sustainability

Article

Drivers of Artificial Intelligence and Their Effects on Supply Chain Resilience and Performance: An Empirical Analysis on an Emerging Market

Mengmeng Wang and Xiaoming Pan *

College of Business, Gachon University, Seongnam 13120, Republic of Korea
* Correspondence: 202055027@gachon.ac.kr

Abstract: The global supply chain has suffered an unprecedented impact Affected by multiple factors such as anti-globalization, rising trade protectionism and the COVID-19 pandemic. Based on the technology-organization-environment framework and resource-based theory, this study attempts to explore and analyze what drives a firm's willingness to adopt artificial intelligence technology and how such willingess to adopt artificial intelligence technology may contribute to supply chain resilience and supply chain performance. Using survey data collected from 318 firms in China, we empirically test our arguments and hypotheses through the structural equation modeling approach. The results suggest that the relative advantages of enterprise artificial intelligence technology, supply chain collaboration, and environmental uncertainty are the three major factors affecting the adoption of artificial intelligence technology, which subsequently provide a positive impact on supply chain resilience and supply chain performance. This study expands the application field and scope of artificial intelligence technology, fills the relatively large gap in the research on the behavior of enterprise users adopting artificial intelligence technology in the supply chain field. This provides a useful reference for enterprises to adopt artificial intelligence technology.

Keywords: artificial intelligence technology; supply chain resilience; supply chain performance; environmental uncertainty; supply chain collaboration

check for updates

Citation: Wang, M.; Pan, X. Drivers of Artificial Intelligence and Their Effects on Supply Chain Resilience and Performance: An Empirical Analysis on an Emerging Market. *Sustainability* **2022**, *14*, 16836. https://doi.org/10.3390/su142416836

Academic Editor: Ting Chi

Received: 6 October 2022
Accepted: 9 December 2022
Published: 15 December 2022

1. Introduction

With the continuous development of economic globalization seen in the past few decades, the world has formed a pattern of international industrial division of labor and economic development that is interdependent in nature. This has led to the traditional price competitiveness of emerging countries gradually weakening, as well. It is difficult to obtain a competitive advantage in the global supply chain only by relying on low labor costs and land costs. COVID-19 has ravaged the world for nearly three years, bringing a lot of uncertainty to the global supply chain and disrupting the supply chain of global enterprises. Global trade and investment have plummeted as they face challenges such as suppliers not meeting delivery obligations, unpredictable customer demand, and panic buying. Using the new technologies of the Fourth Industrial Revolution to enable enterprises to quickly recover from supply chain risks and build supply chain resilience has become a common scholarly concern [1–3].

Currently, scholars have different opinions on whether artificial intelligence technology provides support for businesses and the economy. Some argue that artificial intelligence technology is not a fix-all solution but nonetheless can change the business and global economic landscape, providing advantages such as increasing productivity, reducing human error, helping companies to make timely and accurate decisions, predicting customer preferences, and maximizing sales [4]. Following the positive impact of artificial intelligence on improving business operations, service processes and improving productivity, promoting the transformation of the manufacturing industry through artificial intelligence technology greatly reduces the number of employees and labor costs of enterprises, helping enterprises to achieve sustainable development goals. The adoption of artificial intelligence technology has become an inevitable choice for enterprises to ensure competitive advantages [5–7]. For example, as one of the globally largest companies and leaders in the global artificial intelligence industry, Alphabet, the parent company of Google, has invested heavily in researching and developing artificial intelligence-oriented products and services, including an autonomous self-driving technology development company called Waymo and a general-purpose artificial intelligence technology development company named DeepMind Technologies. At the same time, many Chinese firms are increasingly putting focus and investing heavily on not only developing artificial intelligence technologies but also integrating into artificial intelligence technologies into many facets of their business practices. In particular, BAT (Baidu, Alibaba, and Tencent) are some of the key players within artificial intelligence industry and are reshaping the industry landscape by applying artificial intelligence technologies to their key businesses. Therefore, artificial intelligence is a key technology of the fourth industrial revolution and has been applied to manufacturing, services, and other fields given its capacity to solve various real-life problems.

In the supply chain management process, artificial intelligence technology has broad prospects in helping enterprises to deal with order picking issues, customer relationship management, demand planning and forecasting, procurement and supply management, inventory control, and purchasing decisions [8–10]. Other scholars also argue that the opportunities and risks of artificial intelligence technology coexist. Artificial intelligence has an impact on the internal and external situations of any type of organization— internally, it can make tasks faster, better, and at the lowest cost. Externally, it will affect the partners, customers, competitors, and society, affecting both labor-intensive and knowledge-intensive industries such as consulting, finance, and service services that are forced to undergo significant changes due to its adoption.

Although the adoption of artificial intelligence technology has many benefits, there also exist many risks when enterprises it. After its adoption, enterprises need to obtain more competitive hardware or data to maintain a lasting competitive advantage, making the competition between enterprises and competitors revolve around hardware and data. The types of jobs undertaken by corporate employees will also change. Although artificial intelligence is unlikely to completely replace human jobs, more tasks will be outsourced to artificial intelligence, and corporate employees who cannot progress with artificial intelligence technology will be laid off.

In terms of customers, most find it difficult to believe the advice given by the artificial intelligence systems and it is also difficult to accept the use of their personal data in the enterprise artificial intelligence system. Even the smartest artificial intelligence system will routinely make very noticeable mistakes. Artificial intelligence systems are ultimately controlled by humans, and should it remain this way, there may be a risk of deliberate intrusion [11]. Some scholars are also worried that the adoption of artificial intelligence technology will make various fields in business and economics face many challenges. Enterprises need to prepare for the severance payment of employees, calculate the depreciation and amortization reserves of robots, and consider which part of the balance sheet will be managed by human resources managers [12].

Given that artificial intelligence technology is only limited to a few regions in the world, there will be an "AI gap" in the global economy, which will promote inequality in the global social, economic, and cultural fields. Moreover, artificial intelligence is mainly software, which is prone to loopholes remaining to be solved [4]. In summary, different scholars have different opinions on artificial intelligence technology, and it is crucial to clearly understand whether artificial intelligence technology can solve specific problems such as supply chain resilience and supply chain performance through empirical analysis.

Hence, integrating the TOE framework (technology-organization-environment framework) and the resource-based theory (RBT), the primary purpose of this study is to theorize and empirically explore what drives the firms' willingness to adopt artificial intelligence technology and how such willingness may explain the variation in the supply chain resilience and supply chain performance among the firms. This study provides new insights into the strategic use of artificial intelligence technology in the supply chain management by clearly clarifying the relationship between the willingness to adopt artificial intelligence technology, and supply chain flexibility and supply chain performance improvement, and thus fills important research gaps in the supply chain management literature.

In this study, we provide several contributions to understanding the forces driving a firm's willingness to adopt AI and how such a willingness to adopt AI may contribute positively to the firm's supply chain resilience and supply chain performance. First, we theorize and empirically find that a stronger willingness of a firm to adopt AI is related to AI technology, supply chain collaboration, and environmental uncertainty, suggesting that the importance of the different forces driving the firm's willingness to adopt AI has important implications for the effectiveness of strategies aimed at improving supply chain resilience and supply chain performance. Our findings provide the first empirical evidence of the role of different forces in driving a firm's willingness to adopt AI. Further, we argue and empirically show how differences in the willingness to adopt AI may explain the variation in supply chain resilience and supply chain performance. Therefore, we clarify theoretically the positive effect of a firm's willingness to adopt AI on the firm's supply chain resilience and supply chain performance, and thus provide novel insights into the relationships between a firm's willingness to adopt AI and the firm's supply chain resilience and supply chain performance. Finally, we clarify empirically the role of the willingness to adopt AI in fully or partially mediating the effects of different forces on the firm's supply chain resilience or supply chain performance.

The rest of the study is organized as follows. We first review the relevant literature and present our conceptual model and hypotheses. Then, we describe the data ad empirical approaches. Third, we present the empirical results. Finally, we conclude by discussing the findings and future research avenues in the final section.

2. Literature Review and Hypothesis Development

The TOE theoretical framework believes that the adoption of new technologies by organizations is affected by technical, organizational, and external environmental factors. Technical factors generally include existing technologies and technologies that have not been cited in the market, mainly referring to the characteristics of new technologies themselves and the technical conditions of enterprises. Organizational factors generally include organizational characteristics such as enterprise scale, senior management support, and human resource status. These factors mainly come from external pressure and support for adopting new technologies [13–16].

Resource-based theory holds that enterprises have different tangible and intangible resources, and the heterogeneity of these resources determines the difference in the competitiveness of enterprises. Only with scarce, irreplaceable, and non-replicable resources can an enterprise gain a lasting competitive advantage [17–20]. Simultaneously, when the enterprise has the unique advantages of specific resources, it also creates value [21]. As a resource, digital technology helps enterprises to gain competitive advantages. The application and innovation of digital technology based on the original tangible and intangible resources of enterprises optimizes the allocation of enterprise resources [22].

Artificial intelligence technology is one of the main emerging technologies of the Fourth Industrial Revolution. This study combines both the TOE and the RBT theories to propose the model shown in Figure 1 below. Specifically, according to the TOE theory, H1, H2, and H3 represent that artificial intelligence technology compatibility, supply chain cooperation, and environmental uncertainty have a positive impact on enterprises' adoption of artificial intelligence technology.

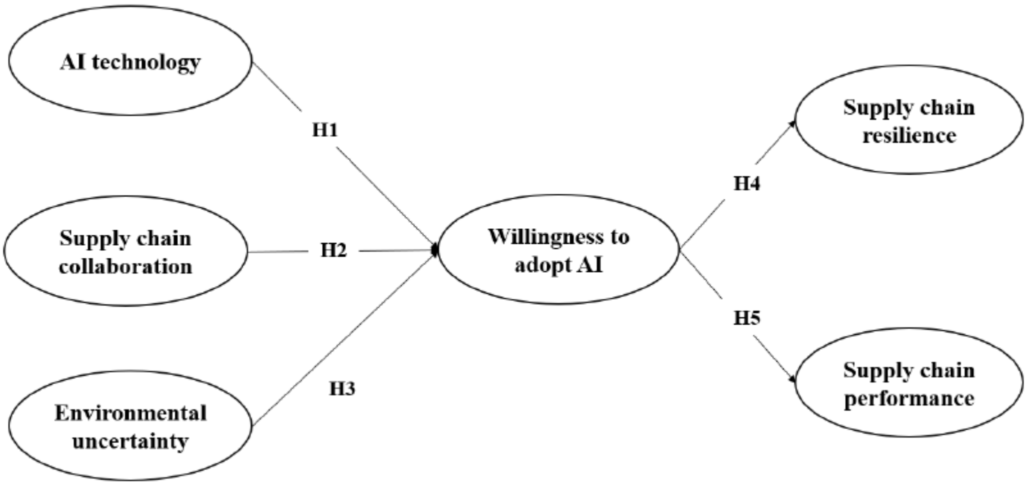

Figure 1. Research model.

2.1. Artificial Intelligence Technology Compatibility and Adoption Willingness

Artificial intelligence studies how to make machines do things, with categories such as weak intelligence (Artificial Narrow Intelligence or ANI), strong intelligence (Artificial General Intelligence or AGI), and super intelligence (Artificial Super Intelligence or ASI). Weak intelligence can only perform a specific task, strong intelligence has the same intelligence as humans and can complete any governance tasks that humans can do and can think, plan, and solve problems, while super intelligence is intelligence that far surpasses human beings in scientific research, overall cognitive abilities, and social skills [23]. According to the TOE theory, technical factors mainly refer to the characteristics of new technologies themselves. These include the basic technical conditions of enterprises, such as the technical infrastructure, technical capabilities, comparative advantages, and compatibility of technologies adopted by enterprises. Although artificial intelligence technologies have great potential, if they are incompatible with the current operating system of enterprises or bring great inconvenience in the implementation process, enterprises may instead delay or even refuse to adopt them [24]. In sum, artificial intelligence technology itself will have a positive impact on the adoption of artificial intelligence technology by enterprises. Accordingly, the following assumptions are proposed herein:

Hypothesis 1: *There is a positive relationship between the compatibility of artificial intelligence technology and a firm's adoption of artificial intelligence technology.*

2.2. Supply Chain Collaboration and Willingness to Adopt

Supply chain collaboration is a partnership where enterprises share information, resources, and risks together, maximize the value of cooperation, and create more benefits than independent actions [25]. This means that enterprises in the supply chain make the supply chain operate normally through coordination and cooperation: when there is a sudden change in the supply-demand relationship, upstream and downstream enterprises in the supply chain need to coordinate business activities through cooperation and integrate the information and resources of each enterprise. Here, artificial intelligence technology is crucial: it reduces the information and cognitive overload caused by a large amount of data, turns data into usable information, and helps enterprises to control supply chain risks [26]. Hence, when enterprises in the supply chain want to strengthen collaboration, their willingness to adopt artificial intelligence technology may become stronger. Based on this, this study proposes the following hypothesis:

Hypothesis 2: *There is a positive relationship between supply chain collaboration and a firm's adoption of artificial intelligence technology.*

2.3. Environmental Uncertainty and Willingness to Adopt

According to the TOE theory, environmental factors are external pressure and support that affect the technology adoption of enterprises, mainly referring to the external environmental factors that affect the organization's adoption of new technologies and have a positive impact on the willingness to adopt technologies [14–16,26–29]. This result has been verified in many fields. Environmental uncertainty is the uncertainty caused by changes in the external environment. In the context of increased environmental uncertainty, companies believe that adopting new technologies faster than competitors ensure they maintain a competitive advantage and play an important role in supply chain integration and operational performance [30]. It can therefore be expected that environmental uncertainty will have a positive impact on the adoption of artificial intelligence technology. Hence, this study proposes the following hypothesis:

Hypothesis 3: *There is a positive relationship between environmental uncertainty and a firm's adoption of artificial intelligence technology*.

2.4. Willingness to Adopt and Supply Chain Resilience

Supply chain resilience is an active and passive strategy for companies to deal with supply chain turbulence [31]. The purpose of companies building resilient supply chains is to quickly recover from supply chain disruptions, are insensitive to disruptions and can ensure continuous and timely delivery of enterprise products and services to end customers [32]. When disruptive emergencies lead to changes in supply and demand, companies often need to collect large amounts of data from customers and suppliers and extract useful information from them. As an information processing tool, artificial intelligence helps to analyze rich data, and the AI-led innovative decision-making also helps to improve supply chain resilience [33–35]. It can therefore be expected that once enterprises adopt artificial intelligence technology, there will be a positive impact on building supply chain resilience. Based on this, this study proposes the following hypothesis:

Hypothesis 4: *There is a positive relationship between a firm's adoption of artificial intelligence technology and the firm's supply chain resilience*.

2.5. Willingness to Adopt and Supply Chain Performance

On between artificial intelligence and supply chain, according to previous literature, the use of artificial intelligence technology improves the relationship between partners and customers in the supply chain, and significantly improves the operational performance of enterprises [36,37]. Applying artificial intelligence technology causes the supply chain to jointly make price decisions and forecast demand reduce the economic loss caused by "out of stock" by more than 56% [38]. The application of artificial intelligence in product inspection improves the effect of product inspection and its use on personalized recommendation systems for digital publicity can improve the return on advertising investment. Its use on customer relationship management also enhances customer experience and bring closer distance from customers [36].

Supply chain performance is the efficiency of an enterprise's supply chain operation, reflecting the extent to which the supply chain reduces costs and meets the needs of end customers [39]. Given that artificial intelligence technology has broad prospects in enterprises dealing with issues such as order picking problems, customer relationship management, demand planning and forecasting, procurement and supply management, inventory control, and purchasing or purchasing decisions [8]. The adoption of artificial intelligence technology by enterprises is therefore expected to have a positive impact on the performance of the supply chain. Hence, the following hypothesis is proposed herein:

Hypothesis 5: *There is a positive relationship between a firm's adoption of artificial intelligence technology and the firm's supply chain performance*.

3. Methodology

3.1. Sampling and Data Collection

To empirically examine our proposed hypotheses, we collected data on a sample of firms in China through a survey approach. China is a suitable setting to examine what motivates firms to be more willing to adopt AI and how such willingness may explain the variation in supply chain resilience and supply chain performance among firms.

With successful technological innovation and investment, as well as policy support for developing emerging intelligent technologies, China is now rapidly emerging as the globally leading economy in filing artificial intelligence (AI) patents and applying the latest AI technologies to boost economic growth and transform businesses. According to a report released by Stanford University, China applied more than half of all the world's AI patents and the AI journal papers and AI citations produced by Chinese researchers in 2021 accounted for approximately one-third in the world, while US researchers only contributed 12 percent in the same period. China is therefore making great contributions to global AI. Furthermore, the Chinese government is making continued efforts to support and promote AI innovation and the growth of AI-related industries by legislating new supportive enabling policies. For example, the Chinese government had launched a plan to support and promote the development of new AI technologies, aiming at making the AI industry a major new growth engine and become the pioneer in leading global AI innovation in the coming decades.

Moreover, China is becoming a pioneer in leading the world's investment in the global AI industry since 2014. For example, the country achieved the fastest growth of investment in AI startups by attracting $17 billion for AI startups in 2021 [40]. Last, AI applications have been widely adopted in China to promote industrial upgrading and business transformation. It is expected that AI technologies will be further adopted in the coming decade in more sectors such as automotives, manufacturing, transportation and logistics, and healthcare, allowing tremendous opportunities for AI growth [41]. According to forecasts made by McKinsey, the new opportunities for the next wave of AI growth in China are expected to create an annual economic value of upward of 600 billion USD for the country, which is almost equivalent to the GDP of Shanghai in 2021 (4.32 trillion RMB or approximately 638 billion USD) [40].

A survey was employed to extract data in two major regions: Shanghai and Beijing. According to the report released by Daxue Consulting, these two regions represent the center of innovative AI development in China [42]. It is estimated that more than 28,000 and 17,000 high-tech firms are operating in Beijing and Shanghai, respectively. The questionnaire used for the study was developed by following a careful preparation process: first, we developed a English version of a questionnaire and had it translated into Chinese through two independent bilingual translators. We also back-translated the Chinese version of questionnaire into English through two additional independent translators to ensure conceptual accuracy [43]. Six in-depth online interviews were conducted online with managers of Chinese firms that are actively engaging in developing AI technologies or adopting AI in their businesses to check for the content and validity of the measures.

A pre-test on the questionnaire with 20 managers from Chinese firms before formally administering the survey, which further modified the questionnaire to improve the clarity of the measurement. Since prior research has suggested the importance of developing a good relationship and trust with respondents to improve their participation and ensure high-quality response [44], we collected the data by hiring a research company known for its success in collecting high-quality data in the local Chinese market. Ultimately, a total of 329 questionnaires were received. After excluding 11 with incomplete responses, a total of 318 usable questionnaires for the final data analysis were utilized. Of the 318 firms, most (69.5%) had less than 500 employees, and 72.6% had been established less than 20 years.

3.2. Bias Testing

To check for the possibility of nonresponsive bias in our data, we compared the differences between responding and nonresponding firms as well as the early-responding and late-responding firms in key firm characteristics (e.g., firm sales, number of employees, and age) [45], with results suggesting that there was no statistically significant difference between the respective groups of firms. Therefore, response bias is less likely to arise in the data [45].

Moreover, we also checked for the presence of potential common method variance (CMV) that may arise in self-reported survey data. However, CMV may be less likely to arise in our study due to the following reasons: first, we ensured all respondents of the anonymity and confidentiality of their responses in the cover letter accompanying each questionnaire. The respondents were informed that there were no right nor wrong answers to the questions included in the questionnaire and that their responses would only be used for academic research. Second, we carefully structured the questionnaire by including the items in several subsections using different formats. Particularly, by randomizing the order of the items included in the questionnaire using a unique survey software, which is expected to mitigate the possible presence of a simple "straight line" pattern of response [46,47]. Last, following the recommendation of Podsakoff, MacKenzie, Lee, and Podsakoff (2003) [48], we checked for the potential occurrence of CMV by performing Harman's one-factor analysis. Then, we conducted exploratory factor analysis by entering all the variables of interest in the study into a nonrotated factor analysis. The results of the one-factor analysis provided no evidence that a general factor is apparent in the unrotated factor structure and accounted for a majority of the variance, again suggesting that CMV is less likely to arise in the data.

3.3. Variables and Measurement

All the dependent and independent variables were measured using multiple-item, seven-point Likert scales ("strongly disagree" = 1, "strongly agree" = 7). To measure supply chain resilience, ten items from prior studies were adopted [49,50]. Following Alshamaila, Papagiannidis, and Li (2013) [51], we measured firm willingness to adopt AI using four items. Following Rogers (2003) [52], we captured the degree of AI technology's relative advantage using six items, which were derived from related prior studies (e.g., Agarwal and Prasad, 1997; Kurnia et al., 2015; Papastathopoulou, Avlonitis, and Panagopoulos, 2007) [53–55] and appropriately modified to meet the purpose of this study. Relative advantage assesses the degree to which AI technology is perceived as superior to existing technologies. Following prior studies (e.g., Zaridis, Vlachos, and Bourlakis, 2020) [56], five items were used to capture the degree of supply chain collaboration. Seven items from Sreedevi and Saranga (2017) [57] and Wong, Lai, Shang, and Lu (2014) [58] were used to measure the degree of environmental uncertainty, we adopted. In addition, we also incorporated several control variables into the analysis: firm size measured as the natural logarithm of the total number of employees in a firm, firm age operationalized as the number of years from firm establishment, and an industry dummy variable (1 = industrial firms, 0 = others).

4. Analyses and Results

Partial least squares (PLS) structural equation modeling (SEM) as employed to empirically test our hypotheses [59,60]. Before testing our hypotheses, we first assessed the reliability and validity of the constructs by checking the measurement model.

4.1. Measurement Reliability and Validity

We present the results of the measurement model assessment in Table 1, which reports the means, standard deviations, factor loadings, construct reliabilities, and the average variances extracted (AVEs). Following the abovementioned, since all the items used in the study to measure respective constructs were well-established and derived from the literature, all measures demonstrate strong evidence of reliability and validity. Following Table 1, both the Cronbach's alpha values and composite reliabilities of all constructs are greater than 0.80, exceeding the threshold of 0.70 [61,62], thereby providing strong evidence of internal reliability. Moreover, factor loading of all constructs are greater than 0.70, suggesting that the measurement model is strongly reliable [63,64].

Table 1. Descriptive statistics and assessments of the construct reliability and validity.

Construct and Indicators	Mean	STD	SFL
AI technology advantage (PT: AVE = 0.597, alpha = 0.866, CR = 0.899)			
The use of artificial intelligence technology can improve enterprise risk control capabilities.	5.868	0.782	0.782
The use of artificial intelligence technology will reduce the operating costs of the entire enterprise.	5.909	0.821	0.768
The use of artificial intelligence technology will improve the IT technical service capabilities of enterprises.	5.921	0.763	0.778
The use of artificial intelligence technology will improve the input-output ratio of enterprises to IT.	5.799	0.721	0.756
The company has a comparative advantage in leveraging artificial intelligence technology.	5.846	0.838	0.776
Adopting AI technology can give companies a competitive advantage.	5.903	0.793	0.777
Supply chain collaboration (SCC: AVE = 0.605, alpha = 0.837, CR = 0.885)			
The company has access to the information systems of other companies in the supply chain.	5.572	0.984	0.771
Collaboration between supply chain companies to improve production processes.	5.755	0.863	0.786
Cooperation between supply chain enterprises to obtain supply in an economical way.	5.780	0.840	0.788
Cooperation between supply chain enterprises to improve competitiveness.	5.849	0.953	0.779
Co-pricing products between supply chain companies.	5.626	0.905	0.767
Environmental uncertainty (EU: AVE = 0.590, alpha = 0.884, CR = 0.910)			
The global business environment is full of challenges.	6.091	0.884	0.82
The changing global business environment.	5.836	0.951	0.765
The global business environment offers many opportunities for change.	5.903	0.897	0.783
Customer demand fluctuates wildly over and over again.	5.761	0.812	0.759
The product mix produced by the company changes dramatically over and over again.	5.814	0.862	0.752
Supply requirements change every week.	5.887	0.858	0.765
The company's products need a lot of technical transformation.	5.881	0.804	0.729
Willingness to adopt AI (WTA: AVE = 0.645, alpha = 0.871, CR = 0.879)			
The company is willing to experiment with artificial intelligence technology.	6.116	0.895	0.827
The company plans to adopt artificial intelligence technology soon.	5.78	0.922	0.793
The company has adopted artificial intelligence technology.	5.827	0.816	0.788
The company is expected to adopt artificial intelligence technology in the future.	5.906	0.923	0.804
Supply chain resilience (SCR: AVE = 0.554, alpha = 0.911, CR = 0.925)			
The company has the ability to quickly restore the flow of materials.	5.695	1.008	0.749
The company has the ability to quickly resume operations.	5.796	0.974	0.756
Enterprise supply chains are recovering quickly.	5.682	0.998	0.75
Enterprise supply chains can quickly return to normal.	5.748	0.914	0.73
The company can flexibly deal with interference problems.	5.758	0.919	0.742
The Company Can Respond Quickly to Disruptions.	5.591	0.943	0.735
The company can take adequate measures to deal with the crisis.	5.824	0.915	0.77
The company has a response team to alleviate the crisis.	5.934	0.928	0.732
The company can reduce the impact of losses through our ability to deal with the crisis.	5.789	0.909	0.734
The company can recover from the crisis at a lower cost.	5.528	0.977	0.744
Supply chain performance (SCP: AVE = 0.590, alpha = 0.913, CR = 0.928)			
Suppliers deliver materials, components, products on time.	5.821	0.814	0.788
Suppliers provide safe and reliable materials, components, and products.	5.959	0.848	0.749
Suppliers provide materials, components, products at the lowest cost.	5.918	0.854	0.763
The quantity required is supplied on order.	5.947	0.789	0.763
Enterprise Supply Chain Improves Efficiency.	5.915	0.881	0.755
Enterprise supply chains become more stable.	5.874	0.906	0.757
Over the past three years, enterprise supply chains have been optimized.	5.947	0.858	0.768
Corporate supply chains improve customer satisfaction.	6.028	0.837	0.775
The delivery speed and time of the enterprise supply chain is shortened.	5.884	0.855	0.792

Note: SFL = standardized factor loading, AVE = average variance extracted, CR = composite reliability, STD = standard deviation.

To assess convergent validity, AVE values for the constructs were calculated for the constructs. Results exhibit that the AVE values of all constructs are much higher than the threshold of 0.50, suggesting that the measures used in the study showed adequate convergent validity and reliability [61]. Furthermore, to assess discriminant validity of measures, we compared the square root of AVE of each construct and correlation between the construct and other constructs in the model. The results shown in Table 2 indicate that the square root of AVE of each construct is indeed much higher than the correlation between the construct and other constructs in the models, illustrating an adequate discriminant validity of the measures [61].

Table 2. Correlations and discriminant validity among the constructs.

Constructs	1	2	3	4	5	6
1. AI technology advantage	***0.773***					
2. Supply chain collaboration	0.333	***0.778***				
3. Environment Uncertainty	0.323	0.277	***0.768***			
4. Willingness to adopt AI	0.335	0.396	0.33	***0.803***		
5. Supply chain Resilience	0.363	0.505	0.433	0.462	***0.744***	
6. Supply chain performance	0.279	0.437	0.364	0.457	0.564	***0.768***

Note: Values in italicized bold denote the square root of the AVE of each construct.

To further assess the discriminant validity of the measures, we also compared the loading values of each single indicator with the cross-loadings of other indicators where results exhibit that each indicator loading is higher than the respective cross loadings, thereby suggesting the measures used in the study have adequate discriminant validity. Moreover, we checked for the heterotrait-monotrait ratio (HTMT) of the correlations [65], where the results show that the values of all HTMT correlations are well below 0.85, providing strong evidence of adequate discriminant validity for all constructs in the model. Last, following prior studies [66,67], we used Stone–Geisser's Q2 to verify the predictive validity of the latent constructs in the model. Results indicate that the values of cross-validated communality and redundancy are higher than zero, providing strong evidence of adequate predictive validity in the model [63,68]. Overall, all the constructs and their respective indicators demonstrate strong evidence of both adequate reliability and validity in the study.

4.2. Hypothesis Testing

After checking for the reliability and validity of all constructs by performing a measurement model, we empirically tested our hypotheses and reported the subsequent results in Figure 2. Following Chin's recommendation [63], we examined the coefficient of determination R^2 and the path coefficient with their respective *p*-values. As shown in Figure 2, the R^2 values for the three endogenous variables (e.g., supply chain resilience, supply chain performance, and willingness to adopt AI) demonstrate satisfactory explanatory power for our model (0.236–0.404). Overall, the results reported in Figure 2 are consistent with our proposed hypotheses. Specifically, the results show a significant positive relationship between AI technology advantage ($b = 0.178$, $p < 0.01$), supply chain collaboration ($b = 0.283$, $p < 0.001$), environmental uncertainty ($b = 0.195$, $p < 0.01$), and the willingness to adopt AI. Therefore, the results provide strong support for Hypotheses 1–3. As noted in Figure 2, we also find strong evidence of a positive and statistically significant relationship between the willingness to adopt AI and supply chain resilience ($b = 0.223$, $p < 0.01$) and supply chain performance ($b = 0.272$, $p < 0.001$). Therefore, we find strong support for Hypotheses 4–5. Overall, all the hypotheses proposed in our theoretical framework are strongly supported.

Furthermore, while examining the potential role of the willingness to adopt AI in mediating the effect of AI technology advantage, supply chain collaboration, and environmental uncertainty on supply chain resilience and supply chain performance, respectively, seems beyond the scope of our study, we examined the mediating role of the willingness to adopt AI aiming at offering more insightful implications both for researchers and business practitioners. Following Zhao et al.'s (2010) [69] approach, we tested the mediating effect and summarized the results of mediating effect assessment in Figure 2 and Table 3.

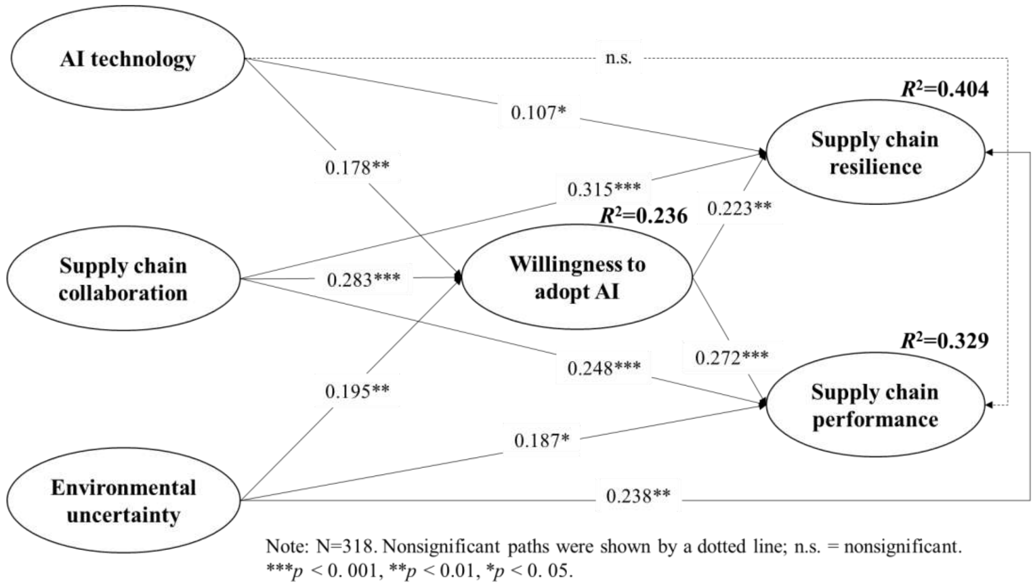

Figure 2. Estimated results of the hypothesis tests using a structural equation modeling.

Table 3. Results of structural model assessment for direct and indirect effects.

Indirect Effect	**Estimate**	***p*-Values**
Direct effects		
AI technology advantages → Willingness to adopt AI	0.178	**
Supply chain collaboration → Willingness to adopt AI	0.283	***
Environmental uncertainty → Willingness to adopt AI	0.195	**
AI technology advantages → Supply chain resilience	0.107	*
Supply chain collaboration → Supply chain resilience	0.315	***
Environmental uncertainty → Supply chain resilience	0.238	**
AI technology advantages → Supply chain performance	0.044	n.s.
Supply chain collaboration → Supply chain performance	0.248	***
Environmental uncertainty → Supply chain performance	0.187	*
Willingness to adopt AI → Supply chain resilience	0.223	**
Willingness to adopt AI → Supply chain performance	0.272	***
Indirect effects		
AI technology advantages → Willingness to adopt AI → Supply chain resilience	0.040	*
Supply chain collaboration → Willingness to adopt AI → Supply chain resilience	0.063	**
Environmental uncertainty → Willingness to adopt AI → Supply chain resilience	0.043	*
AI technology advantages → Willingness to adopt AI → Supply chain performance	0.048	*
Supply chain collaboration → Willingness to adopt AI → Supply chain performance	0.077	**
Environmental uncertainty → Willingness to adopt AI → Supply chain performance	0.053	**

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; n.s. = nonsignificant.

First, as shown in Table 3, the indirect effects of AI technology advantage (SCR: b = 0.040, $p < 0.05$; SCP: b = 0.048, $p < 0.05$), supply chain collaboration (SCR: b = 0.063, $p < 0.01$; SCP: b = 0.077, $p < 0.01$), and environmental uncertainty (SCR: b = 0.043, $p < 0.05$; SCP: b = 0.053, $p < 0.01$) on supply chain resilience and supply chain performance are all positive and statistically significant (a × b).

Second, while we did not find a significant direct effect of AI technology advantage on supply chain performance (b = 0.044, n.s.), we found positive and statistically significant direct effects of supply chain collaboration (SCR: b = 0.315, $p < 0.001$; SCP: b = 0.248, $p < 0.001$) and environmental uncertainty (SCR: b = 0.238, $p < 0.01$; SCP: b = 0.187, $p < 0.05$) on both supply chain resilience and supply chain performance (c), respectively, and a positive and statistically direct effect of AI technology advantage on supply chain resilience (b = 0.107, $p < 0.05$).

Third, following Table 3, both the positive and statistically significant effects are in the same direction (a $\times$ b $\times$ c). Since the mediating effect of AI technology advantage on supply chain performance is positive and significant, and its respective direct effect (path c) is positive but insignificant, we therefore only found an indirect mediation role of the willingness to adopt AI in the relationship between AI technology advantage and supply chain performance. Moreover, since the mediated effects of supply chain collaboration and environmental uncertainty on supply chain performance are both positive and statistically significant and their direct effects on supply chain performance are likewise, we thus found a complementary mediation role of the willingness to adopt AI in the relationships between supply chain collaboration and environmental uncertainty, and supply chain performance.

Additionally, since the mediated effects of AI technology advantage, supply chain collaboration, and environmental uncertainty on supply chain resilience are all positive and statistically significant and all their direct effects on supply chain resilience are all positive and statistically significant, we also found a complementary mediation role of the willingness to adopt AI in the relationships between AI technology advantage, supply chain collaboration, environmental uncertainty, and supply chain resilience. Overall, our results of the mediation assessments demonstrate that while the willingness to adopt AI plays an important role in fully mediating the effect of AI technology advantage on supply chain performance, it only partially mediates the effects of supply chain collaboration and environmental uncertainty on supply chain performance. Simultaneously, the willingness to adopt AI was found to partially mediate the effects of AI technology advantage, supply chain collaboration, and environmental uncertainty on supply chain resilience. The following section discusses these results and their implications.

5. Discussion and Conclusions

5.1. Theoretical and Practical Implications

During increased environmental uncertainty, such as the COVID-19 pandemic and the subsequent restructuring of global supply chains, companies are both eager and reluctant to take advantage of the new technologies of the Fourth Industrial Revolution to improve supply chain resilience and supply chain performance. To enhance the confidence of more enterprises in adopting artificial intelligence technology, guide enterprise users to use artificial intelligence technology in a scientific and standardized manner and promote the virtuous circle development of artificial intelligence industry.

Based on TOE theory and resource-based theory, this study conducts an in-depth exploration on the different impacts of enterprise users' adoption of artificial intelligence technology on supply chain elasticity and supply chain performance, expands the application field and scope of artificial intelligence technology, and fills the gap in the literature on enterprise users' adoption of artificial intelligence technology in the supply chain field. The study takes the technical, organizational and environmental factors in the TOE framework as the three major influencing factors for the adoption of artificial intelligence technology, further expanding the application field and adaptation scope of the TOE framework, allowing for better understanding of the adoption behavior of enterprise users in adopting artificial intelligence technology from the dimensions of artificial intelligence technology, supply chain collaboration, and environmental uncertainty.

Meanwhile, through the empirical analysis of 318 enterprises, this study also confirms that the adoption of artificial intelligence technology by enterprises positively impacts the elasticity and performance of the supply chain, also verifying that the adoption of new technology by enterprises can give them sustainable competitive advantage, providing new ideas and bases for the follow-up research on the adoption of artificial intelligence technology. This study is expected to provide valuable suggestions for enterprises to build a resilient supply chain and improve supply chain performance. The specific research conclusions and inspirations are as follows:

In influencing the adoption of artificial intelligence technology, artificial intelligence technology itself has primarily played a positive role in promoting enterprises' willingness to adopt artificial intelligence technology. Previous literature emphasized that artificial intelligence technology can change the business and global economic landscape [4], ensure competitive advantages [5], and reduce economic losses caused by "out of stock" [38]. This study extends this thought and proves that once enterprises have artificial intelligence technology infrastructure and technical capabilities, they tend to adopt artificial intelligence technology with the relative advantages and compatibility of artificial intelligence technology. Results suggest that before considering adopting artificial intelligence technology, enterprises should first promote the construction of artificial intelligence infrastructure and improve their ability to use artificial intelligence technology and fully consider whether the enterprise's artificial intelligence technology is compatible with the technical system, development strategy, IT capabilities, etc., to allow more enterprises to adopt artificial intelligence technology.

Second, this study found that supply chain collaboration has a positive impact on the willingness to adopt a supply chain. Since the relationship between enterprises in the supply chain is relatively loose, the upstream and downstream enterprises in the supply chain need to coordinate business activities through cooperation to integrate the information and resources of each enterprise, thus forming a supply chain collaboration [25]. As an information processing tool, artificial intelligence technology can reduce the problem of information and cognitive overload caused by a large amount of data and turn said data into useful information for enterprises [26]. This study empirically verifies that enterprises are more willing to adopt artificial intelligence technology if they want to strengthen supply chain collaboration.

Finally, this study found that environmental uncertainty has a positive impact on the willingness to adopt artificial intelligence technology. Coinciding with previous research results, external pressure and policy support will affect organizations' willingness to adopt new technologies [14–16,26–29]. Opportunities and challenges coexist in the global business environment, and supply and demand relations and economic policies of various countries change at any time. Under the circumstance of increasing environmental uncertainty, enterprises are more willing to adopt artificial intelligence technology faster than their competitors. More enterprises realize that the active adoption of artificial intelligence technology is an inevitable choice for development and prioritizing artificial intelligence technology will allow them to benefit from it. In sum, if enterprises want to boost the development of artificial intelligence technology, they should accelerate the implementation of artificial intelligence from three aspects: artificial intelligence technology itself, supply chain cooperation, and environmental uncertainty.

For the impact of artificial intelligence technology adoption, the results of this study show that the willingness to adopt artificial intelligence technology has a positive impact on supply chain resilience and supply chain performance. Paralleling results from previous literature, the adoption of artificial intelligence technology improves supply chain resilience [33]. Through empirical analysis, the positive impact of artificial intelligence technology on building an elastic supply chain has been reconfirmed. Although emergencies such as the COVID-19 have disrupted the global supply chain, enterprises must rely on artificial intelligence technology to make the operation mode more dynamic and responsive, connect with the external ecosystem and internal processes, improve the adaptability, and transform the entire supply chain in an elastic state if they want to restore the supply chain to its original state.

Second, this study also found that the adoption of artificial intelligence technology has a positive impact on supply chain performance. Previous literature has emphasized that the adoption of artificial intelligence technology improves the operational performance of enterprises [36,37]. Through empirical analysis, this study found that the adoption of artificial intelligence technology helps suppliers to provide the required materials, components, and products on time, improve the operational efficiency of the supply chain, and promote the supply chain to become more stable and optimized. Although the adoption of artificial intelligence technology is challenging, enterprises generally recognize the role of artificial intelligence technology in building supply chain resilience and improving supply chain performance.

5.2. Limitations and Future Research Avenues

Four limitations are noticed in this study. First, due to limits in time, costs, and resources, this research only investigated enterprises in the Chinese market. Because the artificial intelligence technology infrastructure and technical capabilities of enterprises in different countries are different, the external pressure and support for adopting artificial intelligence technology are also different, and the causes and consequences of adoption intentions are likewise different. In the future, it is necessary to expand the research object to more countries and regions to improve the universality of this research result. Second, we empirically tested our arguments using survey data collected from firms operating in Beijing and Shanghai, the two largest, most important regions in China. However, the economic, industry and institutional environments may vary significantly across the subnational regions of a large emerging economy, such as China, our focus on firms operating in Beijing and Shanghai, may limit the generalizability of our findings to firms operating in other regions within China. Future research is thus encouraged to investigate whether the findings of our study vary among the different regions within China in which the firms operate. Second, the response rate of questionnaires for corporate users is low compared to surveys for individual users. During the investigation, many companies were reluctant to disclose sensitive information, such as financial status, development, and use of artificial intelligence technology. For future studies, it is necessary to obtain more reliable information related to the study by additional interviews or collecting second-hand data to further enhance the persuasiveness. Third, this study only considers the impact of enterprises' willingness to adopt artificial intelligence technology on supply chain resilience and supply chain performance. It is therefore necessary for future research to expand to other areas of supply chain, hoping to provide more new and useful insights. Fourth, because the relationship between supply chain enterprises is complex and enterprises in different positions have different partners, future studies must refine and compare the upstream and downstream positions of supply chain enterprises. Finally, we tested our arguments using survey cross-sectional data and thus we were unable to explore the relationships proposed in our theoretical model for causality. We hope future research could address this limitation and increase the validity of our theoretical model using large-scale, longitudinal datasets combined with archival data.

Author Contributions: Conceptualization, writing, investigation and methodology, M.W.; writing—review and editing and investigation, X.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data will be available upon request. The data are not publicly available due to privacy or ethical restrictions.

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

Abbreviations

AI	artificial intelligence
SCM	supply chain management

References

1. Spieske, A.; Birkel, H. Improving Supply Chain Resilience through Industry 4.0: A Systematic Literature Review under the Impressions of the COVID-19 Pandemic. *Comput. Ind. Eng.* **2021**, *158*, 107452. [CrossRef] [PubMed]
2. Chen, J.-K.; Huang, T.-Y. The Multi-Level Hierarchical Structure of the Enablers for Supply Chain Resilience Using Cloud Model-DEMATEL–ISM Method. *Sustainability* **2022**, *14*, 12116. [CrossRef]
3. Grzybowska, K.; Tubis, A.A. Supply Chain Resilience in Reality VUCA—An International Delphi Study. *Sustainability* **2022**, *14*, 10711. [CrossRef]
4. Soni, N.; Sharma, E.K.; Singh, N.; Kapoor, A. Artificial Intelligence in Business: From Research and Innovation to Market Deployment. *Procedia Comput. Sci.* **2020**, *167*, 2200–2210. [CrossRef]
5. Chien, Y.-H.; Yao, C.-K. Development of an AI Userbot for Engineering Design Education Using an Intent and Flow Combined Framework. *Appl. Sci.* **2020**, *10*, 7970. [CrossRef]
6. Tong, S.; Jia, N.; Luo, X.; Fang, Z. The Janus face of artificial intelligence feedback: Deployment versus disclosure effects on employee performance. *Strateg. Manag. J.* **2021**, *42*, 1600–1631. [CrossRef]
7. Agrawal, R.; Wankhede, V.A.; Kumar, A.; Luthra, S.; Majumdar, A.; Kazancoglu, Y. An Exploratory State-of-the-Art Review of Artificial Intelligence Applications in Circular Economy using Structural Topic Modeling. *Oper. Manag. Res.* **2022**, *15*, 609–626. [CrossRef]
8. Min, H. Artificial Intelligence in Supply Chain Management: Theory and Applications. *Int. J. Logist. Res. Appl.* **2010**, *13*, 13–39. [CrossRef]
9. 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]
10. Dubey, R.; Bryde, D.J.; Blome, C.; Roubaud, D.; Giannakis, M. Facilitating Artificial Intelligence Powered Supply Chain Analytics through Alliance Management during the Pandemic Crises in the B2B Context. *Ind. Mark. Manag.* **2021**, *96*, 135–146. [CrossRef]
11. Kaplan, A.; Haenlein, M. Siri, Siri, in My Hand: Who's the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence. *Bus. Horiz.* **2019**, *62*, 15–25. [CrossRef]
12. Dirican, C. The Impacts of Robotics, Artificial Intelligence on Business and Economics. *Procedia Soc. Behav. Sci.* **2015**, *195*, 564–573. [CrossRef]
13. Tornatzky, L.G.; Fleischer, M.; Chakrabarti, A.K. *Processes of Technological Innovation*; Lexington Books: Blue Ridge Summit, PA, USA, 1990.
14. Lin, H.-F. Understanding the Determinants of Electronic Supply Chain Management System Adoption: Using the Technology–Organization–Environment Framework. *Technol. Forecast. Soc. Chang.* **2014**, *86*, 80–92. [CrossRef]
15. Gutierrez, A.; Boukrami, E.; Lumsden, R. Technological, Organisational and Environmental Factors Influencing Managers' Decision to Adopt Cloud Computing in the UK. *J. Enterp. Inf. Manag.* **2015**, *28*, 788–807. [CrossRef]
16. Ghaleb, E.A.A.; Dominic, P.D.D.; Fati, S.M.; Muneer, A.; Ali, R.F. The Assessment of Big Data Adoption Readiness with a Technology–Organization–Environment Framework: A Perspective towards Healthcare Employees. *Sustainability* **2021**, *13*, 8379. [CrossRef]
17. Wernerfelt, B. A Resource-Based View of the Firm. *Strat. Mgmt. J.* **1984**, *5*, 171–180. [CrossRef]
18. Barney, J. Firm Resources and Sustained Competitive Advantage. *J. Manag.* **1991**, *17*, 99–120. [CrossRef]
19. Grant, R.M. The Resource-Based Theory of Competitive Advantage: Implications for Strategy Formulation. *Calif. Manag. Rev.* **1991**, *33*, 114–135. [CrossRef]
20. Hart, S.L.; Dowell, G. Invited Editorial: A Natural-Resource-Based View of the Firm: Fifteen Years After. *J. Manag.* **2011**, *37*, 1464–1479. [CrossRef]
21. Helfat, C.E.; Peteraf, M.A. The Dynamic Resource-Based View: Capability Lifecycles. *Strat. Mgmt. J.* **2003**, *24*, 997–1010. [CrossRef]
22. Halldorsson, A.; Kotzab, H.; Mikkola, J.H.; Skjøtt-Larsen, T. Complementary Theories to Supply Chain Management. *Supply Chain Manag.* **2007**, *12*, 284–296. [CrossRef]
23. Baum, S.; Barrett, A.; Yampolskiy, R.V. *Modeling and Interpreting Expert Disagreement About Artificial Superintelligence*; Social Science Research Network: Rochester, NY, USA, 2017.
24. Baker, J. The Technology–Organization–Environment Framework. *Inf. Syst. Theory* **2012**, *28*, 231–245. [CrossRef]
25. Soosay, C.A.; Hyland, P. A Decade of Supply Chain Collaboration and Directions for Future Research. *Supply Chain Manag.* **2015**, *20*, 613–630. [CrossRef]
26. Baryannis, G.; Validi, S.; Dani, S.; Antoniou, G. Supply Chain Risk Management and Artificial Intelligence: State of the Art and Future Research Directions. *Int. J. Prod. Res.* **2019**, *57*, 2179–2202. [CrossRef]
27. Pan, M.J.; Jang, W.Y. Determinants of the Adoption of Enterprise Resource Planning within the Technology-Organization-Environment Framework: Taiwan's Communications Industry. *J. Comput. Inf. Syst.* **2008**, *48*, 94–102. [CrossRef]
28. Singeh, F.W.; Abrizah, A.; Kiran, K. Bringing the Digital Library Success Factors into the Realm of the Technology-Organization-Environment Framework. *Electron. Libr.* **2020**, *38*, 659–675. [CrossRef]
29. Malik, S.; Chadhar, M.; Vatanasakdakul, S.; Chetty, M. Factors Affecting the Organizational Adoption of Blockchain Technology: Extending the Technology–Organization–Environment (TOE) Framework in the Australian Context. *Sustainability* **2021**, *13*, 9404. [CrossRef]

30. Wong, C.Y.; Boon-itt, S.; Wong, C.W.Y. The Contingency Effects of Environmental Uncertainty on the Relationship between Supply Chain Integration and Operational Performance. *J. Oper. Manag.* **2011**, *29*, 604–615. [CrossRef]
31. Durach, C.F.; Wieland, A.; Machuca, J.A.D. Antecedents and Dimensions of Supply Chain Robustness: A Systematic Literature Review. *Int. J. Phys. Distrib. Logist. Manag.* **2015**, *45*, 118–137. [CrossRef]
32. Ponomarov, S.Y.; Holcomb, M.C. Understanding the Concept of Supply Chain Resilience. *Int. J. Logist. Manag.* **2009**, *20*, 124–143. [CrossRef]
33. Belhadi, A.; Mani, V.; Kamble, S.S.; Khan, S.A.R.; Verma, S. Artificial Intelligence-Driven Innovation for Enhancing Supply Chain Resilience and Performance under the Effect of Supply Chain Dynamism: An Empirical Investigation. *Ann. Oper. Res.* **2021**, 1–26. [CrossRef] [PubMed]
34. Yin, W.; Ran, W. Supply Chain Diversification, Digital Transformation, and Supply Chain Resilience: Configuration Analysis Based on fsQCA. *Sustainability* **2022**, *14*, 7690. [CrossRef]
35. Frederico, G.F.; Kumar, V.; Garza-Reyes, J.A.; Kumar, A.; Agrawal, R. Impact of I4.0 technologies and their interoperability on performance: Future pathways for supply chain resilience post-COVID-19. *Int. J. Logist. Manag.* 2021; *ahead-of-print*. [CrossRef]
36. Grover, P.; Kar, A.K.; Dwivedi, Y.K. Understanding Artificial Intelligence Adoption in Operations Management: Insights from the Review of Academic Literature and Social Media Discussions. *Ann. Oper. Res.* **2022**, *308*, 177–213. [CrossRef]
37. Dubey, R.; Gunasekaran, A.; Childe, S.J.; Bryde, D.J.; Giannakis, M.; Foropon, C.; Roubaud, D.; Hazen, B.T. Big Data Analytics and Artificial Intelligence Pathway to Operational Performance under the Effects of Entrepreneurial Orientation and Environmental Dynamism: A Study of Manufacturing Organisations. *Int. J. Prod. Econ.* **2020**, *226*, 107599. [CrossRef]
38. Bottani, E.; Centobelli, P.; Gallo, M.; Kaviani, M.A.; Jain, V.; Murino, T. Modelling Wholesale Distribution Operations: An Artificial Intelligence Framework. *Ind. Manag. Data Syst.* **2018**, *119*, 698–718. [CrossRef]
39. Tarafdar, M.; Qrunfleh, S. Agile Supply Chain Strategy and Supply Chain Performance: Complementary Roles of Supply Chain Practices and Information Systems Capability for Agility. *Int. J. Prod. Res.* **2017**, *55*, 925–938. [CrossRef]
40. Shen, K.; Tong, X.; Wu, T.; Zhang, F. The Next Frontier for AI in China Could Add $600 Billion to Its Economy. McKinsey. 2022. Available online: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-next-frontier-for-ai-in-china-could-add-600-billion-to-its-economy (accessed on 2 September 2022).
41. Ma, S. China Emerging as Global AI Pioneer. China Daily. 2022. Available online: https://global.chinadaily.com.cn/a/202207/29/WS62e32108a310fd2b29e6f050.html (accessed on 3 September 2022).
42. Daueconsulting. The AI Ecosystem in China. 2020. Available online: https://daxueconsulting.com/wp-content/uploads/2020/03/AI-in-China-2020-White-Paper-by-daxue-consulting-1.pdf (accessed on 1 September 2022).
43. Hult, G.T.M.; Ketchen, D.J.; Griffith, D.A.; Finnegan, C.A.; Gonzalez-Padron, T.; Harmancioglu, N.; Huang, Y.; Talay, M.B.; Cavusgil, S.T. Data Equivalence in Cross-Cultural International Business Research: Assessment and Guidelines. *J. Int. Bus. Stud.* **2008**, *39*, 1027–1044. [CrossRef]
44. Hoskisson, R.E.; Eden, L.; Lau, C.M.; Wright, M. Strategy in Emerging Economies. *Acad. Manag. J.* **2000**, *43*, 249–267. [CrossRef]
45. Armstrong, J.S.; Overton, T.S. Estimating Nonresponse Bias in Mail Surveys. *J. Mark. Res.* **1977**, *14*, 396–402. [CrossRef]
46. Chang, S.-J.; van Witteloostuijn, A.; Eden, L. From the Editors: Common Method Variance in International Business Research. *J. Int. Bus. Stud.* **2010**, *41*, 178–184. [CrossRef]
47. Johnson, R.E.; Rosen, C.C.; Djurdjevic, E. Assessing the Impact of Common Method Variance on Higher Order Multidimensional Constructs. *J. Appl. Psychol.* **2011**, *96*, 744–761. [CrossRef] [PubMed]
48. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.-Y.; Podsakoff, N.P. Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [CrossRef] [PubMed]
49. 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]
50. 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. [CrossRef]
51. Alshamaila, Y.; Papagiannidis, S.; Li, F. Cloud Computing Adoption by SMEs in the North East of England: A Multi-perspective Framework. *J. Enterp. Inf. Manag.* **2013**, *26*, 250–275. [CrossRef]
52. Rogers, E.M. *Diffusion of Innovations*, 5th ed.; Free Press: New York, NY, USA, 2003.
53. Agarwal, R.; Prasad, J. The Role of Innovation Characteristics and Perceived Voluntariness in the Acceptance of Information Technologies. *Decis. Sci.* **1997**, *28*, 557–582. [CrossRef]
54. Kurnia, S.; Choudrie, J.; Mahbubur, R.M.; Alzougool, B. E-Commerce Technology Adoption: A Malaysian Grocery SME Retail Sector Study. *J. Bus. Res.* **2015**, *68*, 1906–1918. [CrossRef]
55. Papastathopoulou, P.; Avlonitis, G.J.; Panagopoulos, N.G. Intraorganizational Information and Communication Technology Diffusion: Implications for Industrial Sellers and Buyers. *Ind. Mark. Manag.* **2007**, *36*, 322–336. [CrossRef]
56. Zaridis, A.; Vlachos, I.; Bourlakis, M. SMEs Strategy and Scale Constraints Impact on Agri-Food Supply Chain Collaboration and Firm Performance. *Prod. Plan. Control* **2021**, *32*, 1165–1178. [CrossRef]
57. Sreedevi, R.; Saranga, H. Uncertainty and Supply Chain Risk: The Moderating Role of Supply Chain Flexibility in Risk Mitigation. *Int. J. Prod. Econ.* **2017**, *193*, 332–342. [CrossRef]

58. Wong, W.Y.C.; Lai, K.-H.; Shang, K.-C.; Lu, C.-S. Uncovering the Value of Green Advertising for Environmental Management Practices: Green Advertising and Environmental Management. *Bus. Strat. Environ.* **2014**, *23*, 117–130. [CrossRef]
59. Richter, N.F.; Sinkovics, R.R.; Ringle, C.M.; Schlägel, C. A Critical Look at the Use of SEM in International Business Research. *Int. Market. Rev.* **2016**, *33*, 376–404. [CrossRef]
60. Cepeda-Carrion, G.; Cegarra-Navarro, J.-G.; Cillo, V. Tips to use partial least squares structural equation modelling (PLS-SEM) in knowledge management. *J. Knowl. Manag.* **2019**, *23*, 67–89. [CrossRef]
61. Fornell, C.; Larcker, D.F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
62. Nunnally, J.C. *Psychometric Theory*; McGraw-Hill: New York, NY, USA, 1978.
63. Chin, W.W.; Marcoulides, G. The Partial Least Squares Approach to Structural Equation Modeling. *Organ. Res. Methods* **1998**, *295*, 295–336.
64. Hulland, J. Use of Partial Least Squares (PLS) in Strategic Management Research: A Review of Four Recent Studies. *Strat. Mgmt. J.* **1999**, *20*, 195–204. [CrossRef]
65. Henseler, J.; Ringle, C.M.; Sarstedt, M. A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [CrossRef]
66. Geisser, S. The Predictive Sample Reuse Method with Applications. *J. Am. Stat. Assoc.* **1975**, *70*, 320–328. [CrossRef]
67. Stone, M. Cross-Validatory Choice and Assessment of Statistical Predictions. *J. R. Stat. Society Ser. B Methodol.* **1974**, *36*, 111–133. [CrossRef]
68. Henseler, J.; Ringle, C.M.; Sinkovics, R.R. The Use of Partial Least Squares Path Modeling in International Marketing. In *New Challenges to International Marketing (Advances in International Marketing, 20)*; Sinkovics, R.R., Ghauri, P.N., Eds.; Emerald Group Publishing Limited: Bingley, UK, 2009; pp. 277–319.
69. Zhao, X.; Lynch, J.G.; Chen, Q. Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *J. Consum. Res.* **2010**, *37*, 197–206. [CrossRef]