. Table 1 shows the respondent profile. Most of the companies participated in the survey are owned by Malaysian owners (80,3%). The result is followed by joint ventures (12,3%) and non-Malaysian-owned companies (7,5%). The electrical and electronics companies have been identified as the main contributor in this survey (59,2%), followed by foods and beverages (14,7%), textiles (9,6%), and the rest mentioned in Table 1. The results show that most respondents come from medium size companies consisting of 100 to 200 employees (46,1%) and 201 to 300 employees (26,7%).

In PLS-SEM, common methods bias is a problem caused by the measurement method in SEM studies (Kock, 2020). The research uses a questionnaire to measure each variable. Therefore, there is a possibility of bias in the respondents' responses.

The research uses the full collinearity assessment (FCVIF) approach suggested by Kock (2015) to overcome the problem of data bias. The method is used because latent variables are calculated based on an aggregation of indicators in PLS. Variance Inflation Factors (VIFs) are generated for all latent variables in the model. When the VIF value is > 3,3, the model is contaminated by common method bias. Meanwhile, if all variables have a VIF value of ≤ 3,3, the model is free from common method bias. Table 2 shows that all latent variables produce FCVIF values of < 3,3, so the research data are free from bias.

Table 1 Respondents' Profiles in the Research

Profile	Category	Frequency	Percentage
Ownership	Malaysian	301	80,3
	Joint Venture	46	12,3
	Non-Malaysian	28	7,5
Type of Manufacturing	Electrical and Electronics	222	59,2
	Foods and Beverages	55	14,7
	Chemical	20	5,3
	Textile	36	9,6
	Plastics	28	7,5
	Furniture	14	3,7
Number of Employees	< 100 Employees	80	21,3
	100−200 Employees	173	46,1
	201−300 Employees	100	26,7
	301−400 Employees	20	5,3
	> 400 Employees	2	0,5

Table 2 Common Method Bias in the Research

	DDSC	DSG	DTA	FR	MDS
DDSC		1,371	1,376	1,394	1,334
DSG	1,821		1,522	1,616	1,851
DTA	2,020	1,681		1,990	1,740
FR	1,269	1,173	1,287		1,288
MDS	1,464	1,552	1,332	1,547	

Note: DTA = Data-Driven Supply Chains; DSG = Data Security Governance; DTA = Digital Technology Adoption; MDS = Marketing Data Sharing; FR = Firm's Resilience

Next, the evaluation of the measurement model aims to test the instrument's validity and reliability. Therefore, the validation of measurement is critical before hypothesis testing. The questionnaire data are coded and analysed using an algorithm function. Table 3 shows that each measured variable produces an FL of more than 0,70 and an AVE of more than 0,50. These results indicate that each item can reflect the variable being measured. Furthermore, the five variables studied produce a CR value of more than 0,70 and do not exceed 0,95. All items have a high level of consistency in measuring each variable.

Furthermore, the measurement of discriminant validity uses the HTMT method. The discriminant validity assessment aims to ensure that the reflective construct has the most robust relationship with its indicators compared to other constructs in the PLS path model (Hair Jr et al., 2021). Table 4 shows that the correlation values between variables are 0.279–0,700. The correlation value is less than 0,9, so it can be concluded that the discriminant validity test is fulfilled.

The next stage evaluates the structural model representing the path model's theory (see Figure 1). Assessment of the structural model results aims to display the model's ability to predict one or more target variables. The target variables in the research are the firm's resilience, data security governance, digital technology adoption, data-driven supply chain, and marketing data sharing. All variables are computed using the PLS bootstrapping function. Figure 2 shows the result of the structural model to visualize the result validation.

Table 3 Validity and Reliability Tests in the Research

Variable	Item	FL	AVE	CR
Data-Driven Supply Chains	DDSC1	0,922	0,847	0,941
	DDSC2	0,933		
	DDSC3	0,919		
	DDSC4	0,908		
Data Security Governance	DSG1	0,828	0,674	0,839
	DSG2	0,855		
	DSG3	0,800		
	DSG4	0,800		
Digital Technology Adoption	DTA1	0,846	0,710	0,903
	DTA2	0,788		
	DTA3	0,836		
	DTA4	0,902		
	DTA5	0,837		
Marketing Data Sharing	MDS1	0,942	0,813	0,928
	MDS2	0,903		
	MDS3	0,928		
	MDS4	0,831		
Firm's Resilience	FR1	0,783	0,657	0,912
	FR2	0,835		
	FR3	0,745		
	FR4	0,901		
	FR5	0,779		

Table 4 Discriminant Validity Using HTMT Method

	DDSC	DSG	DTA	FR	MDS
DDSC					
DSG	0,474				
DTA	0,498	0,700			
FR	0,303	0,526	0,388		
MDS	0,468	0,449	0,616	0,279	

Note: DTA = Data-Driven Supply Chains; DSG = Data Security Governance; DTA = Digital Technology Adoption; MDS = Marketing Data Sharing; FR = Firm's Resilience

Table 5 and Figure 2 provide clear information about hypothesis testing in the structural model. As a result, digital technology adoption positively affects marketing data-sharing practices (β_1 = 0,562; t-stats = 10,843 > 1,96; and p-value = 0,000 < 0,05). In addition, this relationship produces an R^2 value of 0,316. It means that digital technology adoption can explain marketing data-sharing practices moderately by 31,6%.

The following hypothesis is that marketing data-sharing practices positively affect data-driven supply chains (β_2 = 0,261; t-stats = 2,999 > 1,96; and p-value = 0,003 < 0,05). In the end, digital technology adoption positively affects data-driven supply chains (β_3 = 0,315; t-stats = 4,472 > 1,96; and p-value = 0,000 < 0,05). However, the relationship model of marketing data-sharing practices and digital technology adoption weakens data-driven supply chains because the R^2 value is 0,261.

Digital technology adoption positively affects data security governance (β_4 = 0.529; t-stats = 8,239 > 1,96; and p-value = 0,000 < 0,05). Similarly, data-driven supply chains positively affect data security governance (β_5 = 0,180; t-stats = 3,411 > 1,96; and p-value = 0,001 < 0,05). However, the relationship model of digital technology adoption and data-driven supply chains describes a weak relationship in forming data security governance because the R^2 value is 0.400. Finally, data security governance positively affects a firm's resilience (β_6 = 0,464; t-stats = 8,603 > 1,96;

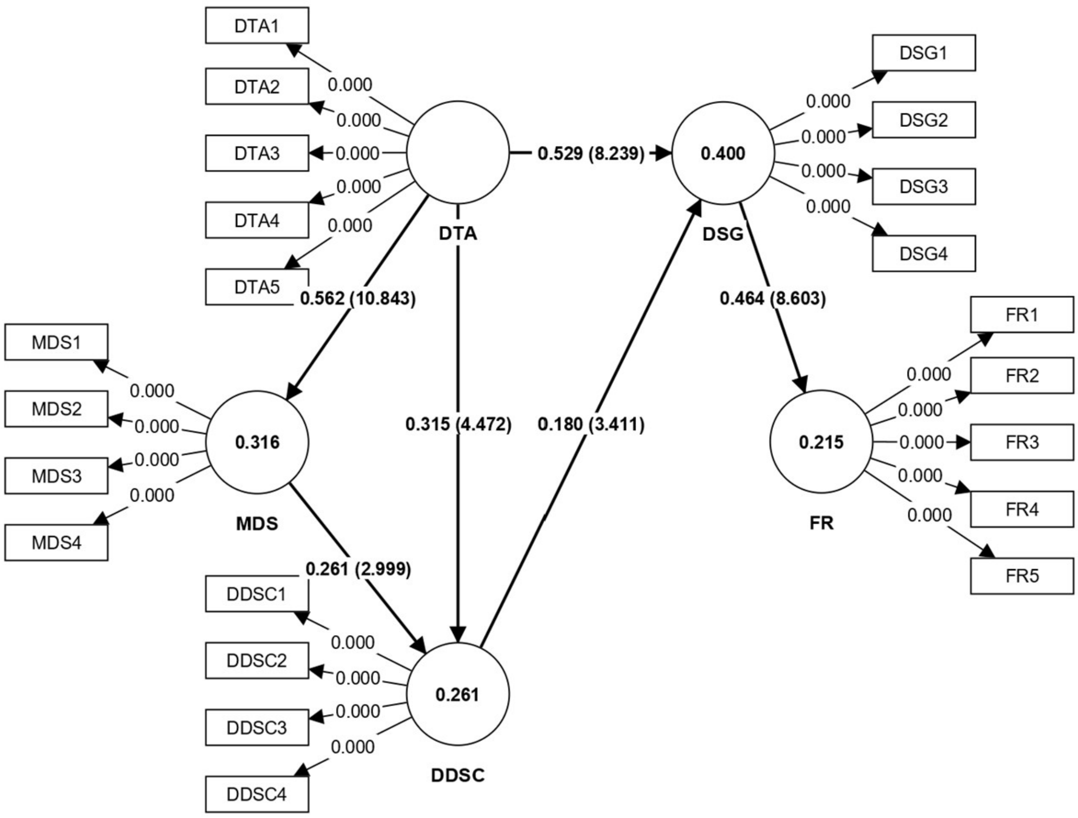

Figure 2 Structural Model

Note: DTA = Data-Driven Supply Chains; DSG = Data Security Governance; DTA = Digital Technology Adoption; MDS = Marketing Data Sharing; FR = Firm's Resilience

Table 5 Result of Hypothesis Testing

Path	STD	STDEV	T-Stats	P-Values
DTA→MDS	0,562	0,052	10,843	0,000
MDS→DDSC	0,261	0,087	2,999	0,003
DTA→DDSC	0,315	0,071	4,472	0,000
DTA→DSG	0,529	0,064	8,239	0,000
DDSC→DSG	0,180	0,053	3,411	0,001
DSG→FR	0,464	0,054	8,603	0,000

Note: DTA = Data-Driven Supply Chains; DSG = Data Security Governance; DTA = Digital Technology Adoption; MDS = Marketing Data Sharing; FR = Firm's Resilience

and p-value = 0,001 < 0,05). This relationship pattern explains a weak relationship because it produces an R2 value of 0,215. Overall, all hypotheses in the research are accepted.

Table 6 provides information about the strength of the relationship between variables at the structural level. As a result, digital technology adoption strongly influences marketing data sharing practices. However, three relationships are considered weak (Marketing Data Sharing on data-driven supply chains, digital technology adoption on data-driven supply chains, and data-driven supply chains on data security governance). The aggregate value for each relationship is low. Hence, future research can increase the number of samples to boost the relationship.

The final step is to predict the PLS model's performance to strengthen the relevance of the model's predictions. According to Shmueli et al. (2019), the research can use the PLSpredict algorithm to predict the performance of the PLS model. Table 7 shows the results.

Table 7 presents the PLSpredict results. The Root Mean Square Error (RMSE) value in the PLS-SEM model is smaller than the RMSE value in the simple Linear Model (LM). Hence, the model has high predictive power. Marketing data sharing practices and digital technology adoption provide weak influencing forces in data-driven supply chains. Furthermore, digital technology adoption strongly influences data security governance. However, data-driven supply chains have a weak effect on data security governance. Finally, data security governance moderately affects a firm's resilience.

The research has managed to answer the research objective that examines the direct relationship among variables. The results find that the data-driven supply

Table 6 Result of Effect Size (F^2) in the Research

Path	F^2	Decision
DTA→MDS	0,462	Strong
MDS→DDSC	0,063	Weak
DTA→DDSC	0,092	Weak
DTA→DSG	0,366	Strong
DDSC→DSG	0,043	Weak
DSG→FR	0,274	Moderate

Note: DTA = Data-Driven Supply Chains; DSG = Data Security Governance; DTA = Digital Technology Adoption; MDS = Marketing Data Sharing; FR = Firm's Resilience

Table 7 Result of PLSpredict in the Research

	Q^2predict	PLS-SEM_RMSE	LM RMSE	PLS LM
DDSC1	0,188	0,637	0,645	-0,008
DDSC2	0,192	0,643	0,655	-0,012
DDSC3	0,178	0,636	0,668	-0,032
DDSC4	0,150	0,622	0,638	-0,016
DSG1	0,165	0,488	0,491	-0,003
DSG2	0,224	0,493	0,501	-0,008
DSG3	0,317	0,465	0,475	-0,010
DSG4	0,266	0,460	0,465	-0,005
FR1	0,060	0,539	0,540	-0,001
FR2	0,061	0,547	0,555	-0,008
FR3	0,050	0,615	0,616	-0,001
FR4	0,144	0,576	0,584	-0,008
FR5	0,057	0,621	0,622	-0,001
MDS1	0,259	0,574	0,589	-0,015
MDS2	0,304	0,535	0,550	-0,015
MDS3	0,206	0,637	0,653	-0,016
MDS4	0,235	0,671	0,673	-0,002

Note: DTA = Data-Driven Supply Chains; DSG = Data Security Governance; DTA = Digital Technology Adoption; MDS = Marketing Data Sharing; FR = Firm's Resilience

chain that conceptualises marketing data sharing, data security, and digital technology to predict a firm's resilience statistically impacts the direct path of the relationship. First, digital technology adoption affects marketing data sharing. The manufacturing companies have utilised the digital platform to collect marketing data and share it to benefit supply chain stakeholders. The finding is in line with Van der Burg, Wiseman, and Krkeljas (2021) that a firm's readiness for digital technology solutions can impact quality data sharing.

Second, the result shows that data-driven supply chains can be optimised using digital technology adoption. According to Sundarakani, Ajaykumar, and Gunasekaran (2021), the success of a big data-driven supply chain depends on how well the firm adopts digital technology in logistics and supply chains. Third, the statistical result shows the direct effect of digital technology adoption on data security governance. Digital adoption must be aligned with data security governance. Based on AlGhamdi, Win, and Vlahu-Gjorgievska (2020), firms must prioritise information security to sustain business value.

Fourth, the result shows that marketing data sharing directly affects data-driven supply chains. The manufacturing firms that can utilise the marketing data and share it among supply chain networks can have better outcomes. Therefore, the data-driven supply chain has impacted marketing data sharing to predict business demand and customer preferences. The result is consistent with Liu, Yan, Li, and Wei (2020), arguing that data-driven marketing is necessary for an Internet platform-based supply chain.

Fifth, well-managed data-driven supply chains have significantly affected data security governance. A data-driven analysis has assisted the firms in sustaining the supply chain and anticipated disruption (Bui et al., 2021). In the end, the result indicates that data security governance directly affects the firm's resilience. The data systems governed by the best information security practices enhanced the firm's resilience. In addition, according to Fernando, Chidambaram, and Wahyuni-TD (2018), data security practices have improved service supply chain performance.

CONCLUSIONS

The research has filled the research gaps. It shows the research model that can provide some alternative solutions for the manufacturing supply chain to utilise the data-driven supply chain to improve the sharing accuracy of the data marketing. Furthermore, data security governance has impacted the firm's resilience and extended the firm's resilience literature. In terms of practical implications, the finding argues that manufacturing firms should consider integrating strategic digital marketing to lead to better data-driven supply chain implementation. In Malaysia's manufacturing context, data-driven supply chains, marketing data sharing, and digital technology adoption have been implemented well. At the same time, the effect of data security governance on a firm's resilience is relatively moderate.

The manufacturing firms' ability to manage the market turbulence and uncertainty has also impacted the firm's resilience. The firm is suggested to be innovative and utilise the digital platform securely. The information should be shared based on mutual benefit, and each partner must ensure the confidentiality of data. Moreover, manufacturing firms are suggested to practice data security governance. The customer preference data can be utilised to predict demand and improve the firm's resilience.

The research has achieved the research objective. However, the research has limited access to explore how a data-driven supply chain can directly affect data security governance and a firm's resilience. The research does not conceptualize the relationship between a data-driven supply chain that can directly affect data security governance and a firm's resilience. Future research can consider those two variables as the intervening domain in the research model.

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