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| RESEARCH ARTICLE

Impact of Digital Transformation of Logistics and Supply Chain in the Automotive Manufacturing Industry

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| ABSTRACT
With the continuous promotion of digital transformation of logistics and supply chain in the automotive manufacturing industry, the demand for new technologies is increasing day by day. This article empirically analyzes the impact of digital transformation of logistics and supply chain in the automotive manufacturing industry on the adoption of blockchain technology, based on research data from domestic automakers and third-party automotive logistics companies. The research results found that the digital transformation of logistics and supply chain in the automotive manufacturing industry has promoted employees' adoption of blockchain technology as a whole. The impact of digital transformation of logistics and supply chain in the automotive manufacturing industry on the adoption of blockchain technology varies in different application scenarios. The research results will help promote the innovative application of blockchain technology in the digital transformation of logistics and supply chain in the automotive manufacturing industry, providing new paths and opportunities for industrial upgrading and transformation.

| KEYWORDS
Automobile manufacturing industry, logistics and supply chain management, digital transformation, blockchain technology

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1. Introduction

The digital transformation of logistics and supply chain is the core part of the digital transformation of the entire automotive manufacturing industry [1-2]. Blockchain is a new digital technology based on encryption algorithms, consensus mechanisms, and smart contracts [3]. It has the potential to cause disruptive changes in the digital transformation of various industries, and more and more of them are actively exploring its applications. In recent years, the Chinese government has continuously deployed the application and innovation of blockchain technology. Among them, the policies related to blockchain issued have doubled compared to the "Action Plan for Accelerating the Development of Blockchain Technology Application Promotion" proposed in 2019 [4].

The integration of blockchain technology with industry is necessary and urgent. In the era of global business complexity and highly digitized information, traditional data management and exchange methods are no longer sufficient to meet the needs of information flow. Due to its trusted interactive environment, blockchain technology makes data flow more transparent and efficient. However, its application in logistics and supply chain management in the automotive manufacturing industry is currently limited [5-7]. Although the logistics and supply chain of the automotive manufacturing industry can accelerate information transmission through digital technology in various aspects such as IoT technology application, inventory optimization, and online order management, there are still problems such as multiple transmission nodes, opacity, and data that can be artificially modified [8]. Blockchain technology can fundamentally solve such problems. Some employees of certain companies have experienced the allure of digitization, which can change their inherent thinking and increase their acceptance of blockchain technology. However, its various links involve a large amount of data exchange and third-party operations, and have high requirements for the stability of production and supply chains. Employees may also hold a conservative attitude towards adopting new technologies. Therefore, further exploration is required to understand the impact of digital transformation in the automotive supply chain on the adoption of blockchain technology. This will help determine the technology's potential application value in this sector [9].

This article conducts a survey on employees of well-known domestic automobile manufacturing enterprises and large-scale third-party automobile logistics companies. The digital transformation of automobile manufacturing logistics and supply chain is divided into control group and processing group. Using propensity score matching method, the impact of digital transformation of automobile manufacturing logistics and supply chain on the adoption of blockchain technology is studied. Traditional linear regression, generalized linear regression, and XGBoost regression models are used to comprehensively analyze the degree of impact of digital transformation of automobile manufacturing logistics and supply chain on the adoption of blockchain technology in segmented scenarios. Here are the three core points of the study summarized as:

- Developed a systematic evaluation framework and provided a first-time theoretical segmentation of blockchain applications for the digital transformation of the automotive supply chain.
- Analyzed how digital transformation influences blockchain adoption in specific scenarios to identify future challenges and guide strategic investment.
- Aims to deepen industry understanding and provide practical guidance for effectively implementing blockchain technology.

2. Theoretical Basis and Research Hypotheses

The logistics and supply chain in automotive manufacturing refers to all logistics activities and the supply chain network involved in the production process. This includes everything from component procurement and warehousing to assembly and the final delivery of the complete vehicle. It is a further improvement of automotive logistics [10]. As shown in Figure 1, the main participants include suppliers, distribution centers, host factories, spare parts warehouses, vehicle warehouses, sales centers, and customers.

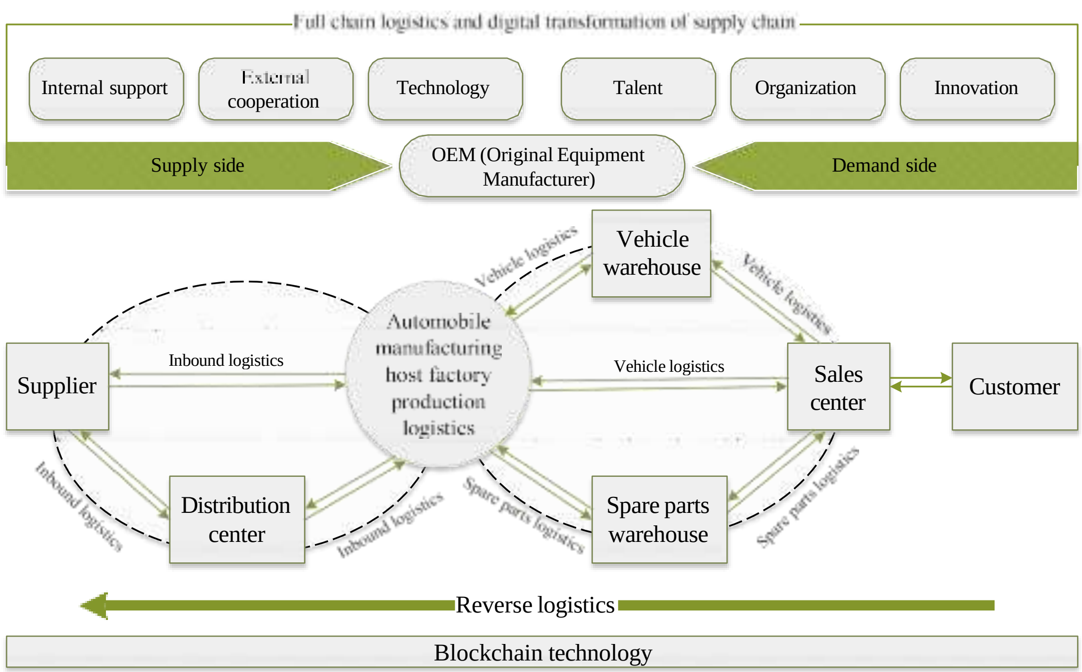

Figure 1. Logistics and supply chain management framework for automotive manufacturing industry

It can be seen in Figure 1 that the physical flow of parts from suppliers to distribution centers or host factories belongs to inbound logistics. The physical flow of parts from warehouses or other workshops to production lines belongs to production logistics. The physical flow of vehicles from the host factory to the vehicle warehouse or sales center is reflected in vehicle logistics, while the physical flow from the host factory or spare parts warehouse to the sales center maintenance site belongs to spare parts logistics. The entities involved in returns, recalls, and waste recycling flow through reverse logistics. These steps are crucial to ensuring that components arrive on time at the production line and are delivered to customers on time. Logistics and supply chain management in the automotive manufacturing industry cover planning, procurement, warehousing, distribution, transportation, and other aspects of these processes. Its main goals are to ensure production efficiency, reduce costs, and improve product and service quality.

The digital transformation of logistics and supply chain in the automotive manufacturing industry provides a good application foundation for blockchain technology. Digital transformation mainly enhances the automotive manufacturing industry's ability to respond to the environment and improve organizational performance and operational management efficiency through effective digital technology and business cooperation [11-12]. In terms of technology, digital transformation of enterprises usually involves digital technologies such as big data, cloud computing, and artificial intelligence, providing key technical support for the application of blockchain technology in the logistics and supply chain fields of the automotive manufacturing industry [13-14]. In terms of organizational management, digital transformation can improve the innovation performance of manufacturing enterprises, which creates an open and innovative organizational atmosphere for the exploration of blockchain technology [15]. From a business process perspective, digital transformation has spurred business model innovation, in line with innovation diffusion theory. The digitalization of the automotive supply chain is one such innovation, creating a foundation for leveraging blockchain's transparency and decentralization [16-17]. The digital transformation has created favorable conditions for the application of blockchain technology, making it easier to accept and adopt. Therefore, this article proposes the following hypothesis:

H1: The digital transformation of logistics and supply chain in the automotive manufacturing industry has driven the adoption of blockchain technology.

The logistics and supply chain management of the automotive manufacturing industry involves a large number of automotive components and suppliers. Blockchain technology needs to be tailored to specific business scenarios and combined with its own characteristics in order to better serve logistics and supply chain [18]. Related studies have shown that users' adoption of blockchain technology varies in different contexts or resource conditions in supply chain management [19]. At the same time, according to the technology acceptance model, perceived usefulness and perceived ease of use are two important indicators for measuring whether new technologies are adopted [20]. Digital transformation will have different impacts on the perceived usefulness and perceived ease of use of blockchain technology in different business scenarios. For example, material management of production flows has been digitized in digital transformation, and the combination with blockchain technology will enhance data transparency. However, it also faces technical compatibility issues, which may lead to an increase in perceived usefulness and a decrease in perceived ease of use, thereby affecting the attitude towards adopting blockchain technology. In addition, employee emotions have become an important challenge for companies when applying digital technology. There are positive and negative emotions among different employees in different business scenarios [21], and based on the expectancy confirmation theory, the adoption of new technologies can also generate similar emotions. The digital transformation of parts traceability and inventory statistics in human factory logistics has made traceability employees more efficient, but for inventory statistics, it may turn the simple manual counting of quantities into systematic data analysis, which may cause employees to worry about unemployment and technological substitution, leading to negative emotions and resistance to the adoption of blockchain technology. For the actual business of logistics and supply chain in the automotive manufacturing industry, different business scenarios have different characteristics, and the emotions and perceptions of different business personnel also vary. Therefore, this article proposes the following hypothesis:

H2: The impact of digital transformation of logistics and supply chain in the automotive manufacturing industry on the adoption of blockchain technology varies in different application scenarios.

3. Design and Method

3.1 Variable Selection

This article aims to explore the impact of digital transformation of logistics and supply chain in the automotive manufacturing industry on the adoption of blockchain technology. The explanatory variable is the digital transformation of logistics and supply chain in the automotive manufacturing industry, and the dependent variable is the degree of adoption of blockchain technology. The control variables include age, unit nature, education level, job position, work experience, degree of emphasis on digital transformation of the enterprise, whether it pays attention to new technologies, city location, and enterprise size.

Explanatory variable: Digital transformation of logistics and supply chain in the automotive manufacturing industry. According to [22-25], this article measures the degree of digital transformation of logistics and supply chain in the automotive manufacturing industry based on the principles of comprehensiveness, operability, adaptability, and objectivity, using 13 indicators from six aspects: internal support ability, external cooperation ability, technology application ability, talent cultivation ability, organizational management ability, and innovative practice ability. The evaluation is based on the Likert 5-point scale method, with scores ranging from 1 to 5. The higher the score, the stronger the ability. Meanwhile, this article will divide digital transformation into two groups based on expert classification results and combined with a random forest classification model, namely, those who have not undergone digital transformation and those who have undergone digital transformation.

The internal support capability includes two indicators: investment in digital transformation funds and training related to digital transformation. External cooperation capability includes two indicators: cooperation between the government and cooperating units, and benchmarking by universities or peers. The technical application capability includes three indicators: centralized information management and monitoring, intelligent warehousing and inventory management, and automated facilities and

equipment. The talent development capability includes two indicators: the level of digital skills of employees and the attraction and retention of digital talents. The organizational management capability includes two indicators: cross departmental cooperation and collaboration, and online business process management; Innovative practice ability includes two indicators: innovative practice in digital transformation and adaptation to new digital technologies.

Dependent variable: the degree of adoption of blockchain technology in different application scenarios. This article combines the technology acceptance model to analyze the degree of adoption of blockchain technology by employees, and divides it into five levels: completely not adopted, not adopted, acceptable, recommended for adoption, and fully adopted, represented by 1-5. Completely rejecting the application of blockchain technology in logistics and supply chain management in the automotive manufacturing industry, believing that the use of blockchain technology cannot bring any positive changes; Not adopting represents a cautious attitude towards the use of blockchain technology, although not completely rejecting it; It can be adopted that representatives can try to use it on the basis of reasonable evaluation; Suggest adopting representatives who have full confidence in the use of blockchain technology; Fully adopting represents full trust in blockchain technology, and the use of this technology will make work more convenient and should be promoted. Based on existing literature research combined with the actual business content of logistics and supply chain management in automotive enterprises, this article draws on the research of [26-29], and evaluates the adoption of blockchain technology from 13 indicators in five aspects: human factory logistics, production logistics, vehicle logistics, spare parts logistics, and reverse logistics.
Human factory logistics includes four indicators: decentralized procurement platform, automotive parts traceability and tracking, smart contracts and payments, and inventory statistics and analysis. Production logistics includes three indicators: material tracking within the factory, asset tracing and verification, and personnel certification and training. Vehicle logistics includes two indicators: paperless waybill for vehicle logistics and compliance management for vehicle logistics. Spare parts logistics includes two indicators: transparent management of spare parts, spare parts tracing, and authenticity verification. Reverse logistics includes two indicators: transparent recycling and dismantling, environmental protection, and carbon emission recording.

3.2 Data Sources
The research data in this article mainly comes from employees of automobile manufacturing enterprises and large-scale third-party automobile logistics companies. The types of enterprises include state-owned enterprises, private enterprises, joint ventures, and foreign enterprises. The research subjects are mainly distributed in the regions where domestic automobile manufacturers are located, such as Northeastern China. Their age and work experience are evenly distributed, and their job positions include on-site operators and management technicians. The formal research period is from January 2025 to June 2025. The research adopts a combination of online and offline methods, with a wide range of data collection dimensions. A total of 510 questionnaires were obtained. After excluding invalid questionnaires such as logical errors and short questionnaire filling time, a total of 406 valid samples were obtained, which meets the research needs of this article.

3.3 Model Construction
Propensity score matching (PSM) can create a more balanced comparison between the treatment group and the control group by establishing a propensity score model and matching samples, thereby improving the credibility and interpretability of research [30]. Due to the exploration of the impact of digital transformation of logistics and supply chain in the automotive manufacturing industry on the adoption of blockchain technology in this article, there are differences in whether digital transformation should be carried out. Therefore, the non-digital transformation group is used as the control group, and the digital transformation group is used as the processing group. The logit model is used to calculate the propensity score value, and one-to-one matching, one-to-one matching, radius matching, and kernel matching methods are used for matching. The average processing effect of blockchain technology adoption in the automotive manufacturing industry is calculated and relevant tests are conducted. The model construction is shown in equation (1),

$$Y_i = \alpha + \beta x_i + c d_i + \varepsilon_i \tag{1}$$

where, Y_i represents the adoption of blockchain technology by enterprise employees through their willingness to adopt blockchain technology; α is the intercept term; β is the impact of digital transformation of logistics and supply chain in the automotive manufacturing industry on the adoption of blockchain technology; x_i is the clustering analysis of whether the enterprise is undergoing digital transformation, with a value of 0 or 1; c is the coefficient of the impact of control variables on the adoption of blockchain technology by enterprise employees; d_i is the control variable; and ε_i is a random perturbation term.

4. Results and Analyses
4.1 Data Processing
The explanatory variable of this article is the digital transformation of logistics and supply chain in the automotive manufacturing

industry, and it is necessary to distinguish between the control group and the processing group. Based on the evaluation results of some experts and the random forest classification algorithm, this article divides 406 sample data into a control group and a processing group according to their degree of digital transformation. The control group is identified as the enterprise that has not undergone digital transformation, while the processing group is identified as the enterprise that has undergone digital transformation. The random forest classification algorithm can effectively handle high-dimensional feature datasets with high classification accuracy [31]. After classification, the first category consists of 107 control groups that have not undergone digital transformation, accounting for 26.35%. The second category consists of 299 processing groups that have undergone digital transformation, accounting for 73.65%. As the number of decision trees increases, the error gradually decreases and tends to stabilize. The accuracy of the training and testing results exceeds 97%, indicating that these variables have a good measurement effect on the classification of logistics and supply chain digital transformation in the automotive manufacturing industry, and have significant differences between the two categories.

The dependent variable of this article is the adoption of blockchain technology, and the entropy weight TOPSIS method is used to comprehensively evaluate the degree of adoption of blockchain technology. The entropy weight TOPSIS method is a combination of weight method and TOPSIS distance method [32]. In this paper, the degree of adoption of blockchain technology is represented by the closeness to the ideal solution, and the higher the closeness, the higher the degree of adoption of blockchain technology. This article combines the weight coefficients and positive and negative ideal values of various evaluation indicators to calculate the degree of closeness between each evaluation object and the optimal solution, that is, the degree of adoption of blockchain technology.

4.2 Tendency Value Estimation

Based on counterfactual inference, it is necessary to eliminate external factors as much as possible and match the processing group with the control group to determine whether the digital transformation of logistics and supply chain in the automotive manufacturing industry affects the adoption of blockchain technology. This article takes the binary variable of whether the logistics and supply chain of the automobile manufacturing industry undergo digital transformation as the dependent variable, and uses 9 control variables as independent variables to construct a binary logit regression model to exclude the influence of external interference factors. The regression results are shown in Table 1.

Table 1. Tendency score logit estimation results

Variable	Coefficient	Standard error	z value
Employee age	-0.51***	0.19	2.77
Educational attainment	0.56**	0.25	2.22
Job position	-0.21	0.15	-1.35
Years of work experience	0.05	0.19	0.25
Degree of emphasis on digital transformation	0.88***	0.13	6.58
Do you pay attention to new technologies?	0.22***	0.84	4.58
Nature of the unit	0.47	0.32	1.45
City of residence	0.20	0.22	0.92
Company size	-0.28*	0.16	-1.69
Constant term	-1.46	1.14	-1.28

Note: ***p<0.01, **p<0.05, *p<0.1. The same below.

According to the regression results, among the control variables, several characteristics such as employee age, degree of emphasis on digital transformation, attention to new technologies, education level, and enterprise size have a significant impact on the digital transformation of logistics and supply chain in the automotive manufacturing industry. Among them, employee age and enterprise size have a significant negative impact. The reason may be that as employees age, their acceptance of new things gradually decreases; At the same time, as the scale of enterprises increases, the cost of digital transformation becomes higher, which hinders the digital transformation of enterprises.

4.3 Matching Results and Verification

The commonly used matching methods for propensity score matching include nearest neighbor matching, radius matching, kernel matching, etc. To ensure the stability of matching quality, this article selected four matching methods as shown in Table 2. We selected matching rules of one-to-one and one to four in nearest neighbor matching.

Table 2. Average processing effect results

Matching method	Processing group mean	Control group mean	*ATT*	Standard error	*T*-test
Before matching	0.76	0.52	0.24***	0.02	11.79
One on one matching	0.74	0.61	0.14***	0.06	2.52
One on four matching	0.74	0.65	0.09***	0.05	1.89

Radius matching	0.73	0.61	0.12***	0.04	2.76
Pit matching	0.74	0.61	0.13***	0.09	2.81
Mean after matching	0.74	0.62	0.12		

Among the four matching methods mentioned above, the average processing effect (ATT) values of the four methods are 0.144, 0.094, and 0.1190.134, respectively, all of which are significant at the 1% level and have little difference. Compared with the ATT value of 0.239 before matching, they have all decreased, indicating that the self-selection bias of the samples has been effectively controlled, the model results are relatively stable, and the matching quality is good. That is, the digital transformation of logistics and supply chain in the automotive manufacturing industry has a positive impact on the adoption of blockchain technology. On average, the adoption of blockchain technology by enterprises after digital transformation increased from 0.619 to 0.741, an increase of 0.123, confirming hypothesis 1. This article takes radius matching (0.01) as an example for further verification.

In the common support domain test, the higher the overlap of the common support domains between two sets of samples, the less the matching loss and the higher the quality of the matching. As shown in Figure 2, Stata16.0 was used to plot the probability density function distribution of logistics and supply chain in the automotive manufacturing industry before and after matching, whether they have not undergone digital transformation or have undergone digital transformation. It is evident that the overlap area between the two groups of samples has significantly increased after matching, indicating that there is a larger common support area between samples that have not undergone digital transformation and those that have already started digital transformation, which has a good matching effect.

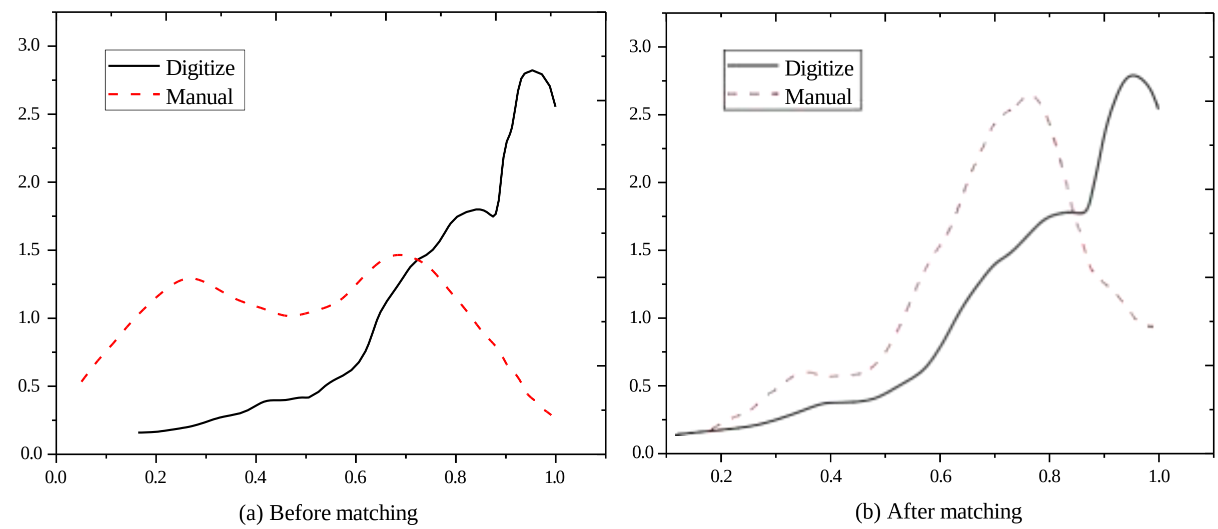

Figure 2. Kernel density function before and after matching

In the balance test, for the differences of different variables between the two groups, Figure 3 show the standardized deviations of variables before and after radius matching, respectively. It can be concluded that after matching, the absolute value of the standardized deviation of most feature variables decreased to below 10%, and the absolute value of the standardized deviation was less than 20%, indicating a good matching effect. At the same time, the standardized deviation ratio has mostly decreased by more than 60%, indicating that the characteristic differences between the treatment group and the control group have been effectively controlled. In addition, there were significant differences in variables such as age, education level, emphasis on digital transformation, and whether attention was paid to new technologies between the treatment group and the control group before matching. There were still differences in the emphasis on digital transformation after matching, but the significance was not high, and the standardized deviation was within an acceptable range, with little impact on the overall situation. There were no significant differences in other variables.

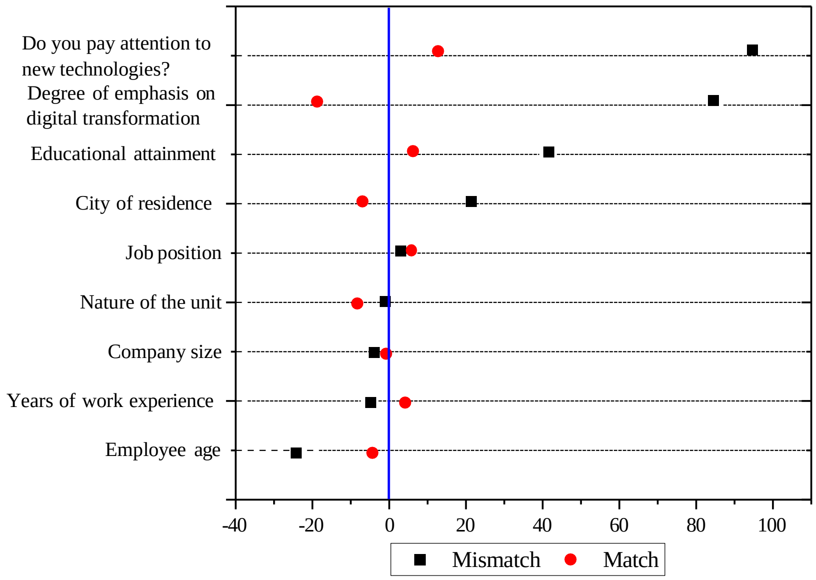

Figure 3. Standardization deviation before and after matching

As shown in Figure 3, it can be seen more clearly that the standardized deviations of each variable are decreasing after matching, indicating that propensity score matching effectively corrects the bias of the sample in external factors and reduces the problem of self-selection, and the matching results balance the data well.

In the balance analysis after variable matching, Table 3 shows that Pseudo R^2 decreased from 0.309 to 0.034, and LR statistic significantly decreased from 144.58 before matching to 14.37. The significance test of probability values changed from significant to non significant, and the mean deviation decreased from 34% to 8.4%, and the median deviation decreased from 21.8% to 6%. Through the above tests, the overall bias of the matched samples is greatly reduced, making the features between the control group and the treatment group similar, and the balance test results are relatively ideal.

Table 3. Balance test of explanatory variables before and after matching

Sample	Pseudo R^2	LR	p	Mean deviation%	Median deviation%
Mismatch	0.31	144.58	0.00	34.00	21.80
Match	0.03	14.37	0.11	8.40	6.00

4.4 Impact on Adoption

To explore the impact of digital transformation of logistics and supply chain in the automotive manufacturing industry on the adoption of blockchain technology in segmented scenarios, this paper uses Rstudio to conduct comparative analysis through three different types of regression methods: traditional linear regression, generalized linear regression, and XGBoost, in order to increase the robustness and credibility of the conclusions. Among them, traditional linear regression can simply and intuitively analyze the influence of explanatory variables on the dependent variable, while generalized linear regression introduces link functions on this basis, enriching the application scope of the model. XGBoost model can avoid overfitting and capture more complex variable relationships [33-34]. This article is represented by Model I, Model II, and Model III respectively, and the results are shown in Table 4.

Table 4. Model analysis results

First index	**Second index**	**Model I**		**Model II**		**Model III**	
		Estimated value	***p***	**Estimated value**	***p***	**Gain**	**Frequency**
Inbound logistics	Decentralized procurement platform	0.20	0.03***	0.40	0.10	0.09	0.16***
	Traceability and tracing of automotive parts	0.10	0.13	0.39	0.10*	0.05	0.08*
	Smart contracts and payments	0.23	0.02***	1.12	0.00***	0.26	0.10***
	Inventory statistics and	0.13	0.09*	0.36	0.17	0.05	0.04

	analysis						
Production logistics	In plant material tracking	-0.21	0.06***	-1.63	0.00***	0.04	0.06
	Asset tracking and verification	0.16	0.05**	0.77	0.02**	0.14	0.09**
	Personnel certification and training	-0.09	0.20	-0.50	0.10	0.03	0.07
Vehicle logistics	Paperless waybill for whole vehicle logistics	0.04	0.60	0.37	0.18	0.05	0.07
	Vehicle logistics compliance management	-0.01	0.99	-0.03	0.91	0.03	0.05
Spare parts logistics	Transparent management of spare parts	-0.20	0.01**	-0.76	0.02**	0.05	0.08
	Traceability and authenticity verification of spare parts	0.16	0.04**	0.62	0.05**	0.12	0.08**
Reverse logistics	Recycling and Disassembly Transparent	0.07	0.35	0.36	0.15	0.06	0.05
	Environmental Protection and Carbon Emission Records	0.06	0.43	0.13	0.63	0.03	0.08**

For traditional linear regression models, the model fitting effect R is 0.726, indicating a good fitting effect. At the same time, this article also conducted collinearity diagnosis and obtained VF values that are all less than 5, indicating the absence of multicollinearity; For the generalized linear regression model, the model fitting effect is usually represented by the Akaike Information Criterion (AIC), with an AC of 272, indicating a good fitting effect. For the XGBoost model, the model fitting effect is usually represented by the Root Mean Square Error (RMSE), with an RMSE of 0.068, indicating a good fitting effect. The "Gain" value is used to represent the degree of influence, which is a measure of importance. "Freguency" represents the frequency of each feature appearing, and a higher frequency than the mean indicates a higher frequency, which can to some extent explain the impact of the digital transformation of logistics and supply chain in the automotive manufacturing industry on the adoption of blockchain technology application scenarios. This article obtains a more robust research conclusion by comparing the analysis results of the three regression models mentioned above.

Based on the analysis results of the three models, it can be found that the digital transformation of logistics and supply chain in the automotive manufacturing industry has a significant positive impact on the adoption of blockchain technology in smart contracts and payment scenarios in human factory logistics, asset traceability and verification scenarios in production logistics, and spare parts traceability and authenticity verification scenarios in spare parts logistics. The adoption of blockchain technology in decentralized procurement platform scenarios and automotive parts traceability and tracking scenarios in human factory logistics has a significant positive impact in both models; The adoption of blockchain technology in the scenarios of transparent management of spare parts logistics and in plant material tracking in production logistics showed a significant negative impact in both Model I and Model II. The negative impact of adopting blockchain technology for transparent management of spare parts may be due to the fact that spare parts management is not a key focus of business in most automobile manufacturing enterprises, and with the deepening of digital transformation, the spare parts management process is relatively simple, with fewer personnel, and is not suitable for investing large amounts of funds and technology. The possible reason for the negative impact of blockchain technology adoption on material tracking scenarios in the factory is that other digital technologies that can achieve similar functions have already been used in digital transformation, but the accuracy is not high. In addition, the automotive manufacturing industry involves a large amount of material handling and movement in the production process, and the introduction of blockchain technology requires integration with existing systems, which can easily lead to inconsistencies or conflicts, affecting later maintenance and production stability. Therefore, the higher the degree of digital transformation, the lower the adoption of blockchain technology. Thus, hypothesis 2 is validated.

5. Conclusion

Using data from automobile manufacturers and logistics companies, this study employs the propensity score matching method to test whether digital transformation of the logistics and supply chain affects blockchain technology adoption in the automotive industry. The results indicate that overall, compared to enterprises that have not undergone digital transformation, enterprises that have undergone digital transformation are significantly more likely to adopt blockchain technology. However, the impact of digital transformation of logistics and supply chain in the automotive manufacturing industry on the adoption of blockchain technology varies in different application scenarios. Based on the above conclusions, in order to better guide automobile manufacturing enterprises to explore in the field of blockchain technology, the following suggestions are proposed:

(1) Encourage innovation and strengthen digital transformation of enterprises. Clearly define business strategic goals, while increasing investment in digital technology innovation and cultivating digital talents, encouraging the use of new technologies and methods combined with blockchain technology, continuously optimizing, evaluating, and improving to maintain the competitiveness of the enterprise. Moreover, attention should be paid to the refinement of management, the precision of services, and the systematization of applications, actively promoting the digital transformation of enterprises.

(2) Proactively cooperate and promote open communication among all parties involved. Fully pay attention to the level of support from all parties involved in logistics and supply chain management in the automotive manufacturing industry for the immutability, decentralization, and smart contract features of blockchain technology, enhance trust between partners, and lay a solid foundation for the application of blockchain technology. Establish open communication channels across departments and levels, enabling employees from different fields to share ideas and knowledge, and promoting the integration of innovative ideas.

(3) Needs assessment, detailed planning to prevent potential risks. Regularly assess the objectives and requirements for blockchain applications in the automotive supply chain. This involves evaluating if the current technology meets business needs, identifying potential alternative digital tools, and comparing their implementation priorities. Before adopting blockchain technology, conduct detailed planning and related risk assessments, such as the impact on production stability and employee operational convenience, and comprehensively analyze cost-effectiveness.

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