

Article

Digital Transformation and Supply Chain Resilience in Electric Vehicle Manufacturing Firms: Evidence from China

Jiang Hu ¹, Yu Chen ¹, Jiayue Wang ^{2,*} and Xinyu Ai ³

¹ Automotive Business School, Hubei University of Automotive Technology, Shiyan 442000, China; jianghu@huat.edu.cn (J.H.); cyu7146@gmail.com (Y.C.)

² Digital Economy School, Hubei University of Automotive Technology, Shiyan 442000, China

³ School of Economics and Management, China Three Gorges University, Yichang 443002, China; 202310039@huat.edu.cn

* Correspondence: jiayuewang@huat.edu.cn

Abstract

Electric vehicle manufacturing firms face increasing supply chain vulnerability due to component shortages, technological interdependence, raw material volatility, and demand uncertainty. This study aims to examine whether digital transformation can be translated into a resilience-building capability and to identify the transmission channels. Using panel data from Chinese A-share listed electric vehicle manufacturing firms from 2014 to 2023, we employ a double machine learning framework to estimate the relationship between digital transformation and supply chain resilience while accounting for high-dimensional firm-level controls. The results show that digital transformation is positively associated with supply chain resilience. This finding remains robust across alternative sample-splitting ratios, different machine learning algorithms, alternative winsorization thresholds, and sample restrictions. It also holds after addressing potential endogeneity using instrumental variable estimation. Mechanism tests indicate that digital transformation contributes to resilience by promoting technological innovation and reducing managerial transaction costs. Heterogeneity analysis further shows that the effect is more pronounced among firms with stronger market positions, larger firms, and vehicle manufacturers. These findings suggest that digital transformation is not merely a tool for operational upgrading but also an important organizational capability for strengthening supply chain resilience in electric vehicle manufacturing.

Keywords: digital transformation; supply chain resilience; electric vehicle manufacturing firms; double machine learning; technological innovation; managerial transaction costs



Academic Editor: Joeri Van Mierlo

Received: 16 June 2026

Revised: 17 July 2026

Accepted: 21 July 2026

Published: 23 July 2026

Copyright: © 2026 by the authors.

Published by MDPI on behalf of the World Electric Vehicle Association.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The rapid expansion of the electric vehicle (EV) industry has reshaped global automotive manufacturing while increasing firms' exposure to supply chain disruptions. In China, EV manufacturing is commonly discussed within the broader category of new energy vehicles, including battery electric vehicles, plug-in hybrid vehicles, and related manufacturers. Compared with conventional automobile production, EV manufacturing depends more heavily on batteries, semiconductors, electric motors, electronic control systems, thermal management systems, intelligent sensors, and digital platforms. These components are embedded in geographically dispersed and technologically interdependent networks, making EV supply chains vulnerable to upstream shocks and systemic disruptions (Huang et al., 2024 [1]). In particular, lithium-ion battery supply chains

face potential bottlenecks arising from the geographic concentration of critical mineral resources and the limited availability of key materials, which may amplify disruption risks for EV manufacturers (Olivetti et al., 2017 [2]). Moreover, the high concentration of the power lithium-ion battery supply chain across resource extraction, material processing, battery production, and downstream markets may further amplify the propagation of upstream supply shocks (Miao et al., 2023 [3]). EV manufacturers therefore face risks arising from raw material price volatility, logistics interruptions, geopolitical uncertainty, technological bottlenecks, and demand fluctuations (Huang et al., 2024 [1]). More broadly, external uncertainty and intensified competition have made industrial and supply chain security increasingly important (Ivanov, 2022 [4]), while evidence from China indicates that longer and more complex production chains can increase exposure to external shocks (Huang et al., 2024 [1]). Supply chain resilience refers to the ability to withstand disruptions, adapt to changing conditions, and restore normal operations after shocks (Ponomarov and Holcomb, 2009 [5]; Tukamuhabwa et al., 2015 [6]). Building resilience requires capabilities that maintain operational continuity and support timely responses throughout a disruption (Christopher and Peck, 2004 [7]). For EV manufacturers, resilience also supports technological upgrading, supplier coordination, production flexibility, and long-term competitiveness by helping stabilize critical component supply and maintain production and delivery (Tukamuhabwa et al., 2015 [6]; Christopher and Peck, 2004 [7]). It is commonly understood through resistance, recovery, and adaptive capacities, which capture how supply chains withstand, respond to, and recover from adverse shocks (Ponomarov and Holcomb, 2009 [5]; Tukamuhabwa et al., 2015 [6]).

Digital transformation provides a potential pathway for strengthening these capabilities. Digital supply chain technologies improve end-to-end connectivity, real-time visibility, and logistics coordination across complex production networks (Dolgui and Ivanov, 2022 [8]; Tang and Veelenturf, 2019 [9]), while procurement digitalization strengthens information sharing and supplier coordination (Harju et al., 2023 [10]). Big data analytics, cloud computing, industrial internet platforms, artificial intelligence, and intelligent manufacturing systems further support supply chain visibility, real-time monitoring, and collaborative decision-making (Li et al., 2025 [11]; Jing and Fan, 2024 [12]; Nasiri et al., 2020 [13]). Together, these capabilities enable earlier risk identification, more efficient procurement and inventory adjustment, and closer coordination with suppliers and customers (Qi et al., 2017 [14]). Prior research shows that digital transformation can reduce supply chain risks, improve organizational coordination, and enhance firms' responses to uncertainty (Tukamuhabwa et al., 2015 [6]; Li et al., 2025 [11]; Jing and Fan, 2024 [12]). Network-level analyses and studies of smart technology adoption also indicate that intelligent technologies strengthen risk sensing, decision support, and cross-unit coordination (Nasiri et al., 2020 [13]; Tian and Cui, 2025 [15]; Ozdemir et al., 2022 [16]). These functions are particularly relevant to EV manufacturing because of its technological complexity and interdependence. Digital transformation can improve component traceability, critical input management, and responses to fluctuations in battery materials, chip supply, and market demand (Li and Sukhotu, 2025 [17]). By integrating real-time data from procurement, production, inventory, logistics, and sales, digital systems strengthen firms' information-processing and coordination capabilities. They improve resistance capacity by enabling firms to detect risk signals and adjust procurement or inventory before disruptions escalate, and they improve recovery capacity by supporting supplier substitution, production rescheduling, and resource reallocation after disruptions occur.

Despite growing attention to digital transformation and supply chain resilience, three important gaps remain. First, existing studies have focused mainly on general manufacturing firms and broad samples of listed companies (Feng et al., 2024 [18];

Wang et al., 2025 [19]). Research has examined digital transformation, innovation output, and transaction costs largely in general manufacturing settings (Meng and Gong, 2024 [20]), while earlier work has emphasized supply chain integration and performance (Qi et al., 2017 [14]). EV manufacturing has received less attention despite its strong dependence on critical components, software–hardware integration, technological compatibility, and multi-tier coordination. Unlike less technology-intensive sectors, disruptions in EV supply chains may involve not only material shortages but also system integration and component compatibility problems. Second, many empirical studies rely on conventional econometric models (Feng et al., 2024 [18]; Meng and Gong, 2024 [20]), which may not adequately address high-dimensional firm-level heterogeneity or potential confounding. Firms with greater resources, stronger governance, or higher innovation capacity may be more likely to undertake digital transformation, requiring empirical strategies that flexibly control for complex covariates. Third, the transmission mechanisms remain insufficiently understood. Existing evidence suggests that digital transformation may strengthen resilience through innovation-related capabilities (Wang et al., 2025 [19]; Huang and Shi, 2024 [21]). Digitalization may also affect innovation output and internal and external transaction costs (Meng and Gong, 2024 [20]), while transaction cost theory explains how lower coordination, monitoring, and governance costs can improve organizational responses under uncertainty (Williamson, 1981 [22]; Coase, 2012 [23]). Resilience capabilities, in turn, shape how firms respond to disruptions and restore operations (Parker and Ameen, 2018 [24]). Further evidence is therefore needed on whether digital transformation can be converted into a resilience-building capability in EV manufacturing and whether technological innovation and managerial transaction costs constitute the main transmission channels.

Accordingly, this study examines Chinese A-share-listed EV manufacturing firms from 2014 to 2023. It investigates whether digital transformation is associated with stronger supply chain resilience, whether technological innovation and managerial transaction costs serve as transmission channels, and whether this relationship varies by market position, firm size, and manufacturing attribute. Supply chain resilience is measured using a firm-level index based on resistance and recovery capacities (Chowdhury and Quaddus, 2017 [25]), while digital transformation is measured using the CSMAR Digital Transformation Index. A double machine learning (DML) framework is employed to flexibly control for high-dimensional covariates and reduce bias arising from model misspecification (Chernozhukov et al., 2018 [26]). The results show a positive association between digital transformation and supply chain resilience. This relationship remains positive and statistically significant across alternative sample-splitting ratios, machine learning algorithms, winsorization thresholds, and a restricted sample excluding municipalities and is further supported by instrumental variable estimation. Mechanism tests indicate that digital transformation contributes to resilience by promoting technological innovation and reducing managerial transaction costs. Heterogeneity analysis reports stronger estimates among firms with stronger market positions, larger firms, and vehicle manufacturers. The study contributes in three ways. First, it provides EV-specific evidence on digital transformation and supply chain resilience (Li and Sukhotu, 2025 [17]). Second, it applies DML to address high-dimensional controls and potential confounding more flexibly (Chernozhukov et al., 2018 [26]). Third, it identifies technological innovation and managerial transaction costs as technological and organizational channels through which digital upgrading supports resilience building.

The remainder of the paper is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data, variables, and methods. Section 4 presents the empirical results. Section 5 discusses the findings, and Section 6 presents the conclusions, practical implications, limitations, and directions for future research.

2. Literature Review and Hypothesis Development

2.1. Digital Transformation and Supply Chain Resilience

Supply chain resilience has become an important concept in operation management and strategic management. The notion of resilience also has broader roots in regional and economic systems, where it describes the capacity to adapt to adverse shocks while maintaining sustainable operations (Martin, 2012 [27]). In the supply chain context, resilience generally refers to the capacity to withstand disruptions, adapt to unexpected changes, and restore normal operations after shocks (Ponomarov and Holcomb, 2009 [5]; Tukamuhabwa et al., 2015 [6]). Building a resilient supply chain therefore requires firms to develop capabilities that maintain operational continuity and support timely responses throughout different stages of a disruption (Christopher and Peck, 2004 [7]). Existing scholarship treats supply chain resilience as a multidimensional construct. Resistance capacity reflects the ability to absorb the initial impact of a disruption without substantial performance deterioration, whereas recovery capacity refers to the speed and completeness with which normal operations are restored after a shock (Ponomarov and Holcomb, 2009 [5]; Tukamuhabwa et al., 2015 [6]). Empirical evidence further suggests that different dimensions of supply chain resilience may have distinct implications for firm performance, reinforcing the importance of treating resilience as a multidimensional organizational capability (Li et al., 2017 [28]). Consistent with the measurement framework adopted in this study, the subsequent analysis focuses on resistance and recovery capacities. In EV manufacturing, supply chain resilience is particularly important because production depends on critical components such as batteries, semiconductors, electric motors, electronic control systems, and thermal management systems. Disruptions in any of these components may affect production continuity, delivery schedules, and market competitiveness. Supply chain resilience is therefore not merely a defensive response to external uncertainty but also a strategic capability that supports long-term industrial competitiveness.

Prior research indicates that operations and supply chain strategies can strengthen internal and external integration and improve supply chain performance (Qi et al., 2017 [14]). Digital transformation extends this logic by enhancing firms' information-processing, coordination, and risk-response capacities. Digital technologies enable firms to collect and integrate data from production, procurement, logistics, inventory, and sales activities, thereby improving supply chain visibility and early risk identification. Technologies such as the Internet of Things, blockchain, cloud computing, artificial intelligence, and big data analytics can reduce information asymmetry, improve access to real-time data, and enhance responsiveness under uncertainty (Nasiri et al., 2020 [13]). Recent literature further identifies visibility, agility, collaboration, and data-driven decision-making as important themes linking digital technologies to supply chain resilience (Wei et al., 2026 [29]). Systematic evidence indicates that artificial intelligence can enhance supply chain management by supporting forecasting, logistics, production planning, and data-driven decision-making, thereby providing an important technological foundation for more responsive supply chain operations (Toorajipour et al., 2021 [30]). At the organizational level, data analytics capability and organizational flexibility may operate as complementary capabilities, enabling firms to process disruption-related information and reconfigure supply chain responses more effectively (Dubey et al., 2021 [31]). Empirical studies further show that digital transformation can strengthen supply chain resilience (Li et al., 2025 [11]) and improve supply chain integration and performance (Jing and Fan, 2024 [12]). Evidence from network-level and manufacturing studies also indicates that digital transformation improves visibility, collaboration, and firms' capacity to respond to supply chain uncertainty (Tian and Cui, 2025 [15]; Li et al., 2026 [32]). Research on big data analytics in disruption-prone supply chains further

emphasizes the importance of data-driven capabilities and collaboration in supporting coordinated responses (Dubey et al., 2019 [33]).

These resilience-enhancing functions are particularly relevant to EV manufacturing. EV supply chains are more technologically complex and interdependent than many traditional manufacturing supply chains, involving battery materials, chips, intelligent sensors, vehicle control systems, and charging-related components. Digital transformation can help EV manufacturers improve component traceability, monitor supplier performance, coordinate production schedules, and respond more quickly to changes in procurement, logistics, production, and market demand (Li and Sukhotu, 2025 [17]). From an information-processing perspective, supply chain disruptions increase uncertainty by weakening firms' ability to observe upstream conditions, evaluate alternative solutions, and coordinate timely responses. Research grounded in organizational information processing theory further indicates that supply and demand visibility provide an important foundation for developing supply chain analytics capability, while organizational flexibility enables firms to translate analytics-generated insights into timely operational responses, particularly under volatile market conditions (Srinivasan and Swink, 2018 [34]). By integrating dispersed information across supply chain activities, digital transformation strengthens resistance capacity by enabling firms to identify risk signals earlier, monitor critical components more effectively, and adjust procurement or inventory strategies before disruptions escalate. It also strengthens recovery capacity by supporting faster supplier substitution, production rescheduling, resource reallocation, and delivery coordination after disruptions occur. Digital transformation is therefore expected to enhance both the resistance and recovery dimensions of supply chain resilience in EV manufacturing firms.

Based on the above discussion, the following hypothesis is proposed:

H1. *Digital transformation positively affects supply chain resilience in EV manufacturing firms.*

2.2. Technological Innovation as a Transmission Channel

Digital transformation may also strengthen supply chain resilience by promoting technological innovation. Digital technologies improve firms' access to information, accelerate knowledge flows, and support data-driven decision-making in R&D, design, testing, and production activities. By integrating digital tools into innovation processes, firms can improve innovation efficiency and develop new products, processes, and organizational routines more effectively. Evidence from Chinese listed manufacturing firms further shows that digital transformation is positively associated with innovation performance (Du and Zhang, 2022 [35]; Xing et al., 2023 [36]).

Technological innovation is closely related to supply chain resilience. Firms with stronger innovation capabilities are better able to develop alternative technologies, improve production processes, reduce dependence on external suppliers, and substitute key inputs when disruptions occur. Research on resilience capabilities indicates that stronger organizational capabilities enable firms to respond more effectively to disruptions and restore operations after shocks (Parker and Ameen, 2018 [24]). Evidence from China's new energy vehicle industry further suggests that innovation plays an important role in strengthening supply chain resilience (Huang and Shi, 2024 [21]). This mechanism is particularly important in EV manufacturing because supply chain stability depends heavily on batteries, power systems, electronic control technologies, intelligent driving systems, and component integration. Digital design systems, intelligent manufacturing platforms, and data analytics tools can support battery system improvement by accelerating the testing of cell configurations, thermal management, and safety performance. They can also help firms evaluate chip-substitution schemes, improve intelligent driving technologies, and redesign components through modularization when specific suppliers or technologies become con-

strained. Nevertheless, technological substitution and battery recycling alone may not be sufficient to eliminate future shortages of critical materials such as cobalt, indicating that technological innovation should be complemented by supplier diversification, resource recycling, and broader supply chain governance (Zeng et al., 2022 [37]).

In the empirical analysis, technological innovation is proxied by the number of patent applications. Patent applications provide observable firm-level evidence of newly developed technical solutions and therefore capture innovation output more directly. Compared with R&D expenditure, which mainly reflects innovation input, patent applications offer a more direct measure of firms' capacity to develop and apply new technologies.

Based on the above discussion, the following hypothesis is proposed:

H2. *Technological innovation mediates the positive relationship between digital transformation and supply chain resilience in EV manufacturing firms.*

2.3. Managerial Transaction Costs as a Transmission Channel

Another important channel through which digital transformation may affect supply chain resilience is the reduction in managerial transaction costs. Managerial transaction costs refer to the internal costs incurred in coordinating, monitoring, communicating, and administering organizational and supply chain activities. Transaction cost theory suggests that firms incur coordination, monitoring, communication, and governance costs when economic activities involve uncertainty, information asymmetry, and complex contractual relationships (Williamson, 1981 [22]; Coase, 2012 [23]; Cuypers et al., 2021 [38]). These costs are particularly relevant in EV supply chains, where production requires frequent coordination among upstream suppliers, component manufacturers, vehicle assemblers, logistics providers, and downstream sales networks. High managerial transaction costs may reduce organizational flexibility, delay information transmission, and slow firms' responses to supply chain disruptions. Research on resilience capabilities further indicates that firms' organizational response capacity plays an important role in how they cope with disruptions and restore operations after shocks (Parker and Ameen, 2018 [24]).

Digital transformation can reduce managerial transaction costs by improving the transparency and efficiency of managerial processes. Digital platforms, enterprise resource planning systems, supply chain management systems, and real-time monitoring tools can integrate information across departments and supply chain partners, reduce information asymmetry, standardize workflows, and improve the speed and accuracy of managerial decisions. The underlying logic is that digital transformation improves information transparency, reduces communication delays, lowers coordination and monitoring costs, improves supply chain response speed, and ultimately strengthens supply chain resilience. In the empirical analysis, managerial transaction costs are proxied by administrative expenses divided by total assets. This proxy is used because administrative expenses reflect the resources consumed by internal management, coordination, monitoring, and organizational operations relative to firm scale. This proxy is not without limitations because administrative expenses may also include items unrelated to transaction governance, such as routine office expenses or general administrative spending. Nevertheless, it provides an observable firm-level measure of the managerial and coordination burden. Digital transformation may increase administrative and adjustment costs in the short run because firms need to invest in digital systems, data integration, process redesign, and employee training. However, once digital systems are embedded in managerial routines, they may reduce communication delays, monitoring costs, and coordination frictions, thereby improving supply chain response speed and resilience.

Based on the above discussion, the following hypothesis is proposed:

H3. *Managerial transaction cost reduction mediates the positive relationship between digital transformation and supply chain resilience in EV manufacturing firms.*

Taken together, these hypotheses define the main variable relationships examined in this study. Digital transformation is the core explanatory variable, supply chain resilience is the dependent variable, and technological innovation and managerial transaction costs are introduced as two transmission channels. Specifically, digital transformation is expected to directly enhance supply chain resilience and to exert indirect effects through technological innovation and managerial transaction cost reduction. Figure 1 presents the conceptual framework and the hypothesized relationships among these variables.

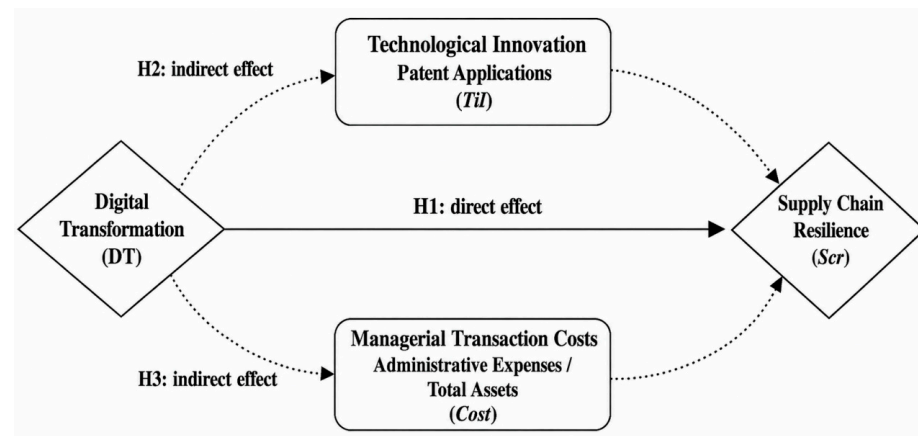


Figure 1. Conceptual Framework and Hypothesized Relationships.

3. Materials and Methods

3.1. Data and Sample

This study uses a panel dataset of Chinese A-share listed electric vehicle (EV) manufacturing firms from 2014 to 2023. In the Chinese industrial context, EV manufacturing firms are commonly classified under the broader category of new energy vehicle manufacturing, including vehicle manufacturers and firms engaged in key EV components. The original data were obtained from the CSMAR database, which provides firm-level financial, governance, innovation, and digital transformation information for Chinese listed companies.

The sample period begins in 2014 because China's new energy vehicle industry entered a stage of rapid industrial expansion and supply chain formation during this period, and the key firm-level variables used in this study can be consistently matched from 2014 onward. The sample ends in 2023 because the construction of the empirical dataset requires complete and comparable information on financial indicators, digital transformation, innovation, and supply chain resilience. At the time of data collection and verification, the corresponding 2024 variables were not yet consistently available for all sample firms. Therefore, 2024 observations were not included in the baseline sample.

The sample was constructed according to the following criteria. First, firms marked as ST or *ST were excluded to reduce the influence of abnormal financial conditions. Second, observations with severe missing values in key variables were removed. Third, limited missing values were interpolated where appropriate to preserve the continuity of the panel data. After these screening procedures, the final sample contains 610 firm-year observations. The empirical analysis was conducted using Stata 18.0.

3.2. Variables and Measurement

Table 1 presents the definitions and measurements of the main variables used in this study, including the dependent variable, the core explanatory variable, the mechanism variables, and the control variables.

Table 1. Variable Definitions.

Variable Type	Variable	Symbol	Measurement
Dependent variable	Supply chain resilience	Scr	Composite index based on resistance capacity and recovery capacity
Core explanatory variable	Digital transformation	DT	Logarithm of the CSMAR Digital Transformation Index
Mechanism variable	Technological innovation	Til	Logarithm of the number of patent applications
Mechanism variable	Managerial transaction costs	Cost	Administrative expenses/total assets
Control variable	Board size	Board	Number of directors
Control variable	Largest shareholder ownership	Top1	Shareholding ratio of the largest shareholder
Control variable	Executive compensation	LnComp	Logarithm of executive compensation
Control variable	Ownership nature	Ownership	Ownership attribute of the firm
Control variable	R&D intensity	RDI	R&D expenditure divided by main business revenue

The dependent variable is supply chain resilience (Scr). Following the literature on supply chain resilience, this study constructs a composite index from two dimensions: resistance capacity and recovery capacity. Resistance capacity reflects a firm's ability to withstand supply chain disruptions, while recovery capacity captures its ability to restore normal operations after disruptions. The detailed indicator system used to construct the supply chain resilience index is presented in Table 2. Since supply chain resilience is measured by multiple indicators, the entropy-weight method is used to obtain the composite index.

Table 2. Supply Chain Resilience Indicator System.

Dimension	Indicator	Measurement	Direction
Resistance capacity	Operating costs	Operating costs of the firm	Negative
Resistance capacity	Employee size	Number of employees	Positive
Resistance capacity	Debt-to-asset ratio	Total liabilities/total assets	Negative
Resistance capacity	Return on assets	Net profit/average total assets	Positive
Resistance capacity	Debt-to-equity ratio	Total liabilities/total owners' equity	Negative
Recovery capacity	Operating revenue	Operating revenue of the firm	Positive
Recovery capacity	Inventory turnover rate	Cost of goods sold/average inventory	Positive
Recovery capacity	R&D personnel ratio	R&D personnel/total employees	Positive
Recovery capacity	Supply chain concentration	(Purchase ratio from the top five suppliers + sales ratio to the top five customers)/2	Negative
Recovery capacity	Return on equity	Net profit/average net assets	Positive

The core explanatory variable is digital transformation (DT). This study measures digital transformation using the CSMAR Digital Transformation Index, which captures firm-level digitalization from the perspectives of strategic orientation, technology application,

and organizational empowerment. To reduce skewness and improve comparability, the logarithmic form of the index is used in the empirical analysis.

This study further examines two mechanism variables. The first is technological innovation (Til), which is measured by the logarithm of the number of patent applications. Patent applications reflect firms' innovation output and their ability to develop and apply new technologies. The second is managerial transaction costs (Cost), measured by administrative expenses divided by total assets. This indicator captures the relative cost of internal coordination, administrative management, and organizational operations.

Several firm-level control variables are included to reduce omitted-variable bias. Board size (Board) is measured by the number of directors. Largest shareholder ownership (Top1) is measured by the shareholding ratio of the largest shareholder. Executive compensation (LnComp) is measured by the logarithm of executive compensation. Ownership nature (Ownership) captures the ownership attribute of the firm. R&D intensity (RDI) is measured by R&D expenditure divided by main business revenue. These variables control for differences in corporate governance, ownership structure, managerial incentives, and innovation input across firms.

3.3. Construction of the Supply Chain Resilience Index

Supply chain resilience is a multidimensional construct that cannot be adequately captured by a single financial or operational indicator. To obtain a more comprehensive measure, this study constructs a composite supply chain resilience index from two dimensions: resistance capacity and recovery capacity. Resistance capacity refers to a firm's ability to withstand supply chain disruptions, whereas recovery capacity reflects its ability to restore normal operations after disruptions. The detailed indicator system is presented in Table 2. The Direction column in Table 2 identifies whether each indicator is treated as a positive or negative indicator during the standardization process.

Based on the indicator system reported in Table 2, the entropy-weight method is used to construct the composite supply chain resilience index. This method assigns weights according to the amount of information contained in each indicator, thereby reducing the subjectivity associated with manually assigned weights. Because the selected indicators differ in units of measurement and directional attributes, all indicators are standardized before aggregation. To ensure transparency and reproducibility, the entropy-weight method is implemented through the following steps.

For positive indicators, the standardized value is calculated as follows:

$$Z_{ijt} = \frac{X_{ijt} - \min(X_j)}{\max(X_j) - \min(X_j)} \quad (1)$$

For negative indicators, the standardized value is calculated as follows:

$$Z_{ijt} = \frac{\max(X_j) - X_{ijt}}{\max(X_j) - \min(X_j)} \quad (2)$$

where X_{ijt} denotes the original value of indicator j for firm i in year t , and Z_{ijt} denotes the standardized value. $\max(X_j)$ and $\min(X_j)$ represent the maximum and minimum values of indicator j in the sample, respectively. As indicated in Table 2, positive indicators are those for which a higher value implies stronger supply chain resilience, whereas negative indicators are those for which a higher value implies greater financial pressure, operational burden, or supply chain dependence.

Because this study constructs a longitudinal firm-level panel index, entropy weights are calculated based on the full panel sample rather than separately for each year. This

approach allows the weights to reflect the information variation in each indicator across all firms and years.

After standardization, the proportion of indicator j for firm i in year t is calculated as follows:

$$P_{ijt} = \frac{Z_{ijt}}{\sum_{(k,\tau) \in \Omega} Z_{k\tau}} \quad (3)$$

where Ω denotes all valid firm–year observations in the full panel sample, and the denominator represents the sum of the standardized values of indicator j across all observations in Ω .

The entropy value of indicator j is then calculated as follows:

$$E_j = -\frac{1}{\ln N} \sum_{i,t} P_{ijt} \ln(P_{ijt}) \quad (4)$$

where N denotes the total number of firm–year observations in the full panel sample. When $P_{ijt} = 0$, the term $P_{ijt} \ln(P_{ijt})$ is defined as zero.

The information utility value of indicator j is calculated as follows:

$$D_j = 1 - E_j \quad (5)$$

The weight of indicator j is then calculated as follows:

$$W_j = \frac{D_j}{\sum_{j=1}^m D_j} \quad (6)$$

Finally, the supply chain resilience index is obtained as follows:

$$Scr_{it} = \sum_{j=1}^m (W_j \times Z_{ijt}) \quad (7)$$

where Scr_{it} denotes the supply chain resilience index of firm i in year t , m denotes the number of indicators, W_j represents the weight of indicator j , and Z_{ijt} is the standardized value of indicator j for firm i in year t . A higher value of Scr_{it} indicates stronger supply chain resilience. The resulting composite index is used as the dependent variable in the subsequent empirical analysis.

3.4. Empirical Strategy

To examine the effect of digital transformation on supply chain resilience, this study first specifies a firm-level panel model with firm and year fixed effects. The baseline model is written as follows:

$$Scr_{it} = \alpha + \beta DT_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

where Scr_{it} denotes the supply chain resilience index of firm i in year t , and DT_{it} denotes the level of digital transformation. X_{it} represents a vector of firm-level control variables, including board size, largest shareholder ownership, executive compensation, ownership nature, and R&D intensity. μ_i denotes firm fixed effects, λ_t denotes year fixed effects, and ε_{it} is the error term. The coefficient β is the main parameter of interest. A significantly positive β would indicate that digital transformation improves supply chain resilience in EV manufacturing firms.

However, digital transformation is not randomly distributed across firms. Firms with stronger governance capacity, larger resource endowments, or higher innovation capability may be more likely to adopt digital technologies, and these characteristics may also affect supply chain resilience. Conventional fixed-effects models may therefore be insufficient

to fully address high-dimensional firm-level heterogeneity and potential confounding. To improve the reliability of the estimation, this study employs a double machine learning (DML) framework. The DML approach was developed to estimate treatment and structural parameters in the presence of high-dimensional nuisance components and has also been applied in recent empirical research on industrial-chain resilience. DML combines machine learning with orthogonalized estimation and is suitable for settings in which the relationship among the outcome variable, treatment variable, and control variables may be complex or nonlinear.

Following the partial linear DML framework, the empirical model can be expressed as follows:

$$\text{Scr}_{it} = \theta \text{DT}_{it} + g(X_{it}) + \mu_i + \lambda_t + \varepsilon_{it} \quad (9)$$

$$\text{DT}_{it} = m(X_{it}) + \mu_i + \lambda_t + v_{it} \quad (10)$$

where θ measures the causal effect of digital transformation on supply chain resilience. $g(X_{it})$ and $m(X_{it})$ are nuisance functions that capture the relationships between the high-dimensional control variables and the outcome variable and treatment variable, respectively. In the estimation process, machine learning methods are first used to predict Scr_{it} and DT_{it} based on the control variables. The residualized outcome and residualized treatment are then used to estimate θ . This orthogonalization procedure helps reduce bias caused by model misspecification and overfitting.

In the baseline DML estimation, a random forest is used to estimate the nuisance functions because it can flexibly capture nonlinear relationships and interactions among firm-level covariates. Sample splitting and cross-fitting are implemented to reduce overfitting bias and improve out-of-sample prediction performance. Firm fixed effects and year fixed effects are included to control for unobservable time-invariant firm characteristics and common macro-level shocks. The subsequent robustness checks further examine whether the results remain stable when alternative sample-splitting ratios and machine learning algorithms are used.

3.5. Additional Empirical Designs

Several additional analyses are conducted to assess the credibility of the baseline estimates and to examine the mechanisms and boundary conditions of the relationship between digital transformation and supply chain resilience.

Instrumental variable estimation is used to address potential endogeneity. Previous studies on digital transformation and supply chain resilience have also used alternative endogeneity correction strategies, such as Heckman-type procedures and instrumental variable estimation, to reduce bias arising from selection effects and omitted variables (Du and Zhang, 2022 [35]). Although the double machine learning framework allows flexible control for high-dimensional firm-level covariates, the estimated relationship may still be influenced by omitted variables, reverse causality, or unobserved regional factors. To mitigate this concern, two instrumental variables are constructed from historical regional communication infrastructure: the interaction between the length of long-distance optical cable lines in each region in 1998 and a time trend, and the interaction between the total volume of postal and telecommunication services in each region in 1998 and a time trend. These historical infrastructure variables are expected to be associated with current firm-level digital transformation, while their direct effect on the current supply chain resilience of EV manufacturing firms should be limited after firm and year fixed effects have been controlled for.

Mechanism tests are used to examine the two transmission channels proposed in Section 2: technological innovation and managerial transaction costs. The model is specified as follows:

$$M_{it} = \alpha + \delta DT_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (11)$$

where M_{it} denotes the mechanism variable, including technological innovation (Til) and managerial transaction costs (Cost). DT_{it} denotes digital transformation, X_{it} is the vector of firm-level control variables, μ_i represents firm fixed effects, λ_t represents year fixed effects, and ε_{it} is the error term. The coefficient δ captures the effect of digital transformation on the proposed mechanism variables.

The robustness checks focus on whether the baseline results are sensitive to alternative empirical settings. Specifically, the analysis changes the sample-splitting ratios in the DML estimation, replaces the baseline machine learning algorithm with alternative algorithms, applies 1% and 5% winsorization to reduce the influence of extreme values, and excludes municipalities from the sample.

Heterogeneity analysis is further conducted by dividing the sample according to market position, firm size, and manufacturing attribute. These tests examine whether the resilience-enhancing effect of digital transformation varies with firms' supply chain position, resource endowment, and role within the EV manufacturing system.

4. Results

4.1. Baseline Results

Table 3 presents the baseline estimates of the effect of digital transformation on supply chain resilience. The key coefficient in Table 3 is the coefficient of DT, which captures the relationship between digital transformation and supply chain resilience. In Column (1), the coefficient of DT is 0.064 and statistically significant at the 1% level. After controlling for firm and year fixed effects, the coefficient remains positive and significant, with a value of 0.077 in Column (2). This coefficient is important because it indicates that the positive association between digital transformation and supply chain resilience is not driven solely by time-invariant firm characteristics or common year-level shocks. These baseline results support H1.

Table 3. Baseline Results.

	(1)	(2)
	Scr	Scr
DT	0.064 *** (0.021)	0.077 *** (0.026)
Firm fixed effects	No	Yes
Year fixed effects	No	Yes
Observations	610	610

Note: Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.2. Robustness Checks

Table 4 reports the robustness checks for the baseline estimates. The key information in Table 4 is whether the coefficient of DT remains positive and statistically significant across alternative empirical settings. Columns (1) and (2) change the sample-splitting ratios in the DML estimation by setting the number of folds to three and eight, respectively. The coefficients of DT remain positive and significant, indicating that the baseline result is not sensitive to the sample-splitting procedure. Columns (3) and (4) replace the baseline machine learning algorithm with a neural network and gradient boosting, and the coeffi-

cients remain positive and significant. Columns (5) and (6) apply 1% and 5% winsorization thresholds, suggesting that the baseline result is not driven by extreme observations. Column (7) excludes firms located in municipalities directly under the central government, and the coefficient of DT remains significant. Overall, Table 4 shows that the positive relationship between digital transformation and supply chain resilience is stable across model adjustments, data processing procedures, and sample restrictions.

Table 4. Robustness Checks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Changing sample-splitting ratios		Replacing machine learning algorithms		Winsorization		Excluding municipalities
	K-folds = 3	K-folds = 8	Neural network	Gradient boosting	1% win-sorization	5% win-sorization	K-folds = 5
	Scr	Scr	Scr	Scr	Scr	Scr	Scr
DT	0.056 ** (0.025)	0.075 *** (0.027)	0.117 *** (0.038)	0.080 *** (0.023)	0.071 *** (0.023)	0.046 *** (0.017)	0.041 *** (0.015)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	610	610	610	610	610	610	500

Note: Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.3. Endogeneity Test

Potential endogeneity may arise from omitted variables, reverse causality, or unobserved regional characteristics. To mitigate this concern, this study employs an instrumental variable approach using historical regional communication infrastructure. Two instruments are constructed: the interaction between the length of long-distance optical cable lines in each region in 1998 and a time trend, and the interaction between the total volume of postal and telecommunication services in each region in 1998 and a time trend. These variables capture the historical foundation of regional information infrastructure, which is likely to be associated with current firm-level digital transformation. After controlling for firm and year fixed effects, however, their direct relationship with the current supply chain resilience of EV manufacturing firms is expected to be limited.

Table 5 presents the instrumental variable estimates. The key coefficients in Table 5 are the instrumental variable estimates of DT, which indicate whether the baseline relationship remains after addressing potential endogeneity. The coefficient of DT is 0.618 in Column (1), significant at the 5% level, and 0.369 in Column (2), significant at the 1% level. These results are consistent with the baseline estimates and suggest that the positive association between digital transformation and supply chain resilience remains after potential endogeneity concerns are addressed.

Table 5. Instrumental Variable Estimates.

	(1)	(2)
	Scr	Scr
Instrumental variable	IV1	IV2
DT	0.618 ** (0.251)	0.369 *** (0.141)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	610	610

Note: Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.4. Mechanism Tests

Table 6 presents the results of the mechanism tests. The analysis examines the two transmission channels proposed in Section 2: technological innovation and managerial transaction costs. The key coefficients in Table 6 are the effects of DT on technological innovation and managerial transaction costs, which indicate whether the proposed mechanisms are supported. In Column (1), the coefficient of DT is 1.363 and statistically significant at the 1% level, indicating that digital transformation is associated with higher technological innovation. This coefficient is important because it supports the view that digital transformation can improve firms' innovation output and strengthen the technological foundation of supply chain resilience. In Column (2), the coefficient of DT is -0.036 and statistically significant at the 1% level, indicating that digital transformation is associated with lower managerial transaction costs. This coefficient is important because it suggests that digital transformation can reduce internal coordination and managerial frictions. Taken together, these results support H2 and H3. They indicate that digital transformation contributes to supply chain resilience through both a technological innovation channel and a managerial transaction cost channel.

Table 6. Mechanism Tests.

	(1)	(2)
	Til	Cost
DT	1.363 *** (0.248)	-0.036 *** (0.014)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	610	610

Note: Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.5. Heterogeneity Analysis

Table 7 presents the heterogeneity results by market position, firm size, and manufacturing attribute. The heterogeneity analysis classifies firms by market position, firm size, and manufacturing attribute. Market position is measured by the ratio of a firm's annual sales revenue to the total annual sales revenue of all firms in the same industry. Firms above the year-specific industry median are defined as high-market-position firms, while the remaining firms are defined as low-market-position firms. Firm size is measured by total assets, with firms above the year-specific industry median classified as large firms and those below it classified as small firms. Manufacturing attribute is identified according to firms' main business scope, distinguishing vehicle manufacturers from component suppliers.

Columns (1) and (2) compare firms with high and low market positions. The coefficient of DT is 0.072 and statistically significant for firms with high market positions, while the coefficient for firms with low market positions is not statistically significant. This result suggests that the positive association between digital transformation and supply chain resilience is more evident among firms with stronger market positions. It does not imply that digital transformation is ineffective for low-market-position firms; rather, the empirical results do not provide sufficient statistical evidence for this subgroup.

Columns (3) and (4) compare large and small firms. The coefficient of DT is 0.072 and statistically significant for large firms, while the coefficient for small firms is not statistically significant. This finding indicates that firm size may condition the effectiveness of digital transformation, as larger firms usually have stronger resource bases, digital infrastructure, and organizational capacity to integrate digital technologies into supply chain management. Again, the insignificant coefficient for small firms should be interpreted

as a lack of statistical significance rather than as evidence that digital transformation has no effect.

Table 7. Heterogeneity Analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
	Market position		Firm size		Manufacturing attribute	
	High market position	Low market position	Large firms	Small firms	Vehicle manufacturers	Component suppliers
	Scr	Scr	Scr	Scr	Scr	Scr
DT	0.072 ** (0.034)	0.025 (0.023)	0.072 ** (0.032)	0.034 (0.021)	0.224 *** (0.078)	0.027 ** (0.012)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	435	175	498	112	180	430

Note: Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Columns (5) and (6) distinguish between vehicle manufacturers and component suppliers. The coefficient of DT is 0.224 for vehicle manufacturers and 0.027 for component suppliers, and both coefficients are statistically significant. The effect remains significant for component suppliers, but its magnitude is smaller. One possible explanation is that component suppliers usually have a narrower coordination scope and may depend more heavily on the digital standards, production schedules, and coordination requirements of lead vehicle manufacturers. By contrast, vehicle manufacturers often occupy a central position in EV supply chain coordination, production scheduling, system integration, and final delivery, so digital transformation may generate broader resilience benefits for these firms.

It should also be noted that the sample sizes differ between the two manufacturing-attribute groups, with 180 observations for vehicle manufacturers and 430 observations for component suppliers. Therefore, the manufacturing-attribute heterogeneity results should be interpreted with caution. Overall, these results suggest that the resilience-enhancing effect of digital transformation is more pronounced among firms with stronger market positions, larger firms, and vehicle manufacturers, while the insignificant coefficients for low-market-position firms and small firms should be interpreted as a lack of statistical significance rather than as evidence of ineffectiveness.

To provide a clearer overview of the empirical evidence, Figure 2 summarizes the findings from the baseline estimation, robustness and endogeneity tests, and mechanism and heterogeneity analyses. The baseline estimate shows that digital transformation is positively associated with supply chain resilience. The robustness estimates remain positive and statistically significant across alternative empirical settings, while the instrumental variable estimates provide further support for the baseline result. The mechanism tests provide evidence consistent with two transmission channels: digital transformation is associated with greater technological innovation and lower managerial transaction costs. The heterogeneity analysis further reports larger estimates for firms with stronger market positions, large firms, and vehicle manufacturers. Overall, Figure 2 shows that the positive relationship between digital transformation and supply chain resilience is supported by the robustness and endogeneity tests, is associated with technological innovation and lower managerial transaction costs, and varies across different firm groups.

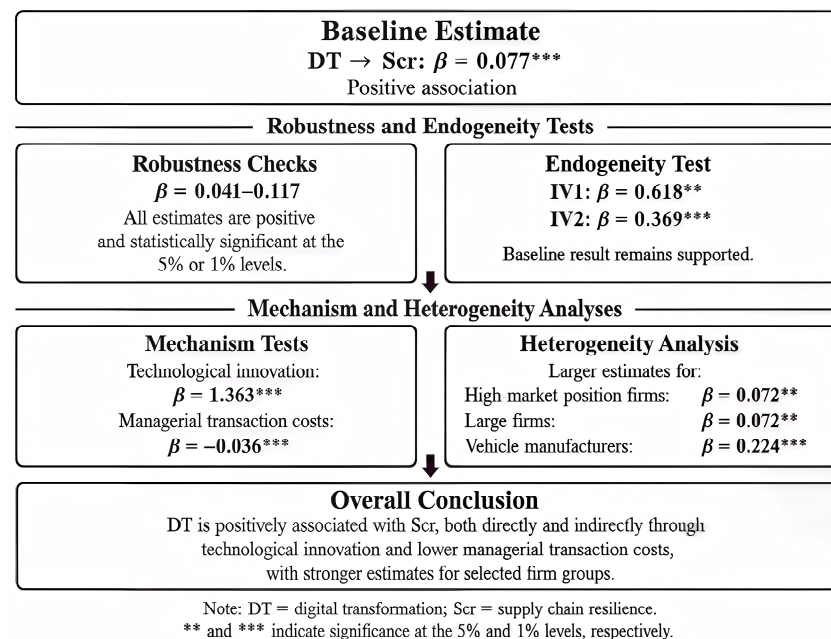


Figure 2. Summary of Empirical Findings.

5. Discussion

The empirical findings summarized in Figure 2 provide consistent evidence of a positive association between digital transformation and supply chain resilience in EV manufacturing firms. This relationship should be interpreted in light of the distinctive structural features of EV supply chains. Unlike many conventional manufacturing sectors, EV production relies on highly interdependent networks involving batteries, semiconductors, electronic control systems, intelligent sensors, software platforms, thermal management systems, and other technology-intensive components (Huang et al., 2024 [1]; Li and Sukhotu, 2025 [17]). Disruptions in any single segment may rapidly propagate across the supply chain, affecting production scheduling, delivery performance, and downstream market responsiveness. In this context, digital transformation contributes to resilience not merely by improving operational efficiency but more fundamentally by strengthening firms' capacity to monitor supply chain conditions, process dispersed information, and coordinate timely responses under uncertainty (Li and Sukhotu, 2025 [17]).

The technological innovation channel reveals the technological foundation of supply chain resilience. In EV manufacturing, resilience depends not only on restoring production after disruptions but also on reducing technological dependence, developing alternative technical solutions, and adapting to changes in component supply and technical standards. Firms with stronger innovation and resilience capabilities are generally better positioned to respond to disruptions and develop feasible substitutes when key technologies or inputs become constrained (Huang and Shi, 2024 [21]; Parker and Ameen, 2018 [24]). Digital transformation facilitates these processes by improving data availability, accelerating knowledge recombination, and enhancing the responsiveness of R&D activities to production and market information. Digital design, simulation, and data analytics tools can support battery system optimization, chip-substitution assessment, intelligent-driving development, and modular component redesign. These capabilities enable firms to respond more flexibly to component shortages and technological bottlenecks, which is consistent with prior evidence linking digital empowerment, innovation capability, and manufacturing supply chain resilience (Wang et al., 2025 [19]; Huang and Shi, 2024 [21]).

The managerial transaction cost channel highlights the organizational foundation of resilience. Transaction cost theory suggests that uncertainty, information asymme-

try, and complex interorganizational relationships increase the costs of coordination, monitoring, communication, and governance (Williamson, 1981 [22]; Coase, 2012 [23]; Cuypers et al., 2021 [38]). Such frictions are particularly salient in EV manufacturing, where procurement, production, logistics, supplier management, inventory control, and customer response must be closely aligned. Digital transformation can mitigate these frictions by increasing information transparency, standardizing workflows, and integrating data across departments and supply chain partners (Meng and Gong, 2024 [20]; Dubey et al., 2019 [33]). Lower managerial transaction costs enable firms to revise procurement plans, coordinate alternative suppliers, reorganize production schedules, and reallocate resources more rapidly when disruptions occur. Digital transformation therefore contributes to supply chain resilience through the joint operation of technological upgrading and more efficient organizational coordination.

The heterogeneity results further indicate that the relationship between digital transformation and supply chain resilience is conditional rather than uniform. Firms with stronger market positions and larger scale appear better able to convert digital investment into resilience-enhancing capabilities. This pattern suggests that the value of digital transformation depends on complementary resources, including financial capacity, digital infrastructure, managerial competence, and skilled personnel. Firms with weaker market positions or a smaller scale may also adopt digital technologies, but they may face greater difficulty in embedding such technologies into supply chain routines and converting digital investment into effective resilience capabilities. Evidence from SME supply chains similarly suggests that resilience development may be constrained by limited organizational resources, coordination barriers, and exposure to multiple operational risks (Ali et al., 2017 [39]). Accordingly, the statistically insignificant coefficients for low-market-position firms and small firms should be interpreted as insufficient statistical evidence rather than as proof that digital transformation is ineffective for these groups.

The larger estimated coefficient for vehicle manufacturers also reflects the governance structure of EV supply chains. Vehicle manufacturers typically occupy central positions in system integration, supplier coordination, production scheduling, and final delivery. Improvements in digital visibility and coordination can therefore generate broader resilience benefits for these firms (Li and Sukhotu, 2025 [17]). Component suppliers may also benefit from digital transformation, but their coordination scope is generally narrower and often depends on the digital standards, production schedules, and technical requirements established by lead vehicle manufacturers. This result suggests that the resilience value of digital transformation depends not only on a firm's internal level of digitalization but also on its structural position and coordination role within the wider supply chain.

The findings also raise an important issue concerning ESG-related factors in EV supply chains. Although ESG performance was not explicitly incorporated into the theoretical framework or empirical model of this study, recent research has identified substantial sustainability challenges throughout EV battery supply and value chains, including raw material extraction, material processing, battery manufacturing, end-of-life management, and recycling (Rajaeifar et al., 2022 [40]). Research on responsible sourcing further shows that battery material supply chains involve environmental, social, and governance risks associated with mineral extraction, supplier accountability, traceability, and upstream sourcing practices (Deberdt and Le Billon, 2021 [41]). The transition toward greener battery technologies also requires addressing challenges related to material availability, environmental impacts, and lifecycle sustainability, highlighting the importance of sustainable battery development in future EV supply chain governance (Larcher and Tarascon, 2015 [42]). ESG-related practices may interact with digital transformation by enhancing supplier transparency, strengthening responsible sourcing, and

supporting more sustainable forms of supply chain governance. Digital traceability systems, for example, may help firms identify environmental and social risks in upstream supply chains and improve compliance monitoring. Digital product and material passports may further organize lifecycle information on material origin, composition, use, recovery, and recycling, thereby supporting traceability and circular resource management across supply chains (Van Capelleveen et al., 2023 [43]). Blockchain-enabled supply chain systems may further enhance data transparency, traceability, and interorganizational information sharing (Li and Chen, 2023 [44]). However, the effective implementation of blockchain-based traceability depends on clearly defined business requirements, reliable data, interoperable information systems, appropriate governance arrangements, and sustained participation among supply chain partners (Hastig and Sodhi, 2020 [45]). Future research could therefore incorporate ESG performance into the empirical framework and examine whether ESG performance moderates or complements the relationship between digital transformation and supply chain resilience.

Finally, the findings should be interpreted within the specific context of Chinese A-share-listed EV manufacturing firms. Several results are closely related to the distinctive characteristics of EV supply chains, including their dependence on batteries and semiconductors, complex component networks, software–hardware integration, and the central coordinating role of vehicle manufacturers (Huang et al., 2024 [1]; Li and Sukhotu, 2025 [17]; Huang and Shi, 2024 [21]). At the same time, this industrial configuration may limit the direct generalizability of the estimated association to countries with different battery supply structures, technological capabilities, and supply chain governance arrangements. Nevertheless, the underlying mechanisms identified in this study—technological innovation, lower managerial transaction costs, stronger information-processing capacity, and improved coordination—may extend beyond the EV industry. These mechanisms may also be relevant to other technology-intensive sectors characterized by complex supplier networks, high coordination requirements, and strong technological interdependence. Future research could examine whether these mechanisms operate similarly in industries such as electronics, high-end equipment manufacturing, renewable energy equipment, and intelligent manufacturing.

6. Conclusions

This study places digital transformation in the context of EV manufacturing supply chain resilience rather than treating it only as a general indicator of enterprise modernization. Using panel data from Chinese A-share listed EV manufacturing firms from 2014 to 2023, the empirical analysis shows that digital transformation is positively associated with supply chain resilience. More importantly, the results indicate that this relationship is not merely a matter of digital technology adoption. Digital transformation contributes to resilience when it is translated into technological innovation, lower managerial transaction costs, and more effective supply chain decision-making.

The main contribution of this study is to show that digital transformation can be understood as a resilience-building capability in EV manufacturing. Existing research has often emphasized the role of digital transformation in improving innovation, productivity, or operational efficiency. This study shifts attention to supply chain resilience, a critical issue for EV manufacturers exposed to component shortages, technological interdependence, logistics disruptions, and demand fluctuations. By identifying technological innovation and managerial transaction costs as two relevant channels, the study also clarifies that digital transformation affects resilience through both technological upgrading and organizational coordination. In addition, the heterogeneity analysis shows that the value of

digital transformation depends on firm resources and supply chain position, which helps explain why digital upgrading may generate different outcomes across firms.

The findings offer practical implications for the development of EV supply chains. For policymakers, promoting digital transformation in the EV industry should not be limited to encouraging firms to purchase digital equipment or software. More attention should be paid to the construction of shared digital infrastructure for supply chain coordination, including industrial internet platforms, component traceability systems, data-sharing standards, intelligent logistics networks, and risk early-warning systems. This infrastructure can improve information transparency across vehicle manufacturers, component suppliers, logistics providers, and downstream distributors, thereby strengthening the resilience of the whole supply chain.

Policy support should also be more differentiated. Smaller firms, firms with weaker market positions, and some component suppliers may face greater barriers in financing, digital infrastructure, technical talent, and organizational integration. For these firms, shared digital platforms, targeted financing tools, digital consulting services, and workforce training may be more effective than broad and undifferentiated subsidies. At the same time, vehicle manufacturers should be encouraged to build more compatible digital interfaces with component suppliers so that digital transformation does not remain concentrated among leading firms but extends to upstream and midstream supply chain partners.

For EV manufacturing firms, the results imply that digital transformation should be embedded in core supply chain activities. Digital tools should be used not only for internal management but also for supplier monitoring, demand forecasting, inventory control, production scheduling, logistics coordination, and risk identification. In practical terms, EV manufacturers should prioritize investment in integrated data platforms, supplier digital integration systems, intelligent manufacturing systems, component traceability tools, and supply chain risk-monitoring platforms. These investments can help firms connect internal production data with supplier information, improve visibility over critical components, and respond more quickly to disruptions in batteries, chips, logistics, and market demand. Firms should also connect digital transformation with R&D and process redesign so that data resources can support technological innovation and improve the flexibility of supply chain adjustment. The practical value of digital transformation depends less on the adoption of digital tools themselves than on whether these tools become part of firms' innovation, coordination, and decision-making routines.

This study has several limitations that point to future research. First, the sample is limited to Chinese A-share listed EV manufacturing firms. Therefore, the findings should not be interpreted as universal evidence for all EV firms. The results may not fully apply to unlisted firms, smaller suppliers, privately held firms, or EV manufacturers in other countries because these firms may differ in financial resources, digital infrastructure, governance structures, and supply chain positions. Future studies could include unlisted firms, small and medium-sized suppliers, or cross-country samples to test the generalizability of the findings. Second, the measurement of digital transformation and supply chain resilience is constrained by available firm-level indicators. Future research could use supplier–customer transaction data, supply chain network data, patent text data, or real-time disruption data to capture supply chain resilience more directly. Third, ESG-related factors are not explicitly incorporated into the theoretical framework or empirical model of this study. Future studies could incorporate ESG performance, environmental compliance, responsible sourcing, supplier responsibility, and corporate governance indicators to examine how digital transformation and sustainable governance jointly shape supply chain resilience in EV manufacturing. Finally, further research could examine the role of specific digital

technologies, such as artificial intelligence, industrial internet platforms, digital twins, and intelligent logistics systems, in shaping the resilience of EV supply chains.

Author Contributions: Conceptualization, J.H. and J.W.; methodology, Y.C. and J.W.; software, Y.C.; validation, J.H., Y.C. and J.W.; formal analysis, J.H. and Y.C.; investigation, J.H. and X.A.; resources, J.H. and J.W.; data curation, J.H. and Y.C.; writing—original draft preparation, J.H.; writing—review and editing, J.W. and X.A.; visualization, X.A.; supervision, J.W.; project administration, J.W.; funding acquisition, J.H. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Doctoral Research Startup Fund (award number: BK202010); the Research on the Value Co creation Mechanism and Implementation Path of Hubei New Energy Vehicle Green Supply Chain from the Perspective of Configuration (award number: 23ZD148); the Dynamic Evolution of New Quality Productivity Development Level Measurement and Diagnosis of Obstacle Factors (award number: D20241805); the 2024 Open Fund of Hubei Collaborative Innovation Center for Modern Logistics and Business (award number: 2024LB02) and the Research on the Innovation Source Capacity of Hubei Province's Low-altitude Economy: Statistical Measurement, Regional Comparison and Enhancement Path (award number: 2025EDA033).

Data Availability Statement: The processed dataset used in this study is publicly available in a GitHub repository at <https://github.com/tksgk6h5hb-wq/Green-innovation/blob/main/data.xls>. (accessed on 6 July 2026). Additional information related to the data processing procedures can be obtained from the corresponding author upon reasonable request.

Acknowledgments: The authors gratefully acknowledge the support received during the preparation of this study and thank all authors for their contributions to the completion of this manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Huang, Z.; Zhou, Y.; Lin, Y.; Zhao, Y. Resilience evaluation and enhancing for China's electric vehicle supply chain in the presence of attacks: A complex network analysis approach. *Comput. Ind. Eng.* **2024**, *195*, 110416. [CrossRef]
2. Olivetti, E.A.; Ceder, G.; Gaustad, G.G.; Fu, X. Lithium-ion battery supply chain considerations: Analysis of potential bottlenecks in critical metals. *Joule* **2017**, *1*, 229–243. [CrossRef]
3. Miao, Y.; Liu, L.; Xu, K.; Li, J. High concentration from resources to market heightens risk for power lithium-ion battery supply chains globally. *Environ. Sci. Pollut. Res.* **2023**, *30*, 65558–65571. [CrossRef]
4. Ivanov, D. Viable supply chain model: Integrating agility, resilience and sustainability perspectives—Lessons from and thinking beyond the COVID-19 pandemic. *Ann. Oper. Res.* **2022**, *319*, 1411–1431. [PubMed]
5. Ponomarev, S.Y.; Holcomb, M.C. Understanding the concept of supply chain resilience. *Int. J. Logist. Manag.* **2009**, *20*, 124–143. [CrossRef]
6. Tukamuhabwa, B.R.; Stevenson, M.; Busby, J.; Zorzini, M. Supply chain resilience: Definition, review and theoretical foundations for further study. *Int. J. Prod. Res.* **2015**, *53*, 5592–5623. [CrossRef]
7. Christopher, M.; Peck, H. Building the resilient supply chain. *Int. J. Logist. Manag.* **2004**, *15*, 1–14. [CrossRef]
8. Dolgui, A.; Ivanov, D. 5G in digital supply chain and operations management: Fostering flexibility, end-to-end connectivity and real-time visibility through internet-of-everything. *Int. J. Prod. Res.* **2022**, *60*, 442–451. [CrossRef]
9. Tang, C.S.; Veelenturf, L.P. The strategic role of logistics in the Industry 4.0 era. *Transp. Res. Part E Logist. Transp. Rev.* **2019**, *129*, 1–11. [CrossRef]
10. Harju, A.; Hallikas, J.; Immonen, M.; Lintukangas, K. The impact of procurement digitalization on supply chain resilience: Empirical evidence from Finland. *Supply Chain Manag.* **2023**, *28*, 62–76. [CrossRef]
11. Li, P.; Chen, Y.; Guo, X. Digital transformation and supply chain resilience. *Int. Rev. Econ. Financ.* **2025**, *99*, 104033. [CrossRef]
12. Jing, H.; Fan, Y. Digital transformation, supply chain integration and supply chain performance: Evidence from Chinese manufacturing listed firms. *SAGE Open* **2024**, *14*, 21582440241281616. [CrossRef]
13. Nasiri, M.; Ukko, J.; Saunila, M.; Rantala, T. Managing the digital supply chain: The role of smart technologies. *Technovation* **2020**, *96*, 102121. [CrossRef]
14. Qi, Y.; Huo, B.; Wang, Z.; Yeung, H.Y.J. The impact of operations and supply chain strategies on integration and performance. *Int. J. Prod. Econ.* **2017**, *185*, 162–174. [CrossRef]

15. Tian, Y.; Cui, L. Supply chain resilience and digital transformation: Perspectives from a supply chain network. *Humanit. Soc. Sci. Commun.* **2025**, *12*, 1738. [\[CrossRef\]](#)
16. Ozdemir, D.; Sharma, M.; Dhir, A.; Daim, T. Supply chain resilience during the COVID-19 pandemic. *Technol. Soc.* **2022**, *68*, 101847. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Li, Y.; Sukhotu, V. Enhanced digital capabilities for building resilient supply chains: Exploring visibility, collaboration, and resilience in China's electric vehicle industry. *World Electr. Veh. J.* **2025**, *16*, 63. [\[CrossRef\]](#)
18. Feng, S.; Zhang, R.; Di, D.; Li, G. Does digital transformation promote global value chain upgrading? Evidence from Chinese manufacturing firms. *Econ. Model.* **2024**, *139*, 106810. [\[CrossRef\]](#)
19. Wang, H.; Chen, Y.; Xie, J.; Liu, C. Research on digital empowerment, innovation vitality and manufacturing supply chain resilience mechanism. *PLoS ONE* **2025**, *20*, e0316183. [\[CrossRef\]](#) [\[PubMed\]](#)
20. Meng, X.; Gong, X. Digital transformation and innovation output of manufacturing companies—An analysis of the mediating role of internal and external transaction costs. *PLoS ONE* **2024**, *19*, e0296876. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Huang, Z.; Shi, Y. Risk perception, innovation, and supply chain resilience in China's new energy vehicle industry. *Int. J. Automot. Technol. Manag.* **2024**, *24*, 217–244. [\[CrossRef\]](#)
22. Williamson, O.E. The economics of organization: The transaction cost approach. *Am. J. Sociol.* **1981**, *87*, 548–577. [\[CrossRef\]](#)
23. Coase, R.H. The nature of the firm. In *The Roots of Logistics*; Klaus, P., Müller, S., Eds.; Springer: Berlin/Heidelberg, Germany, 2012; pp. 317–333.
24. Parker, H.; Ameen, K. The role of resilience capabilities in shaping how firms respond to disruptions. *J. Bus. Res.* **2018**, *88*, 535–541. [\[CrossRef\]](#)
25. Chowdhury, M.M.H.; Quaddus, M. Supply chain resilience: Conceptualization and scale development using dynamic capability theory. *Int. J. Prod. Econ.* **2017**, *188*, 185–204. [\[CrossRef\]](#)
26. Chernozhukov, V.; Chetverikov, D.; Demirer, M.; Duflo, E.; Hansen, C.; Newey, W.; Robins, J. Double/debiased machine learning for treatment and structural parameters. *Econom. J.* **2018**, *21*, C1–C68. [\[CrossRef\]](#)
27. Martin, R. Regional economic resilience, hysteresis and recessionary shocks. *J. Econ. Geogr.* **2012**, *12*, 1–32. [\[CrossRef\]](#)
28. Li, X.; Wu, Q.; Holsapple, C.W.; Goldsby, T. An empirical examination of firm financial performance along dimensions of supply chain resilience. *Manag. Res. Rev.* **2017**, *40*, 254–269. [\[CrossRef\]](#)
29. Wei, S.; Jiang, J.; Chen, J.; Wang, Q. Digital technology and supply chain resilience: A literature review and emerging themes. *Int. Trans. Oper. Res.* **2026**, *33*, 2167–2189.
30. Toorajipour, R.; Sohrabpour, V.; Nazarpour, A.; Oghazi, P.; Fischl, M. Artificial intelligence in supply chain management: A systematic literature review. *J. Bus. Res.* **2021**, *122*, 502–517. [\[CrossRef\]](#)
31. Dubey, R.; Gunasekaran, A.; Childe, S.J.; Fosso Wamba, S.; Roubaud, D.; Foropon, C. Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. *Int. J. Prod. Res.* **2021**, *59*, 110–128.
32. Li, J.; Song, H.; Ma, Y. The mechanism and impact of digital transformation on supply chain resilience in the manufacturing industry. *Sci. Rep.* **2026**, *16*, 7635. [\[CrossRef\]](#) [\[PubMed\]](#)
33. Dubey, R.; Gunasekaran, A.; Childe, S.J.; Roubaud, D.; Wamba, S.F.; Giannakis, M.; Foropon, C. Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. *Int. J. Prod. Econ.* **2019**, *210*, 120–136. [\[CrossRef\]](#)
34. Srinivasan, R.; Swink, M. An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Prod. Oper. Manag.* **2018**, *27*, 1849–1867. [\[CrossRef\]](#)
35. Du, C.; Zhang, Q. Supply network position, digital transformation and innovation performance: Evidence from listed Chinese manufacturing firms. *PLoS ONE* **2022**, *17*, e0279133. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Xing, X.; Chen, T.; Yang, X.; Liu, T. Digital transformation and innovation performance of China's manufacturers? A configurational approach. *Technol. Soc.* **2023**, *75*, 102356. [\[CrossRef\]](#)
37. Zeng, A.; Chen, W.; Rasmussen, K.D.; Zhu, X.; Lundhaug, M.; Müller, D.B.; Tan, J.; Keiding, J.K.; Liu, L.; Dai, T.; et al. Battery technology and recycling alone will not save the electric mobility transition from future cobalt shortages. *Nat. Commun.* **2022**, *13*, 1341. [\[CrossRef\]](#) [\[PubMed\]](#)
38. Cuypers, I.R.; Hennart, J.F.; Silverman, B.S.; Ertug, G. Transaction cost theory: Past progress, current challenges, and suggestions for the future. *Acad. Manag. Ann.* **2021**, *15*, 111–150. [\[CrossRef\]](#)
39. Ali, I.; Nagalingam, S.; Gurd, B. Building resilience in SMEs of perishable product supply chains: Enablers, barriers and risks. *Prod. Plan. Control* **2017**, *28*, 1236–1250. [\[CrossRef\]](#)
40. Rajaeifar, M.A.; Ghadimi, P.; Raugei, M.; Wu, Y.; Heidrich, O. Challenges and recent developments in supply and value chains of electric vehicle batteries: A sustainability perspective. *Resour. Conserv. Recycl.* **2022**, *180*, 106144. [\[CrossRef\]](#)
41. Deberdt, R.; Le Billon, P. Conflict minerals and battery materials supply chains: A mapping review of responsible sourcing initiatives. *Extr. Ind. Soc.* **2021**, *8*, 100935. [\[CrossRef\]](#)

42. Larcher, D.; Tarascon, J.M. Towards greener and more sustainable batteries for electrical energy storage. *Nat. Chem.* **2015**, *7*, 19–29. [[PubMed](#)]
43. Van Capelleveen, G.; Vegter, D.; Olthaar, M.; van Hillegersberg, J. The anatomy of a passport for the circular economy: A conceptual definition, vision and structured literature review. *Resour. Conserv. Recycl. Adv.* **2023**, *17*, 200131. [[CrossRef](#)]
44. Li, Y.; Chen, T. Blockchain empowers supply chains: Challenges, opportunities and prospects. *Nankai Bus. Rev. Int.* **2023**, *14*, 230–248.
45. Hastig, G.M.; Sodhi, M.S. Blockchain for supply chain traceability: Business requirements and critical success factors. *Prod. Oper. Manag.* **2020**, *29*, 935–954. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.