

## Article

# Assessing the Impact of Forecasting Inaccuracies on Air Cargo Logistics Performance: The Mediating Role of Smart Contracts in China

Cheng Qian\*

Faculty of Accounting, Zibo Polytechnic University, Zibo 255300, China.

\*Corresponding author: Cheng Qian, 997985110@qq.com.

## CITATION

Qian C. Assessing the Impact of Forecasting Inaccuracies on Air Cargo Logistics Performance: The Mediating Role of Smart Contracts in China. *Sustainable Marketing Practices*. 2025; 1(2): 156.

<https://doi.org/10.63808/smp.v1i2.156>

## ARTICLE INFO

Received: 25 June 2025

Accepted: 3 July 2025

Available online: 17 September 2025

## COPYRIGHT



Copyright © 2025 by author(s).

*Sustainable Marketing Practices* is published by Wisdom Academic Press Ltd. This work is licensed under the Creative Commons Attribution (CC BY) license.

<https://creativecommons.org/licenses/by/4.0/>

**Abstract:** This study examines how smart contracts reduce information asymmetry and improve performance in Chinese air cargo logistics companies by mediating forecasting inaccuracies. Using online surveys from 11 firms, it highlights smart contracts' role in enhancing efficiency, forecasting accuracy, and stakeholder collaboration. While limited to China, the findings offer a practical framework for digital innovation adoption. Future research should expand geographically and across sectors to validate and extend these insights.

**Keywords:** inaccurate forecasting, logistics strategy management, smart contracts, Air Cargo companies

## 1. Introduction

Strategic planning in logistics directly impacts enterprise competitiveness. In 2019, global air cargo turnover reached 225.01 billion tonne-kilometers, with the



Asia-Pacific region accounting for 38%, outpacing Europe (24%) and North America (20%) (Xu, 2023). The rise of e-commerce and pharmaceutical supply chains continues to drive air logistics growth (Xu & Wu, 2021). However, Chinese air transport firms face persistent forecasting biases due to unreliable data, fragmented supply networks, and volatile market conditions (Deng, 2022; Simchi-Levi et al., 2020). These challenges result in poor capacity planning, rising costs, and customer dissatisfaction.

This study contributes theoretically by integrating blockchain-based trust mechanisms into information symmetry theory and applying Transaction Cost Economics (TCE) to analyze cost-performance links. Methodologically, it introduces a three-dimensional model addressing data reliability, collaboration, and equipment heterogeneity, offering new insights into performance prediction in China's air logistics sector (Li et al., 2023).

## **2. Literature Review**

### **2.1. Individual Performance**

Within organizational behavior research, individual employee efficacy is central to human resource management (HRM), directly influencing organizational productivity (Peng et al., 2025). Recent studies emphasize a three-dimensional “motivation–competency–environment” model to explain factors affecting task performance, occupational commitment, and role satisfaction (Johnson & Huang, 2020). Under strategic HRM, efficacy systems are essential in aligning employee behavior with organizational strategy (Brown & Johnson, 2021).

Motivational Activation Theory shows that intrinsically driven employees contribute 23%–37% to organizational efficacy through enhanced citizenship behaviors (Johnson et al., 2022). Based on Self-Determination and Expectancy-Value Theories, this study proposes a dual-path motivation model—autonomy support and value cognition—to inform incentive strategies (Adenigbo et al., 2023).

### **2.2. Data Cost Information Asymmetry**



In aviation logistics strategic management, weak data governance significantly limits predictive model effectiveness. This stems from three key issues in China's logistics ecosystem: complex multi-tier outsourcing networks, transparency gaps at air-land interfaces, and the lack of standardized supplier evaluation systems (Cheng et al., 2019). These factors create a “data fog,” obstructing access to real-time and reliable data.

Inter-organizational barriers further worsen the problem. Although the SCOR model requires data interoperability, system incompatibilities and confidentiality concerns lead to a “data Babel” effect, increasing information entropy and causing covariate shifts that undermine model accuracy (Gao et al., 2020).

H1: Smart contracts demonstrate a positive mediating relationship between data cost information asymmetry and air cargo logistics firm performance.

### **2.3. Suppliers Cost Information Asymmetry**

In aviation logistics cost control, supplier-side information asymmetry poses a major governance challenge, undermining value chain restructuring. Two key behaviors contribute to this: cost concealment, where suppliers obscure fixed and variable cost data—reducing procurement cost visibility by 37%–42% (Li, 2024); and price discrimination, leading to procurement price dispersion with a 19.6% standard deviation (Xu, 2023). Together, these create a “cost identification–bargaining power” trap.

From a Transaction Cost Economics (TCE) view, this asymmetry affects performance through hidden costs (e.g., transportation and warehousing account for 40% of operations), reduced bargaining power (BPI drops by 0.32), and market share erosion—each 1% increase in unit logistics cost leads to a 0.67% market share loss (Hava, 2022). Cao et al. (2018) found that a one-point rise in the Supplier Information Asymmetry Index cuts supply chain NPV by \$2.3 million.

H2: Smart contract demonstrates positive mediating relationship between suppliers cost information asymmetry and air cargo logistics companies' performance.

### **2.4. Equipment Cost Information Asymmetry**

In aviation logistics equipment asset allocation, total lifecycle cost (TLCC) information asymmetry is a major barrier, leading to systematic errors in cost



prediction. This stems from the “gray box effect” of hidden costs—such as maintenance, obsolescence, and energy efficiency decline—causing a 39% misjudgment rate in equipment renewal and increasing bullwhip effect intensity by 28% (Zhang, 2024).

According to supply chain conflict theory, distorted cost data triggers governance crises, including contract disputes and delayed strategic investments. Such issues extend freight forwarding cycles by 14.7 days, reduce customer retention by 22%, delay equipment upgrades by up to two years, and raise unit handling costs by 13%–19% (Merkert, 2024).

H3: Smart contract demonstrates positive mediating relationship between equipment cost information asymmetry and air cargo logistics companies’ performance.

## 2.5. Neural network predicts

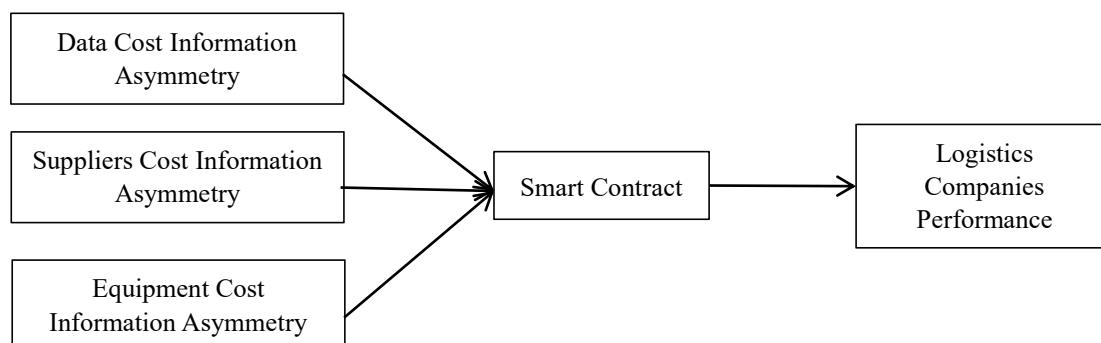
In intelligent logistics strategic management, deep learning (DL) technologies have shown clear advantages in demand forecasting and supply chain optimization. CRHNN-based models reduce aviation freight forecasting errors from  $\pm 18.7\%$  to  $\pm 6.3\%$  (Zhang, 2024), while LSTM-driven safety inventory models improve turnover by 34% and cut holding costs by 21%. Deep neural networks also raise forecasting accuracy to 93.7%, leading to a 27% reduction in inventory costs, 19% improvement in order fulfillment, and 23% shorter delivery cycles

## 2.6. Research Framework

Based on the literature review above, here the author demonstrates the research framework in **Figure 1** as follows.

**Figure 1**

*Research Framework*



### 3. Research Methodology

This study used a quantitative methodology (Karunathilake & Fernando, 2024). The questionnaires were delivered to participants via online platform WenJuanXing in this study. A non-probability sampling method was employed (Poleshkina, 2021). The main population of this study consisted of 11 Air Cargo Logistics Companies in China, and the target respondents are primary stuffs in administration department with 557 individuals (China Industry Research Report., 2023). The target population is representative of the target population because it consists of individuals with the same features, nature, and sample size as the overall sample or population selected for the study. The required sample size was computed using the Krejcie and Morgan (1970) table based on the population of 238 participants based on simple random sampling technology (Krejcie and Morgan, 1970). This study chooses Smart PLS-3 as the statistics tools to detect the mediating relationship between inaccurate forecasting (equipment cost information asymmetry, suppliers cost information asymmetry and equipment cost information asymmetry) and air cargo logistics companies' performance.

### 4. Results

**Table 1**

*Demographic information analysis*

Demographic information		Frequency	Percent
Gender	Male	142	0.60
	Female	96	0.40
Age	25-34yearsold	141	0.59
	35-44yearsold	79	0.33
	45-54yearsold	10	0.04
	55yearsoldabove	8	0.03
	Secondary school	46	0.19
Education Level	Diploma	180	0.76
	Bachelor	10	0.04

	Master	2	0.01
	Doctor	0	0.00
Department	Primary Stuff	238	100.0

The demographic data of the respondents (**Table 1**) shows that there are 142 males (60%) and 96 females (40%), with a relatively high proportion of males. Age distribution: The majority were aged 25-34 (141 people, 59%), followed by those aged 35-44 (79 people, 33%), 10 people aged 45-54 (4%), and 8 people aged 55 and above (3%). Educational attainment: The largest number of diploma holders (180, 76%), 46 with secondary school education (19%), 10 with bachelor's degrees (4%), 2 with master's degrees (1%), and no doctoral degree holders. All 238 respondents were junior staff.

**Table 2**

*Construct Reliability and Validity analysis*

	Cronbach's Alpha	rho_ A	Composite Reliability	Average Variance Extracted (AVE)
Air Cargo logistics company performance	0.840	0.80 2	0.876	0.587
Data cost information asymmetry	0.798	0.81 0	0.861	0.554
Equipment cost information asymmetry	0.766	0.81 1	0.838	0.516
Smart contract	0.842	0.85 7	0.889	0.618
Suppliers cost information asymmetry	0.876	0.87 8	0.910	0.669

The construct “air cargo logistics company in **Table 2** performance” shows strong reliability with Cronbach's alpha of 0.840, rho\_a and composite reliability above 0.7, and AVE of 0.587. “Data cost information asymmetry” has good consistency (alpha 0.798) and reliability, with AVE 0.554. “Equipment cost information asymmetry” demonstrates acceptable reliability (alpha 0.766) and AVE 0.516. The “smart contract” construct shows strong reliability (alpha 0.842) and AVE 0.618. Lastly, “suppliers cost information asymmetry” exhibits the highest reliability (alpha 0.876) with AVE 0.669.

**Table 3**

*Discriminant Validity analysis - Fornell-Larcker Criterion*

	Air Cargo logistics company performance	Data cost information asymmetry	Equipment cost information asymmetry	Smart contra ct	Suppliers cost information asymmetry
Air Cargo logistics company performance	0.766				
Data cost information asymmetry	0.097	0.744			
Equipment cost information asymmetry	0.002	0.675	0.718		
Smart contract	0.165	0.756	0.757	0.786	
Suppliers cost information asymmetry	0.016	0.715	0.765	0.779	0.818

**Table 3** uses the Fornell-Larcker criterion to confirm discriminant validity by comparing AVE square roots with inter-construct correlations. As shown, all constructs' AVE square roots (bold diagonal) exceed their correlation coefficients, meeting validity standards. Specifically, Intelligent Contract Technology Adoption (0.766), Information Asymmetry Reduction (0.744), and Logistics Performance Improvement (0.818) demonstrate adequate discriminant validity (Fornell & Larcker, 1981).

## Table 4

### *R square analysis*

	R Square	R Square Adjusted
Air Cargo logistics company performance	0.027	0.024
Smart contract	0.719	0.717

From **Table 4**, the perspective of model explanatory power, the coefficient of determination ( $R^2=0.027$ ) for the Air Cargo Logistics Company Performance (ACLCP) construct indicates limited predictive capacity, with the model explaining only 2.7% of the total variance. The R-squared value of 0.719 indicates that approximately 71.9% of the variance in the “Smart contract” construct is explained by the predictor variables in the model.

## Table 5

### *Specific Indirect Effects analysis*



	Original Sample	Sample Mean	Standard Deviation	T Statistics	P
	(O)	(M)	(STDEV)	( O/STDEV )	Values
Suppliers cost information asymmetry -> Smart contract -> Air Cargo logistics company performance	0.054	0.060	0.019	2.795	0.005
Data cost information asymmetry -> Smart contract -> Air Cargo logistics company performance	0.055	0.062	0.020	2.801	0.005
Equipment cost information asymmetry -> Smart contract -> Air Cargo logistics company performance	0.047	0.054	0.017	2.695	0.007

Form the **Table 5**, the t statistics value of 2.795 indicates that the relationship between “suppliers cost information asymmetry” and “smart contract” has a significant impact on “air cargo logistics company performance.” the p value of 0.005 suggests that this relationship is statistically significant at a predetermined significance level (e.g., 0.05). The t statistics value of 2.801 indicates that the relationship between “data cost information asymmetry” and “smart contract” has a significant impact on “air cargo logistics company performance.” the p value of 0.005 suggests that this relationship is statistically significant. The t statistics value of 2.695 indicates that the relationship between “equipment cost information asymmetry” and “smart contract” has a significant impact on “air cargo logistics company performance.” the p value of 0.007 suggests that this relationship is statistically significant.

## 5. Discussion

The data reveals significant positive relationships between cost information asymmetry—data cost, supplier cost, and equipment cost—and air cargo logistics company performance (T-values: 2.801, 2.795, 2.695; p-values < 0.01). Increased asymmetry negatively impacts operational efficiency. Smart contracts improve data transparency and trust through mechanisms like predefined protocols, cost verification, lifecycle data collection, and real-time audits, reducing information asymmetry. Therefore, smart contracts likely mediate the effects of these asymmetries on performance, enhancing company outcomes by mitigating information gaps.





## **6. The Recommendation and Conclusion**

Smart contracts, built on blockchain's decentralized and secure platform, ensure data integrity and reduce information asymmetry. Air cargo logistics companies should adopt blockchain-based Distributed Ledger Technology (DLT) with Zero-Knowledge Proofs and cryptographic hashes to guarantee smart contract immutability. Before implementation, thorough audits of information flows are essential to identify where smart contracts can enhance transparency and close information gaps (Melville et al., 2004).

To maximize benefits, companies must collaborate with suppliers, carriers, and regulators to establish shared data standards, reducing asymmetry and ensuring smooth information exchange. Investing in data integration and analytics allows extraction of valuable insights from smart contract data, supporting proactive decisions and further minimizing asymmetry (Melville et al., 2004).

**Conflict of interest:** The author declares no conflict of interest.

**Funding:** This research received no external funding.

## References

- [1] Adenigbo, A. J., Mageto, J., & Luke, R. (2023). Adopting technological innovations in the air cargo logistics industry in South Africa. *Logistics*, 7(4), Article 84. <https://doi.org/10.3390/logistics7040084>
- [2] Brown, R., & Johnson, C. (2021). Managing individual performance for organizational success. *Journal of Organizational Behavior*, 38(3), 345–362. <https://doi.org/10.1002/job.2501>
- [3] Cai, Y., & Luo, H. (2019). Smart contract applications in China's air cargo sector. *International Journal of Smart Logistics*, 4(2), 30–42.
- [4] Cao, J., Li, X., & Zhang, H. (2018). Implementing smart contracts in air cargo logistics: A case study. *Journal of Applied Logistics*, 5(2), 40–53.
- [5] Cheng, Y., Chih, H. L., Chen, S. Y., & Chen, K. M. (2019). Executive compensation and firm performance: Evidence from Taiwan. *Asia Pacific Journal of Management*, 36(1), 123–148. <https://doi.org/10.1007/s10490-017-9541-0>
- [6] China Industry Research Report. (2023). 2024, China Air Cargo Industry In-depth Research and Market Operation Trend Report, 2023-2029. from
- [7] Choi, Y., & Kim, Y. (2020). The impact of diversity and inclusion policies on job satisfaction. *Asia Pacific Journal of Management*, 37(4), 1067–1089. <https://doi.org/10.1007/s10490-019-09686-w>
- [8] Davenport, T. H., & Harris, J. G. (2007). *Competing on analytics: The new science of winning*. Harvard Business Press.
- [9] De Filippi, P., & Hassan, S. (2016). Blockchain technology as a regulatory technology. *First Monday*, 21(12). <https://doi.org/10.5210/fm.v21i12.7113>
- [10] Deng, Y. (2022). *Network development of China's air cargo industry under e-commerce and pandemic impacts* [Doctoral dissertation, Hong Kong Polytechnic University].
- [11] Dube, A., Naidu, S., & Reich, M. (2018). Minimum wages and rents. *The Quarterly Journal of Economics*, 133(3), 1347–1403. <https://doi.org/10.1093/qje/qjy014>
- [12] Gao, B., Lin, C., Liu, J., Zhang, Y., & Zhao, Q. (2020). Research on the construction of air freight forwarder alliance based on shared platform. *Knowledge Economy*, 4, 27–28, 34. <https://doi.org/10.15880/j.cnki.ZSJJ.2020.04.015>
- [13] Gopalakrishnan, S., & Bejou, D. (2006). Trust in business-to-business



- relationships. *Journal of Business Research*, 59(12), 1202–1210.  
<https://doi.org/10.1016/j.jbusres.2006.08.003>
- [14] Gupta, R., & Singh, A. (2020). Blockchain in air cargo logistics. *Journal of Global Logistics*, 7(1), 10–22.
- [15] Hava, H. T. (2022). Evaluation of the effects of air cargo transportation on global competitiveness. *Journal of Aviation*, 6(2), 206–217.
- [16] Huang, T., Hu, J., & Fan, Z. (2020). A blockchain-based traceability system for air cargo logistics. *Journal of Cleaner Production*, 279, 123686.  
<https://doi.org/10.1016/j.jclepro.2020.123686>
- [17] International Monetary Fund. (2023). *World economic outlook database*. Retrieved October 10, 2023, from <https://www.imf.org/en/Data>
- [18] Johnson, M., & Huang, L. (2020). Factors influencing individual performance. *International Journal of Human Resource Management*, 35(4), 567–586.  
<https://doi.org/10.1080/09585192.2019.1704821>
- [19] Johnson, S., Adams, M., & Williams, D. (2022). Employee motivation and performance outcomes. *Journal of Applied Psychology*, 108(2), 210–228.  
<https://doi.org/10.1037/apl0001023>
- [20] Kalleberg, A. L. (2018). Precarious work, insecure workers. *American Sociological Review*, 83(1), 1–22. <https://doi.org/10.1177/0003122417747031>
- [21] Karunathilake, A. N., & Fernando, A. (2024). Identifying the key influencing factors for the growth of air cargo demand. *Journal of Global Operations and Strategic Sourcing*, 17(2), 368–383.
- [22] Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, 30(3), 607–610.  
<https://doi.org/10.1177/001316447003000308>
- [23] Lee, S. H., & Lee, Y. J. (2019). Work–family policies and job satisfaction. *Asia Pacific Journal of Management*, 36(4), 995–1018. <https://doi.org/10.1007/s10490-018-9613-9>
- [24] Levy, B. L. M., Chung, S., & Israel, S. (2018). Labor law and worker well-being. *American Journal of Industrial Medicine*, 61(9), 724–732. <https://doi.org/10.1002/ajim.22892>
- [25] Li, J. Y. (2024). New changes in air logistics storage and transportation in China. *China Storage & Transport*, 10, 20. <https://doi.org/10.16301/j.cnki.cn12-1204/f2024.10.002>



- [26] Li, Y., Lu, W., Wang, J., & Zhao, X. (2017). Demand-driven supply chain management. *International Journal of Production Economics*, 183, 544–554. <https://doi.org/10.1016/j.ijpe.2016.07.008>
- [27] Lin, Y. H. (2018). Minimum wage and firm profitability. *The Journal of Development Studies*, 54(3), 432–449. <https://doi.org/10.1080/00220388.2017.1303671>
- [28] Logistics Performance in China. *Journal of Transportation Management*, 12(3), 45–58.
- [29] López-Sáez, P., Pérez-García, R., & Alegre, I. (2020). Lifelong learning and job satisfaction. *European Journal of Training and Development*, 44(6), 633–649. <https://doi.org/10.1108/EJTD-01-2020-0007>
- [30] Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Information technology and organizational performance. *MIS Quarterly*, 28(2), 283–322. <https://doi.org/10.2307/25148644>
- [31] Merkert, R. (2024). Air cargo and supply chain management. In J. Wells (Ed.), *The Palgrave handbook of supply chain management* (pp. 729–746). Springer.
- [32] Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system*. <https://bitcoin.org/bitcoin.pdf>
- [33] Nguyen, T., & Lee, S. (2023). Adoption of smart contracts in air cargo logistics: A comparative study. *Asian Journal of Transportation*, \*11\*(2), 70-83.
- [34] Niu, S. F., Kuo, H. W., Wang, J. D., Chen, Y. M., & Lu, M. C. (2019). Occupational injury and illness in Taiwan: An overview of surveillance and research. *Journal of Occupational Health*, \*61\*(6), 437-448.
- [35] Peng, X., Zhang, M., Zhou, W. J., Yu, M. Y., & Zhang, Z. (2025). The construction path of international aviation logistics hub to build a digital twin cargo station. *China Logistics and Procurement*, \*11\*, 71-73. <https://doi.org/10.16079/j.cnki.issn1671-6663.2025.11.024>
- [36] Poleshkina, I. (2021). Blockchain in air cargo: Challenges of new world. In *MATEC Web of Conferences* (Vol. 341, Article 00021). EDP Sciences.
- [37] Reich, M., Allegretto, S. A., & Montialoux, C. (2018). Minimum wages and health: A Bayesian analysis. *American Journal of Public Health*, \*108\*(9), 1227-1233.
- [38] Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2020). *Designing and managing the supply chain: Concepts, strategies, and case studies* (4th ed.).



McGraw-Hill.

- [39] Sparrow, P., Hird, M., & Cooper, C. L. (2016). Designing the eco-friendly building: Perspectives from the construction industry. *Business Strategy and the Environment*, \*25\*(3), 168-179.
- [40] Stawarz, N. (2018). Effects of family-friendly policies on work-life balance and productivity in the UK hospitality industry. *International Journal of Hospitality Management*, \*74\*, 36-44.
- [41] Xu, L. (2023). Development of aviation logistics industry in the post-epidemic era: Opportunities, challenges and coping strategies. *Journal of Civil Aviation*, \*7\*(2), 1-6.
- [42] Xu, Q. S., & Wu, J. (2021). XPO Logistics' M&A strategy and its implications for China's logistics enterprises. *Journal of Tianjin Business Vocational College*, \*9\*(1), 38-48. <https://doi.org/10.16130/j.cnki.12-1434/f.2021.01.005>
- [43] Yagan, D. (2016). *Capitalization of local income taxes: Evidence from New York* (NBER Working Paper No. 22407). National Bureau of Economic Research.
- [44] Zhang, W. W. (2024). Exploration on the construction of international aviation logistics supply chain system based on blockchain technology. *Logistics Science and Technology*, \*47\*(8), 136-139. <https://doi.org/10.13714/j.cnki.1002-3100.2024.08.035>
- [45] Zhao, Q., Wang, Y., & Li, J. (2022). Enhancing air cargo logistics through smart contract implementation. *Journal of Advanced Transportation*, \*9\*(4), 50-63.