

Enterprise Benefit Allocation in AI-Empowered Industrial Chain Collaboration

Ying Zhao

*Faculty of Natural, Mathematical & Engineering Sciences, King's College London, London, UK
zy_yingzhao2004@163.com*

Abstract. Artificial intelligence is transforming industrial supply chains through instantaneous data exchange, enhanced decision-making capabilities, and automated management processes. AI can enhance efficiency and generate additional value, but it may also exacerbate disparities in benefit distribution. This is because major enterprises and digital platforms often control the algorithms, infrastructure, and aggregated data, while smaller suppliers typically contribute operational insights, production capabilities, and specialized expertise. This research utilizes a qualitative literature review and case analysis methodology to explore the key issues and underlying factors that lead to benefit disparities in AI-driven industrial supply chains. The Thai tuna supply chain serves as a case study, illustrating how data providers may receive minimal benefits from the value generated through traceability and data monetization. The analysis identifies disproportionate control over digital assets, unequal bargaining power, and inadequate assessment of contributions as the primary factors contributing to this imbalance. It argues for the necessity of multi-faceted contribution accounting, adaptive benefit-sharing agreements, data rights protection, and collaborative algorithmic governance to promote equity, transparency, and sustainable stability within supply chains.

Keywords: Artificial intelligence, industrial chain collaboration, benefit allocation, data governance, algorithmic governance

1. Introduction

AI is turning linear industrial chains into digital ecosystems with real-time information sharing, predictive decision-making, and automated coordination. Machine learning, digital twins, and algorithmic optimization help firms estimate demand, track suppliers, manage inventories, and respond faster to disturbances. Digital supply-chain collaboration improves integration, agility, and value co-creation by lowering information asymmetry, transaction costs, and operational uncertainty [1, 2]. Evidence shows that AI benefits depend strongly on organizational capabilities, data quality, and governance [3].

An equitable distribution of value is not always the result of these efficiency gains. While smaller suppliers provide production capacity, operational data, specialist knowledge, and relationship-specific investments, focal organizations and digital platforms typically control algorithms, customer interfaces, and consolidated datasets. As a result, AI might increase the overall collaborative surplus

while giving technologically dominant actors a disproportionate share. Without sufficient control over data use, performance evaluation, or the terms on which jointly created value is distributed, suppliers may also bear digitalization costs and algorithm-related risks.

Utilizing contemporary research and the Thai tuna supply-chain example, this study investigates the primary issues, underlying factors, and enhancement strategies for inter-company benefit distribution across AI-driven industrial networks. It proposes a unified structure grounded in multi-faceted contribution assessment, adaptive benefit-sharing agreements, data-rights safeguarding, and collaborative algorithmic oversight.

2. Major problems and current conditions of inter-enterprise benefit allocation

2.1. Basic benefit-allocation models

Benefit allocation pertains to the guidelines governing the distribution of income, cost efficiencies, risks, and supplementary economic surplus among firms engaged in an industrial network. In conventional supply chains, distribution is typically manifested in purchasing costs, wholesale rates, service charges, and mutual agreements. The ultimate allocation of profit is determined not solely by productive input but also by negotiating leverage, informational superiority, and switching costs.

In AI-enhanced industrial chains, two relevant contract models are identified: coordination through revenue-sharing and cost-sharing agreements. These configurations aim to synchronize the motivations of autonomous enterprises, allowing suppliers to benefit from downstream earnings and sharing the costs of AI systems. Prior studies indicate that revenue-sharing frameworks can enhance supply chain alignment when companies would typically follow divergent goals [4]. Nonetheless, set agreements may prove inadequate in AI-facilitated collaboration due to the unpredictable and evolving nature of digitalization's costs and advantages. At the outset of an AI initiative, organizations may be uncertain whether the primary benefits will stem from increased sales, reduced inventory, lower financing costs, or improved operational efficiency. A predetermined share ratio can thus result in excessive compensation for one party while neglecting to acknowledge another entity's input in data provision, innovation, or risk assumption.

The second framework utilizes cooperative game theory, particularly the Shapley value to allocate collaborative surplus based on each firm's projected marginal contribution. This is essential for AI-driven industrial networks, where value arises from data exchange and inter-company collaboration. Studies indicate that collaboration can enhance overall profitability, whereas consistent allocation guidelines are essential to deter companies or sub-groups from disengaging from partnerships [5]. However, cooperative-game frameworks do not inherently guarantee fairness. The outcomes are contingent upon how each company's contribution is assessed. If the primary organization governs the data and computational framework, it could inflate its own input while downplaying the inputs of lesser suppliers. Consequently, these approaches necessitate mutually accepted metrics, clear assumptions, and impartial data validation.

Overall, contract-based coordination serves as an effective tool for distributing costs, profits, and risks, but cooperative-game approaches present a more structured means of allocating collaboratively generated surplus. Integrating the two can facilitate a harmonious equilibrium between operational efficacy and equitable distribution in AI-driven industrial networks.

2.2. Unequal recognition and appropriation of data value

Data play a dual role in AI-driven industrial cooperation, serving as input for training algorithms and output for generating commercial insights, risk assessments, and market predictions. Small and medium-sized enterprises generate essential data for AI systems, while primary business or technology suppliers provide the framework to transform this data into economic value. Insights produced collaboratively are viewed as exclusive assets by the algorithm's overseer.

The Thai tuna supply chain case exemplifies the complexities of data sharing across various stakeholders, including fishers, merchants, processors, and technology suppliers. AI and blockchain can improve traceability related to harvesting, quality, and sustainability, potentially reducing fraud and enhancing food safety [6]. However, the distribution of benefits remains problematic, as smaller players like fishermen may remain unpaid while larger entities capitalize on the data. This situation raises concerns about the transparency of value distribution; knowing a product's origin does not clarify the benefits of that information. Additionally, mandated data sharing might weaken suppliers' bargaining positions, enabling buyers to negotiate more aggressively by leveraging comprehensive production data. Thus, while data transparency can reduce supply chain information asymmetry, it may increase disparities between powerful buyers and individual suppliers.

The critical issue is therefore not whether data should be shared, but under what conditions. Effective industrial networks require data amalgamation, yet unregulated extraction may dissuade contributors from providing precise information. Over time, inequitable appropriation could diminish data integrity as providers may be motivated to conceal, postpone, or distort information. Equitable remuneration for data input ought to be perceived as a prerequisite for AI precision rather than only an ethical responsibility.

2.3. Algorithmic opacity and platform governance

AI increasingly affects supplier selection, order allocation, pricing, and performance. Suppliers typically lack expertise in the algorithm's data, indications, and weightings, which impairs industrial chain advantages. Algorithmic opacity is a governance and technological challenge. Complex machine-learning models cause technical opacity, while platform owners not disclosing decision criteria cause institutional opacity. Without suppliers understanding how their ratings are determined, even a simple scoring scheme can be unjust. Explainable AI research reveals that interpretability helps users evaluate algorithmic decisions [7]. Explainability does not guarantee fairness. An algorithm can explain that slower delivery reduced orders for a supplier, ignoring firm size, financial resources, and emergency capacity. Artificial intelligence systems might further bolster the influence of central organizations. When a single platform governs supplier information, performance metrics, and appeal processes, automated decisions may exacerbate existing power imbalances [3]. Research underscores the importance of transparency, equity, responsibility, and human supervision as fundamental governance tenets [8, 9]. Therefore, providers should be made aware of the primary decision-making criteria, given the opportunity to rectify erroneous data, and granted access to human review. To determine if SMEs are consistently disadvantaged, periodic algorithmic audits are also required. Without these protections, AI might enhance coordination while portraying unequal benefit distribution as an objective technological result.

3. Causes of benefit imbalance in AI-empowered industrial chains

3.1. Asymmetric control of data, algorithms and digital infrastructure

The primary reason for the disparity in benefits is the uneven governance of critical digital assets. AI-powered collaboration requires operational data, algorithms, cloud infrastructure, and expertise. Despite suppliers collectively creating production, inventory, quality, and delivery data, focus organizations and technology providers usually dictate data collection, processing, and commercialization. This lets the platform owner turn collaborative data into a unique asset. Control multiplies benefits. Large datasets allow organizations to create more accurate algorithms, attract more participants, and generate more data. This infrastructure is difficult for small suppliers to reproduce owing to financial and technical constraints. Recent studies show that AI-facilitated value co-creation in B2B marketplaces requires complementary resources, knowledge absorption, trust, and organizational interaction [10]. However, additional input does not guarantee advantage.

The corporation with the digital framework can gain more recognition than the many vendors whose data improves the system. This asymmetry is further reinforced by digital supply-chain monitoring. In addition to providing focal organizations with wide access to suppliers' production circumstances and network relationships, AI can enhance visibility and identify disruption threats across various supply-chain layers [11]. The information gathered for coordination may be utilized to evaluate capacity limitations, compare suppliers, or improve the buyer's negotiating position. AI not only increases visibility in supply chains but also enhances informational advantages for focal enterprises, exacerbating asymmetries in decision-making authority and data ownership. Value measurement and distribution can be decided by the same company that controls the platform, performance metrics, and benefit-allocation model. Thus, while concentrating its appropriation among technologically superior entities, AI may raise the overall value of the supply chain.

3.2. Bargaining-power asymmetry and inadequate contribution measurement

The second main cause is unequal bargaining power and difficulties measuring multi-dimensional contributions. Core firms and digital platforms often control major consumers, orders, and market data. Suppliers may agree to platform regulations, but leaving would cause significant business losses. By needing relationship-specific investment, AI can increase reliance. Suppliers may need buyer-specific data standards, specialist software, or production process changes. Switching partners is expensive once these investments are hard to recover. The focal enterprise can demand cheaper costs, more data, or tougher performance. This resembles a contractual hold-up problem: one party invests before all future conditions can be specified.

In contrast, the more powerful party later captures a larger share of the jointly created value. Narrow contribution indicators exacerbate the issue. While AI-enabled cooperation also relies on data quality, innovation, adaptability, emergency capability, and sustainability performance, traditional allocation processes primarily recognize capital, sales, and direct output. Economic, environmental, social, and managerial aspects of performance should be considered in addition to operational efficiency, according to research on AI-integrated sustainable supply chains [12]. However, these more comprehensive contributions are hard to measure and are frequently left out of allocation algorithms. Cooperative gaming techniques cannot completely solve this issue. The indicators included and the method used to calculate marginal contribution determine the outcomes. The focus enterprise may overestimate the value of its infrastructure while underestimating supplier

expertise, adaptability, or risk-taking if it controls the data and model. Benefit imbalance therefore results from unequal negotiating power and unequal authority to determine what constitutes worth.

These two elements create a self-reinforcing structure where stronger companies control the platform and the standards, limiting weaker suppliers' ability to invest in digital skills and further weakening their negotiation power. Therefore, resource control and the governance of contribution measurement must be addressed in a more equitable allocation system.

4. Optimization pathways for benefit equilibrium under AI-enabled value co-creation

4.1. Multi-dimensional contribution accounting and dynamic benefit-sharing contracts

Using multi-dimensional contribution-accounting instead of bargaining-power-based allocation is the first optimization path. As mentioned in Sections 2 and 3, suppliers supply operational data, specialized knowledge, creativity, flexibility, and risk-taking in addition to physical production and capital. Traditional pricing and profit-sharing models often ignore these less evident benefits. AI-enabled value co-creation requires complementary resources, knowledge integration, and firm engagement, so benefit sharing should account for data-generating suppliers and digital infrastructure owners [11]. A good framework might divide profits into collaborative surplus and basic pay. Basic compensation covers direct production, digitalization, and fair return. Data quality, innovation input, operational reliability, and sustainability performance could decide collaborative surplus distribution. AI integration could produce data-related value, inventory savings, and revenue. Cooperation-game approaches may help the data model enterprise avoid overstating its marginal contribution; however, their assumptions and contribution estimates must be reviewed together.

The distribution mechanism ought to be integrated into adaptive contracts concerning costs, revenues, and risk-sharing. Static sharing ratios are inappropriate because the advantages of AI vary across different phases of deployment. In the early stages, primary firms ought to assume a greater portion of infrastructure expenses when they get benefits across the entire chain. Once quantifiable improvements are observed, the distribution ratio may be modified based on validated inputs. Contracts further allocate accountability for algorithmic inaccuracies. For instance, when a vendor escalates production due to a buyer-driven, high-confidence projection, the purchaser ought to ensure a minimum acquisition volume or distribute the resulting inventory deficit. This tackles the previous issue where algorithmic governance and fiscal accountability are dissociated.

4.2. Data-rights protection and joint algorithmic governance

The alternative approach involves merging data-rights safeguarding with accountable, inclusive algorithmic management. The Thai tuna incident demonstrates that artificial intelligence and blockchain technology can improve traceability, sustainability, and data monetization via contributions from various stakeholders [6]. Nevertheless, the research fails to establish that the resultant value is inherently distributed equitably. Entities responsible for producing vital data may find themselves at a disadvantage if downstream processors or technology providers dominate its interpretation and commercial application. A layered data governance system is essential to classify various data types, ensuring that vendors retain rights over their raw data. Remuneration ought to be based on the quality and commercial significance of the data, rather than solely on its volume.

Algorithms with significant influence on supplier assessment, order distribution, and pricing must also undergo collaborative supervision. Studies demonstrate that responsible AI is essential for effective human-AI collaboration to yield favorable supply-chain results, indicating that

transparency and accountability are fundamental operational necessities rather than mere ethical enhancements [9]. Platforms ought to reveal their primary metrics and decision-making standards, whereas suppliers must be able to correct erroneous information and seek human evaluation. Independent evaluations ought to assess if small and medium-sized enterprises or new market participants are consistently disadvantaged.

These two routes bolster each other. Contribution accounting identifies the criteria for rewards, whereas data and algorithmic governance establish the authority over the evidence utilized to compute those rewards. In the absence of the first, the distribution of value is limited; without the second, influential corporations could distort seemingly impartial metrics. Combining these strategies can improve efficiency and reduce structural disparities.

5. Conclusion

AI-facilitated collaboration has the potential to enhance forecasting, coordination, traceability, and resource distribution throughout industrial networks; however, the examination presented in this paper indicates that increased overall efficiency does not inherently result in a fair allocation of advantages. The primary issue is in the distinction between value contribution and value governance. The Thai tuna supply-chain case exemplifies this conflict: cohesive data can enhance traceability, sustainability, and the generation of commercial value, but the research fails to show that upstream data providers obtain a fair share of the ensuing advantages. Two interrelated structural factors exacerbate the disparity. Initially, the unequal governance of data and digital frameworks enables technologically superior companies to dictate the metrics of value assessment and allocation. Secondly, imbalanced negotiating power and limited contribution metrics can diminish the worth of supplier expertise, sustainability achievements, and investments tailored to specific relationships. Algorithmic opacity might further validate these results by framing disputed business selections as impartial technology determinations.

Benefit equilibrium necessitates multiple mathematical allocation formulas. Multi-faceted contribution accounting ought to be integrated with adaptive contracts for cost, revenue, and risk-sharing to ensure remuneration corresponds with fluctuating contributions and vulnerabilities. Data contributors must have access, correction, and authorized-use privileges, whereas high-impact algorithms need to be disclosed, subjected to human evaluation, and independently audited. The systems are interdependent: contribution accounting specifies the criteria for rewards, while data and algorithmic governance assess the reliability of the evidence utilized for distribution. Sustainable value co-creation in AI depends on balancing efficiency with transparency and equitable rewards, ensuring supplier engagement and stability in the industrial chain.

References

- [1] Al-Omoush, K. S., de Lucas, A., & del Val, M. T. (2023). The role of e-supply chain collaboration in collaborative innovation and value co-creation. *Journal of Business Research*, 158, 113647.
- [2] Zhu, C., Guo, X., & Zou, S. (2022). Impact of information and communications technology alignment on supply chain performance in the Industry 4.0 era: Mediation effect of supply chain integration. *Journal of Industrial and Production Engineering*. Advance online publication. <https://doi.org/10.1080/21681015.2022.2099472>
- [3] Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions. *Computers in Industry*, 162, 104132.
- [4] Zhou, H., Liu, L., Jiang, W., & Li, S. (2022). Green supply chain decisions and revenue-sharing contracts under manufacturers' overconfidence. *Journal of Mathematics*, 2022, Article 1035966.
- [5] Guardiola, L. A., Meca, A., & Timmer, J. (2024). Cooperation and profit allocation in distribution chains [Preprint]. *arXiv*. <https://doi.org/10.48550/arXiv.2402.04083>

- [6] Tsolakis, N., Schumacher, R., Dora, M., & Kumar, M. (2023). Artificial intelligence and blockchain implementation in supply chains: A pathway to sustainability and data monetisation? *Annals of Operations Research*, 327(1), 157–210. <https://doi.org/10.1007/s10479-022-04785-2>
- [7] Jauhar, S. K., Kamble, S. S., Belhadi, A., & Gupta, S. (2025). Explainable artificial intelligence to improve the resilience of perishable product supply chains by leveraging customer characteristics. *Annals of Operations Research*. Advance online publication. <https://doi.org/10.1007/s10479-024-06348-z>
- [8] Ahangar, M. N., Farhat, Z., Sivanathan, A., & Manoharan, T. (2025). AI trustworthiness in manufacturing: Challenges, toolkits, and the path to Industry 5.0. *Sensors*, 25(14), 4357. <https://doi.org/10.3390/s25144357>
- [9] Vann Yaroson, E., Abadie, A., & Roux, M. (2025). Human-artificial intelligence collaboration in supply chain outcomes: The mediating role of responsible artificial intelligence. *Annals of Operations Research*, 354(1), 35–69.
- [10] Fehrenbach, D., Herrando, C., & Martín-De Hoyos, M. J. (2024). Co-creation with AI in B2B markets: A systematic literature review. *Sustainability*, 16(18), 8009. <https://doi.org/10.3390/su16188009>
- [11] Brintrup, A., Kosasih, E., Schaffer, P., Zheng, G., Demirel, G., & MacCarthy, B. L. (2024). Digital supply chain surveillance using artificial intelligence: Definitions, opportunities and risks. *International Journal of Production Research*, 62(13), 4674–4695. <https://doi.org/10.1080/00207543.2023.2270719>
- [12] Qu, C., & Kim, E. (2024). Reviewing the roles of AI-integrated technologies in sustainable supply chain management: Research propositions and a framework for future directions. *Sustainability*, 16(14), 6186.