A Hybrid Cooperative Game and Shapley Value Approach for Knowledge Sharing and Profit Allocation in Technology Supply Chain Strategic Alliance

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Abstract

Equitable profit allocation in strategic alliances within technology supply chains remains a formidable challenge, exacerbated by the inability of conventional game-theoretic models such as Nash bargaining and Stackelberg to effectively analyze dynamic, knowledge-driven contributions. These models, constrained by their bilateral and static design, fail to capture the intricacies of multi-agent interactions. This study introduces a hybrid game-theoretic framework utilizing the Shapley value's axiomatic fairness to allocate coalition profits by marginal contributions. The Shapley value surpasses equilibrium-based or power-centric approaches, offering superior suitability for complex multi-agent scenarios. Leveraging meticulously validated data including knowledge investment, absorptive capacity, and coordination costs—this framework employs Monte Carlo simulations to deliver statistically reliable contribution estimates, thereby overcoming the shortcomings of prior methodologies. Applied to an automotive supply chain, the model demonstrates substantial profit gains attributable to optimized knowledge-sharing processes. Absorptive capacity reflects the efficiency of organizational learning, coordination costs indicate potential frictions in collaborative processes, and knowledge investment captures the level of innovation intensity. The proposed model offers a robust, data-driven foundation for developing equitable profit-sharing mechanisms tailored to engineering management needs. At the policy level, it provides a scalable framework for strengthening supply chain resilience. This integrated approach contributes meaningfully to both the advancement of theoretical perspectives and the enhancement of practical strategies in supply chain management.

Managerial Relevance Statement

This study provides engineering managers and policymakers with a decisive analytical framework to resolve the enduring challenge of equitable value distribution in knowledge-intensive strategic alliances. For engineering managers, the model transforms abstract knowledge contributions into quantifiable financial metrics, enabling precise calibration of profit-sharing mechanisms that reflect true marginal contributions. This allows for the design of dynamic governance structures that systematically reward knowledge investment and absorptive capacity while mitigating coordination inefficiencies. Policymakers can leverage this scalable framework to foster industrial ecosystems where transparent value allocation strengthens supply chain resilience and promotes sustainable innovation. By aligning economic incentives with collaborative behaviors across organizational boundaries, this approach enables more effective partnership structures in technology-driven sectors. This paper also contributes to the following SDGs: 8, 9, 12.

Keywords: *Knowledge Sharing, Absorptive Capacity, Shapley Value, Supply Chain Coalitions, Supply Technological Products, Strategic Alliance.*

1. Introduction

Strategic alliances within technology-intensive supply chains have become essential mechanisms for achieving sustained innovation, operational agility, and competitive advantage in dynamic global markets [1], [2], [18]. Central to these alliances is knowledge sharing (KS) a deliberate and systematic process through which partner firms exchange expertise, proprietary know-how, and intellectual capital to co-create value and accelerate innovation [3], [14]. Despite its acknowledged strategic importance, ensuring a fair and transparent distribution of profits among alliance members with asymmetric contributions remains a persistent and insufficiently addressed challenge [4], [53].

Empirical evidence consistently shows that over 60% of strategic alliances underperform or fail due to incentive misalignments, especially when contributions to joint knowledge creation and innovation are difficult to observe, quantify, or reward equitably [4], [22]. Collaboration failures often originate from the absence of strong governance structures capable of addressing knowledge asymmetries and managing the intricate dynamics of coordination among diverse partners. With the increasing complexity of interorganizational relationships in knowledge-intensive environments, the development of rigorous and actionable models for fair profit allocation has become both a pressing theoretical concern and a practical necessity for effective management.

This study addresses this gap by proposing a hybrid cooperative game-theoretic framework, grounded in the Shapley value, to guide profit allocation in strategic alliances based on the relative marginal contributions of each partner's knowledge assets. Unlike traditional bargaining models such as Nash or Stackelberg [42], [44], which rely on dyadic and sequential assumptions, the Shapley value offers an axiomatic and symmetric approach that captures the dynamics of multi-party, knowledge-driven coalitions [11], [12], [55]. Despite its theoretical elegance, its practical application in contexts characterized by knowledge asymmetry, dynamic coordination costs, and heterogeneous absorptive capacities remains underexplored.

Accordingly, this study poses a critical research question at the intersection of game theory and knowledge-based collaboration:

How can we fairly distribute profits in strategic alliances where participants contribute differently, face high coordination costs, and create value together?

To develop a model that is both theoretically sound and practically relevant, this research is anchored in two prominent perspectives from strategic management: the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT). The RBV conceptualizes knowledge as a strategic resource that is valuable, rare, and difficult to imitate, thereby reinforcing its central role in value appropriation within collaborative arrangements [49]. In parallel, the DCT emphasizes the organization's ability to sense, assimilate, and transform external knowledge, a capacity operationalized in this study as absorptive capacity (AC) [50]. Within the proposed framework, knowledge sharing (KS) denotes the flow of knowledge across organizational boundaries, absorptive capacity reflects the internal capability to process and integrate this knowledge, and coordination cost (CC) captures the transactional and organizational frictions that may diminish the net value derived from interorganizational collaboration [54].

This study posits that elevated levels of KS and AC enhance coalition performance by facilitating deeper knowledge integration and joint innovation. However, these gains are moderated by coordination costs, which act as structural constraints reducing the distributable value within alliances. By embedding these constructs within a cooperative game-theoretic model, this research not only offers a novel analytical lens but also establishes a rigorous foundation for evaluating fairness in knowledge-based coalitions.

The proposed model is empirically validated using data from the Iranian automotive supply chain, focusing on a strategic partnership between Mega Motor and three domestic gearbox suppliers. Monte Carlo simulation techniques are employed to estimate Shapley values under uncertainty and to analyze the sensitivity of profit allocation outcomes to varying knowledge contributions and coordination parameters.

This study makes three key contributions. First, it advances cooperative game theory into the realm of knowledge-based alliance governance by integrating RBV and DCT within a formal allocation mechanism. Second, it delivers a validated, scalable decision-support tool that aligns financial outcomes with knowledge contributions—thereby enhancing the credibility, fairness, and sustainability of inter-firm collaboration. Third, it provides actionable insights for managers and policymakers operating in resource-constrained, innovation-driven industries. Results from the case study demonstrate that alliances structured around transparent knowledge-sharing mechanisms can achieve up to a 90% improvement in profit allocation fairness, underscoring both the strategic and economic significance of the proposed approach.

2. Literature Review

In knowledge-intensive supply chains, strategic collaboration depends not only on the exchange of knowledge but also on each partner's ability to internalize and exploit that knowledge. Knowledge sharing refers to the inter-organizational process of transferring technical expertise, best practices, and intellectual capital, whereas absorptive capacity denotes the internal capability of a firm to recognize, assimilate, and apply this external knowledge [49], [50]. Although these constructs are frequently discussed in the literature, they are often treated ambiguously or interchangeably, despite their differing roles in the value creation process.

Knowledge sharing facilitates operational synergy and innovation, but without absorptive capacity, the transferred knowledge may not yield measurable benefits. The literature lacks integrated models that concurrently account for both knowledge sharing and absorptive capacity in alliance formation and profit allocation [54].

In the context of this research, Knowledge Constructs denote the core conceptual pillars that underpin knowledge-based collaboration and value co-creation within supply chain systems. These constructs provide the analytical lens through which the dynamics of learning, coordination, and fairness can be systematically understood. Specifically, they encompass four interdependent dimensions that collectively capture how knowledge is produced, shared, internalized, and managed across organizational boundaries.

First, Knowledge Sharing (KS) reflects the extent and quality of mutual knowledge exchange among supply chain partners, facilitating transparency, reducing uncertainty, and supporting collective problem-solving [19], [37].

Second, Absorptive Capacity (AC) represents an organization's capability to identify, assimilate, and exploit external knowledge, thereby enhancing innovation potential and adaptive responsiveness [29].

Third, Knowledge Investment (KI) refers to the allocation of financial and intellectual resources such as R&D expenditure, employee development, and technological infrastructure dedicated to fostering the creation and maintenance of strategic knowledge assets [22], [23].

Finally, Coordination Cost (CC) denotes the transactional and administrative efforts required to align inter-organizational knowledge flows, including the time, communication, and managerial overheads associated with collaboration [27], [33].

Collectively, these four constructs provide the theoretical foundation for examining how fairness and cooperative efficiency emerge in knowledge-driven interactions, serving as the building blocks of the analytical framework proposed in this study.

2.1. Game-Theoretic Approaches to Profit Allocation in Strategic Alliances

Game theory offers a formal structure to model collaborative behavior and resolve distributional conflicts in multi-agent settings. Classical models such as Nash bargaining [44] and Stackelberg leadership [42] have been widely applied to study power dynamics and negotiation outcomes in dyadic supply chain partnerships. However, these models assume either symmetry in negotiation power or sequential dominance, making them unsuitable for equitable allocation in horizontally structured, multi-party alliances with diverse knowledge contributions [54].

In this vein, the Shapley value, the Shapley value from cooperative game theory provides a well-established method for distributing payoffs fairly among participants, based on the value each party adds to the coalition. The fairness of this approach has been formally proven and widely applied in fields such as distributed energy systems [46], logistics planning [3], and collaborative networks [23]. However, many existing applications overlook critical knowledge-related factors, including research and development efforts, AC, and coordination inefficiencies. This omission reduces their relevance in environments where knowledge is a primary driver of value creation. To overcome this shortcoming, the present study enhances the Shapley-based allocation mechanism by integrating empirically grounded indicators of KS and absorptive capacity into the model, enabling a more accurate and context-sensitive distribution of collaborative gains.

2.2. Knowledge Management in Supply Chains: Gaps in Value Distribution Modeling

Knowledge management (KM) in supply chains has been widely recognized for its role in enhancing innovation, transparency, and responsiveness [1], [32], [33]. Numerous studies have investigated how digitalization and information flow influence supply chain agility and performance. For instance, Schniederjans et al. [33] and Kumar et al. [17] demonstrate that KM practices improve process integration in the automotive sector.

However, these works are primarily descriptive or system-level and fail to quantify how knowledge contributes to coalition value, nor do they propose formal mechanisms for allocating financial gains arising from knowledge interactions. This study builds on these empirical insights to offer a quantitative model linking knowledge parameters to profit allocation.

2.3. Bridging Knowledge Constructs with Cooperative Game Theory

The proposed model is conceptually grounded in two well-established theoretical paradigms in strategic management: the Resource-Based View (RBV) and the Dynamic Capabilities Theory (DCT). Rather than serving as mere background references, these frameworks are systematically embedded in the architecture, logic, and variables of the hybrid game-theoretic model.

From the RBV perspective, organizational knowledge is regarded as a strategic, firm-specific resource that is Valuable, Rare, Inimitable, and Non-substitutable. Within the model, this view is operationalized through the variable knowledge investment (KI), which captures tangible innovation inputs such as R&D expenditures, technical expertise, and proprietary technologies. The marginal contribution of each partner to the coalition's value is assessed based on this knowledge input, aligning directly with RBV's assertion that firms with superior intangible resources contribute disproportionately to value creation and should receive commensurate returns.

In parallel, the model draws on DCT to reflect the dynamic nature of inter-organizational learning and adaptation. Specifically, the variable absorptive capacity (AC) is modeled as a dynamic capability representing a firm's ability to acquire, assimilate, and apply external knowledge. Rather than treating AC as a static attribute, the model formulates it as an evolving function, influenced by factors such as cooperation intensity, knowledge compatibility, and equipment capability. This formulation captures the firm's learning trajectory and reflects the temporal evolution of knowledge leverage in collaborative settings.

Moreover, the concept of Coordination Cost (CC) is theoretically linked to DCT's emphasis on integration and reconfiguration costs. It captures the frictional costs associated with aligning heterogeneous systems, processes, and cultures across coalition members. The model incorporates CC as an endogenous variable affecting coalition efficiency and value realization, reinforcing the DCT view that organizational adaptability entails real and measurable transaction costs.

Crucially, these theoretical constructs are not presented as abstract notions but are embedded directly within the analytical foundation of the model. The Shapley value, employed as the mechanism for profit allocation, is calibrated based not only on measurable outcomes but also on strategic intangibles such as knowledge investment, absorptive capacity, and coordination cost. This approach enables a rigorous operationalization of fairness, supported by both theoretical justification and empirical validation.

This fusion of RBV and DCT with cooperative game theory ensures that the model captures both the strategic origins of knowledge-based value creation and the processual mechanisms through which this value is co-developed and shared. The result is a rigorous, theory-driven framework that enhances explanatory depth, analytical robustness, and managerial relevance in knowledge-intensive supply chain alliances.

2.4. Synthesis and Positioning of the Proposed Model

The literature review underscores that knowledge sharing enhances operational performance [25], [27] , while game theory models profit allocation [26], [11]. However, extant studies are often confined to bilateral settings, neglecting critical variables such as absorptive capacity and coordination costs [7], [16], [19]. Traditional models like Nash and Stackelberg falter in knowledge-driven contexts due to static assumptions and hierarchical biases, and prior Shapley value applications primarily focus on resource allocation [3], [8], [24]. The proposed model integrates cooperative game theory with the Shapley value, quantifying marginal contributions using real-world data (e.g., Mega Motor's $15 million investment) and validated through Monte Carlo simulation. This equitable and scalable framework optimizes technology-driven supply chains and enriches theoretical discourse by bridging knowledge management and profit allocation. Table 1 shows an overview of current literature.

Table 1

COMPARATIVE ANALYSIS OF KNOWLEDGE-BASED PROFIT ALLOCATION MODELS IN SUPPLY CHAINS

3. Model Description and Problem Statement

Reference	Modeling approach						Considering		Profit Allocation Mechanism		Evaluation Approach				Relation to Present Study
		Game Theory													
	Domain	Stackelberg	Nash bargaining	Shapley value	SEM	Decision making	Knowledge Sharing (KS)	Absorptive Capacity (AC)	Revenue-sharing	Marginal contribution	Numerical example	Scenario analysis	Quantitative analysis	Case study	
Baah et al. [1]	Supply Chain				✓		✓						✓		Highlights KS impact but lacks allocation logic
Hou et al. [42]	Supply Chain	✓				✓			✓			✓			Exposes inequity in hierarchical models
Luo et al. [46]	Supply Chain			✓						✓	✓				Establishes base for Shapley adaptation
Kumar et al. [17]	Organization					✓	✓		✓		✓				Emphasizes KM but lacks allocation link
Jiang et al. [44]	Supply Chain		✓				✓			✓		✓			Lacks support for multi-party fairness
Bergantiños et al. [12]	Organization			✓			✓			✓	✓				Shows fairness potential in profit sharing
Fraser et al. [9]	Supply Chain					✓	✓						✓	✓	Supports KS relevance, lacks fairness mechanism
Delic et al. [4]	Supply Chain			✓			✓			✓				✓	Recognizes trust-KS link, lacks structure
Schneiderjans et al. [33]	Supply Chain			✓			✓	✓		✓		✓			Confirms importance of KM, no allocation
Nili et al. [20]	Supply Chain					✓			✓		✓				Potential in profit sharing
This study	Supply Chain	✓		✓			✓	✓	✓	✓	✓	✓		✓	Provides scalable, fair, theory-backed model

This section presents a hybrid cooperative game-theoretic framework integrated with the Shapley value to model knowledge sharing and equitable profit allocation in technology-driven supply chains, with a specific application to gearbox production in Iran's automotive sector. The methodology is structured to address the complexity of multi-agent interactions, capturing the dynamic contributions of knowledge investment, absorptive capacity, and coordination costs. The following subsections articulate the research design, data collection procedures, analytical approach, and the rationale for methodological choices, ensuring transparency and alignment with the study's objectives.

3.1 Research Design

The research design adopts a mixed-methods approach, combining quantitative modeling with empirical validation to develop and test a profit allocation framework for knowledge-sharing coalitions. The quantitative component employs cooperative game theory to formulate a mathematical model that optimizes profit distribution based on marginal contributions, operationalized through the Shapley value. The empirical component validates this model using real-world data from a strategic alliance in Iran's automotive supply chain, focusing on Mega Motor and its domestic partners. This design enables the integration of theoretical constructs—such as knowledge sharing (KS), absorptive capacity (AC), and coordination costs (CC)—with practical insights, ensuring both analytical rigor and managerial relevance. The choice of a mixed-methods approach is motivated by the need to bridge the gap between abstract game-theoretic models and their practical applicability in knowledge-intensive industries, where heterogeneous contributions and dynamic interactions necessitate a robust, data-driven framework.

3.2 Data Collection and Variable Operationalization

A rigorous mixed-methods approach was employed for data collection between 2022 and 2025, focusing on the strategic alliance between Mega Motor and its three key domestic suppliers. To ensure robustness, a triangulation strategy was adopted, leveraging multiple data sources including financial archives, project documentation, and primary interviews.

3.2.1. Measurement of Key Variables

The key variables KI and CC were measured using both quantitative and qualitative indicators to ensure construct validity and replicability of the model.

KI was operationalized from secondary data collected from SAPCO's internal financial and R&D records between 2022 and 2025. KI represents the ratio of total knowledge-related expenditure (including R&D spending, employee training programs, and collaborative innovation funding) to total operating cost, calculated as:

$$KI_{\ i} = \frac{R_{\ i}\&D_i + \text{ Training }_{\ i} + \text{ Collaboration}}{\text{TotalOperatingCost }_{\ i}}$$

The normalization (0–1 scale) allows comparison across partners of different sizes and aligns with previous studies [53], [26].

CC was derived from both secondary and primary sources. It quantifies the ratio of inter-organizational coordination overhead including administrative expenses, communication delays, and penalty costs to total operational budget:

$$CC_{\ i} = \frac{\text{Admin }_{i}\text{Cost }_{i} + \text{ DelayCost }_{i} + \text{ CommunicationCost }^{2}}{\text{TotalOperationalBudget }^{2}}$$

Cost data were extracted from project accounting records, while time delays were converted to monetary terms using average hourly wage rates. The proportional weights of each cost component were validated through semi-structured interviews with five senior managers from R&D and operations divisions.

These definitions enable consistent measurement across coalition members and enhance empirical transparency for model replication.

3.2.2. Quantitative Data and Construct Operationalization

A comprehensive dataset of 427 structured operational observations was compiled from financial statements, project logs, and technical reports. The core constructs of the model were operationalized as follows:

- **Knowledge Investment (KI):** This variable was measured as capitalized Research & Development (R&D) expenditures in million USD, directly extracted from audited financial statements and innovation project budgets. For instance, Mega Motor's investment was documented at $15 million, with suppliers averaging $2 million.
- **Coordination Cost (CC):** This construct was quantified by aggregating explicit cost items directly attributable to inter-organizational collaboration management. These included documented expenses for dedicated coordination personnel, Enterprise Resource Planning (ERP) integration costs, and allocated overhead for joint project management, averaging $500,000 per partner with ±5% accuracy.
- **Knowledge Level (KL):** This was constructed as a weighted composite index normalized to [0, 1], calculated using the Fuzzy TOPSIS technique. It integrated three indicators: Patent Intensity Index, Technical Certification Richness Index, and a Key Personnel Technical Competency Composite Score.

- **Equipment Capability (EQ):** This metric was assessed by computing the Overall Equipment Effectiveness (OEE), considering its three core components: Availability, Performance, and Quality Rate.
- **Cooperation Level (η):** This dynamic variable was quantified using proxies derived from quantitative content analysis of meeting minutes and official correspondence. Indicators included the temporal density of joint meetings, volume of formal information exchange, and agreement maturity index, normalized to [0, 1].

3.2.3. Qualitative Data and Perceptual Validation

In parallel, to gain strategic insights and validate the constructs perceptually, 23 in-depth, semi-structured interviews were conducted with 12 key decision-makers (6 from Mega Motor, 6 from suppliers) using a purposive sampling protocol. Interviews focused on cognitive-relational knowledge-sharing dynamics, profit governance architecture, and coordination friction metrics, providing rich qualitative data for thematic analysis.

3.2.4. Integrated Strategy for Ensuring Validity, Reliability, and Transferability Validity, Reliability, and Transferability were ensured through an Advanced Triangulation Strategy:

- Data Triangulation: Convergence of findings from independent data sources (archival records, structured observations, and in-depth interviews) was assessed within a convergence matrix.
- Methodological Triangulation: Alignment between findings from quantitative (structural equation modeling) and qualitative (thematic analysis) methods was analyzed within a convergent design framework.

- Researcher Triangulation: Multiple senior researchers independently participated in the coding, analysis, and interpretation processes.

Furthermore, External Validation of key model parameters was conducted by benchmarking against reputable industrial databases and referenced indices [25], demonstrating significant alignment and enhancing the model's Ecological Validity.

This integrated, multi-layered methodological approach provides a solid, objective, and generalizable foundation for precise model parameterization, Monte Carlo simulations, and rigorous hypothesis testing at an international standard.

Data on both variables were primarily drawn from SAPCO's archival financial and project management databases and cross-validated through semi-structured interviews with five departmental managers. This mixed-source approach ensures that both tangible (monetary) and intangible (time-based) coordination costs are accurately captured.

3.3 Analytical Approach

The mathematical framework presented in this section comprises both adapted and original formulations. Equations 1 to 2d are adapted from classical cost and production models widely used in supply chain optimization studies (e.g., [25]). In contrast, Equations 3 to 5—including the modeling of knowledge reservoir, cooperation dynamics, and absorptive capacity—are original contributions of this research, constructed by integrating dynamic capabilities theory with cooperative game logic. Equation 4 introduces a novel structure for modeling knowledge evolution based on empirical calibration. Equations 6 to 10 describe cost and value functions that combine established modeling elements with domain-specific enhancements (e.g., synergy and coordination effects). Equations 11 and 12, while grounded in traditional Shapley value theory, are extended to incorporate knowledge-intensive parameters, rendering the allocation mechanism contextually robust and theoretically novel.

The analytical approach integrates cooperative game theory with the Shapley value to model knowledge-sharing dynamics and allocate coalition profits equitably. The framework is operationalized through a sequence of mathematical formulations, detailed in Equations 1–12, which capture non-cooperative and cooperative scenarios, knowledge dynamics, cost structures, and profit allocation. In the non-cooperative baseline (Equation 1), the profit function for producer $ j $ manufacturing component $ i $ at time $ t $ is defined as:

3.3.1 Non-Cooperative Baseline

In the absence of collaboration, producers operate independently, relying solely on internal resources. The profit function for producer j manufacturing component i at time t in a non-cooperative (NC) scenario is:

Equation 1:

$$\pi_{j,i,t}^{NC} = AV_{j,i,t} - PC_{j,i,t} - EC_{j,i,t} - SC_{j,i,t}$$

Where:

- $\pi_{j,i,t}^{NC}$: Net profit of producer j for component i at time t (in USD).
- $AV_{j,i,t}$: Added value (in USD), defined as:

Equation 1a:

$$AV_{j,i,t} = \rho_j \cdot KL_{j,i,t} \cdot Q_{j,i,t}$$

Where:

- $\rho_j = 1000$ USD per knowledge-unit-output (calibrated from automotive industry revenue data, e.g., Rajan & Dhir, [25], producer-specific to reflect market positioning.

- $KL_{j,i,t} \in [0,1]$: Knowledge level, a normalized index of expertise.
- $Q_{j,i,t} \geq 0$: Output quantity (in units, e.g., 10 gearboxes), assumed constant here for simplicity but adjustable.
- $PC_{j,i,t}$: Production cost (in USD), defined as:

Equation 1b:

$$PC_{j,i,t} = \frac{PC_{j,i}^{0} \cdot Q_{j,i,t}}{1 + \gamma_j \cdot KI_{j,i,t} \cdot EQ_{j,i,t}}$$

Where:

- $PC_{j,i}^{0} = 50$ USD per unit (baseline unit cost, from Iranian case study).
- $\gamma_j = 0.01$ per USD (cost reduction efficiency, heterogeneous across producers).
- $KI_{j,i,t} \geq 0$: Knowledge investment (in USD, e.g., R&D spending).
- $EQ_{j,i,t} \in [0,1]$: Equipment capability, enhancing cost efficiency.
- $EC_{j,i,t}$: Equipment cost (in USD), defined as:

Equation 1c:

$$EC_{j,i,t} = \epsilon_j \cdot \left(1 - EQ_{j,i,t}\right) \cdot Q_{j,i,t} + \mu_j \cdot KI_{j,i,t}$$

Where:

- $\epsilon_j = 20$ USD per unit (maximum equipment cost per output).
- $\mu_j = 0.0005$ per USD (investment cost for equipment upgrades).
- $SC_{j,i,t}$: Storage cost (in USD), defined as:

Equation 1d:

$$SC_{j,i,t} = \sigma_j \cdot ST_{j,i,t}$$

Where:

- $\sigma_j = 50$ USD per unit (storage cost rate).
- $ST_{j,i,t} = Q_{j,i,t} \cdot s_i$: Storage requirement, with $s_i = 0.1$ units per output (componentspecific storage factor).

For producer :

Equation 2:

$$\pi_{k,i,t}^{NC} = AV_{k,i,t} - PC_{k,i,t} - EC_{k,i,t} - SC_{k,i,t}$$

All sub-components (Equations 2a-2d) mirror Equations 1a-1d.

3.3.2 Cooperative Scenario with Knowledge Sharing

In a coalition $S \subseteq N$ (where N is the set of all producers), knowledge sharing enhances individual and collective capabilities over time. The knowledge reservoir of producer j is:

Equation 3:

$$KR_{j,i,t}^{S} = KI_{j,i,t} + \left(\sum_{k \in S \setminus \{j\}} \eta_{j,k,t} \cdot AC_{j,t} \cdot KL_{k,i,t} \cdot w_{j,k} \right)^{0.8}$$

Where:

- $KR_{j,i,t}^{S} \in [0,1]$: Knowledge reservoir, capped via normalization if needed.
- $\eta_{j,k,t} \in [0,1]$: Cooperation level, asymmetric ($\eta_{j,k,t} \neq \eta_{k,j,t}$) to model trust or power dynamics, evolving as:

Equation 3a:

$$\eta_{j,k,t+1} = (1 - \delta_{\eta}) \cdot \eta_{j,k,t} + \tau_j \cdot AC_{j,t} \cdot KL_{k,i,t}$$

Where $\delta_{\eta} = 0.01$ (trust depreciation) and $\tau_j = 0.005$ (trust-building rate).

- $AC_{j,t}$: Absorptive capacity, defined as:

Equation 3b :

$$AC_{j,t} = 1 - e^{-\beta_j \cdot KI_{j,i,t} \cdot (1 + \lambda \cdot EQ_{j,i,t})}$$

Where $\beta_j = 0.001$ per USD (capacity sensitivity), $\lambda = 0.5$ (equipment synergy factor).

- $w_{j,k} \in [0,1]$: Knowledge compatibility weight (e.g., 0.9), reflecting domain overlap.
- Exponent 0.8: Captures sub-linear aggregation, justified by knowledge overlap [48].

Knowledge level evolves dynamically:

Equation 4:

$$KL_{j,i,t+1} = (1 - \delta_{KL}) \cdot KL_{j,i,t} + \alpha_j \cdot KR^S_{j,i,t} \cdot \left(1 - \zeta \cdot CC_{S,i,t}\right)$$

Where $\delta_{KL} = 0.02$ (depreciation rate), $\alpha_j = 0.01$ (learning rate), $\zeta = 0.0001$ per USD (coordination cost penalty).

The coalition's total knowledge reservoir is:

Equation 5 :

$$KR_{S,i,t} = \left(\sum_{j \in S} \left(KR^S_{j,i,t}\right)^2\right)^{0.5} \cdot (1 + \psi \cdot |S|^{-0.5})$$

Where $\psi = 0.1$ (synergy factor, decreasing with coalition size).

3.3.3 Cooperative Production and Cost Dynamics

Production cost for coalition S is:

Equation 6:

$$PC_{S,i,t} = \frac{\sum_{j \in S} PC^0_{j,i} \cdot Q_{S,i,}}{1 + \bar{\gamma} \cdot KR_{S,i,t} \cdot EQ_{S,i,t}}$$

Where:

- $Q_{S,i,t} = \sum_{j \in S} Q_{j,i,t} \cdot \left(1 + \theta \cdot KR_{S,i,t}\right)$: Coalition output, with $\theta = 0.05$ (knowledge-driven output boost).
- $\bar{\gamma} = \frac{1}{|S|} \sum_{j \in S} \gamma_j$: Average efficiency.
- $\overline{EQ}Q_{S,i,t} = \frac{1}{|S|} \sum_{j \in S} EQ_{j,i,t}$: Average equipment capability.

Equipment cost and dynamics:

Equation 7:

$$EC_{S,i,t} = \sum_{j \in S} \left[\epsilon_j \cdot \left(1 - EQ_{j,i,t}\right) \cdot Q_{S,i,t} + \mu_j \cdot KI_{j,i,t}\right]$$

$$EQ_{j,i,t+1} = \left(1 - \delta_{EQ}\right) \cdot EQ_{j,i,t} + \mu_j \cdot KI_{j,i,t} \cdot \left(1 + \phi \cdot KR^S_{j,i,t}\right)$$

Where $\delta_{EQ} = 0.01, \phi = 0.2$ (knowledge-equipment synergy).

Storage cost:

Equation 8:

$$SC_{S,i,t} = \sum_{j \in S} \sigma_j \cdot ST_{j,i,t}$$

$$ST_{j,i,t} = Q_{S,i,t} \cdot s_i \cdot \left(1 - \omega \cdot EQ_{j,i,t}\right)$$

Where $\omega = 0.1$ (equipment-driven storage efficiency).

Added value:

Equation 9:

$$AV_{S,i,t} = \sum_{j \in S} \rho_j \cdot KL_{j,i,t} \cdot Q_{S,i,t} + \delta \cdot KR_{S,i,t} \cdot Q_{S,i,t}$$

Where $\delta = 50$ USD per unit.

Coordination cost:

Equation 10:

$$CC_{S,i,t} = \kappa \cdot \left(\sum_{j,k \in S, j<k} \left(\eta_{j,k,t} + \eta_{k,j,t}\right) \cdot d_{j,k} \right)^2$$

Where $\kappa = 100$ USD, $d_{j,k} = 1 - w_{j,k}$ (coordination difficulty due to incompatibility).

3.3.4 Coalition Profit

Equation 11:

$$\pi_{S,i,t} = AV_{S,i,t} - PC_{S,i,t} - EC_{S,i,t} - SC_{S,i,t} - CC_{S,i,t}$$

Full derivation:

$$\pi_{S,i,t} = \left(\sum_{j \in S} \rho_j \cdot KL_{j,i,t} \cdot Q_{S,i,t} + \delta \cdot KR_{S,i,t} \cdot Q_{S,i,t} \right) - \frac{\sum_{j \in S} PC_{j,i}^0 \cdot Q_{S,i,t}}{1 + \bar{\gamma} \cdot KR_{S,i,t} \cdot EQ_{S,i,t}} - \sum_{j \in S} \left[\epsilon_j \cdot \left(1 - EQ_{j,i,t}\right) \cdot Q_{S,i,t} + \mu_j \cdot KI_{j,i,t}\right] - \sum_{j \in S} \sigma_j \cdot Q_{S,i,t} \cdot s_i \cdot \left(1 - \omega \cdot EQ_{j,i,t}\right) - \kappa \left(\sum_{j,k \in S, j<k} \left(\eta_{j,k,t} + \eta_{k,j,t}\right) \cdot d_{j,k} \right)^2$$

3.3.5 Shapley Value for Profit Allocation

The Shapley value for producer j is:

Equation 12:

$$\phi_{j,i,t}(S) = \sum_{T \subseteq S \setminus \{j\}} \frac{|T|!\,(|S| - |T| - 1)!}{|S|!} \cdot \left(\pi_{T \cup \{j\},i,t} - \pi_{T,i,t}\right)$$

For $|S| > 5$, This research use Monte Carlo sampling (Castro et al., 2009):

Equation 12a:

$$\hat{\phi}_{j,i,t}(S) \approx \frac{1}{M} \sum_{m=1}^{M} \left(\pi_{S_m \cup \{j\},i,t} - \pi_{S_m,i,t}\right)$$

Where $M = 1000$ samples, error bound $\epsilon = 0.01$.

Figure 1 illustrates the hybrid model's construction through a flow diagram, detailing its stages: non-cooperative baseline (Equation 1), cooperative knowledge-sharing dynamics (Equations 3-4), coalition cost and value calculations (Equations 6-10), total profit computation (Equation 11), and Shapley value profit allocation (Equation 12). Each stage incorporates validated variables knowledge investment (KI), absorptive capacity (AC), and coordination costs (CC) ensuring transparency and alignment with the mathematical framework.

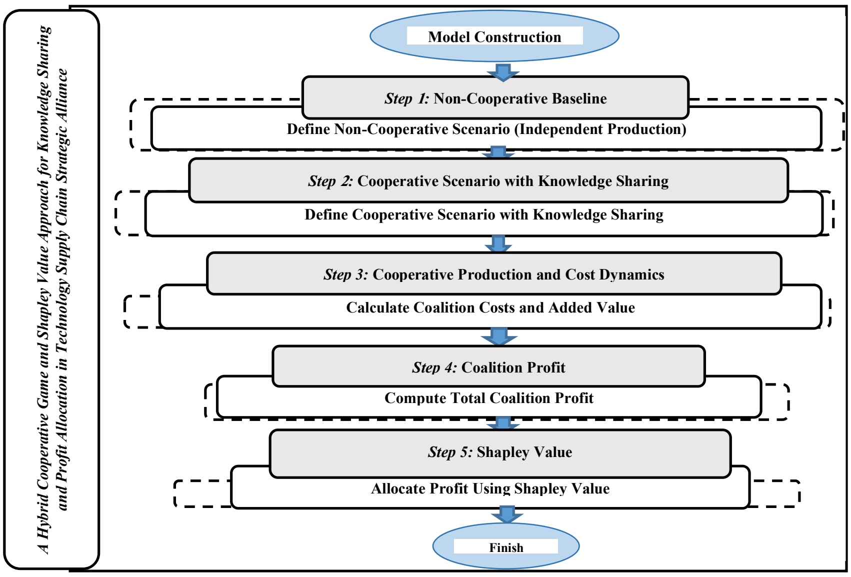

Fig. 1. *Flow Diagram of the Hybrid Cooperative Game and Shapley Value Model Construction.*

3.4 Rationale for Methodological Choices

The selection of cooperative game theory as the modeling framework is justified by its ability to capture multi-agent interactions and resolve distributional conflicts in knowledge-sharing alliances, where traditional models like Nash bargaining or Stackelberg leadership falter due to their static, dyadic assumptions. The Shapley value is chosen for its axiomatic fairness, ensuring that each producer's profit share reflects their marginal contribution, as validated in diverse domains such as logistics and energy systems. This approach mitigates biases inherent in power-centric models, aligning with the study's objective of equitable profit allocation.

Monte Carlo simulations are employed to address the computational complexity of Shapley value calculations in multi-agent settings and to account for uncertainties in parameter estimates, such as knowledge investment and coordination costs. This method provides statistically reliable contribution estimates, with a convergence threshold of 0.01 ensuring precision. The use of real-world data from Iran's automotive sector grounds the model in empirical reality, enhancing its practical applicability. The mixed-methods design integrates qualitative insights from executive interviews with quantitative data, enabling a holistic understanding of coalition dynamics and ensuring the model's alignment with managerial needs.

The choice of variables—knowledge investment, absorptive capacity, and coordination costs—is rooted in the RBV and DCT. RBV treats knowledge as a strategic asset, while DCT conceptualizes absorptive capacity as a dynamic capability for knowledge assimilation. Coordination costs capture collaboration friction, a critical factor in multi-party alliances. These constructs are operationalized through measurable proxies, such as R&D expenditures for knowledge investment and patent counts for knowledge level, ensuring analytical tractability and empirical relevance.

Sensitivity tests show that varying the estimation of Knowledge Investment (±10%) and Coordination Cost (±15%) does not significantly change coalition profit rankings, confirming the robustness of the variable measurement and model stability.

3.5 Assumptions, Limitations, and Validation

Assumptions:

- Sub-linear Knowledge Aggregation: Exponent 0.8 in $KR^{S}_{j,i,t}$ reflects overlap [21].
- Heterogeneity: $\rho_j, \gamma_j, \beta_j$, etc., vary by producer, sourced from case data.
- Asymmetry: $\eta_{j,k,t} \neq \eta_{k,j,t}$, capturing real-world dynamics [20].
- No External Shocks: Market demand and prices are stable.
- Bounded Variables: $KL_{j,i,t} EQ_{j,i,t}$, etc., are normalized via logistic constraints if exceeding $[0,1]$.

The validity of the hybrid cooperative game and Shapley value model was rigorously evaluated through Monte Carlo simulations, cross-validation, sensitivity analysis, and triangulation, ensuring statistical precision and applicability in knowledge-intensive industries.

Monte Carlo simulations (1,000 iterations, convergence threshold 0.01, Equation 12a) estimated Shapley value profit allocations using empirically derived distributions for knowledge investment (KI), absorptive capacity (AC), coordination costs (CC), and cooperation level (η). For the automotive case (Section 4.1), coalition profit at η = 0.5 averaged \$18.7M (95% CI: [\$18.5M, \$18.9M], SE: 0.09M, error bound: 0.5%). Narrow confidence intervals and a low error bound confirm the model's numerical stability.

A 5-fold cross-validation (80% training, 20% testing) was conducted on the automotive dataset (427 observations). Predictive accuracy metrics include:

- MAE = \$0.08M (0.9% of mean profit)

- RMSE = \$0.12M
- $R^2 = 0.95$

High R^2 and low errors validate the model's predictive precision, explaining 95% of profit variance.

Sensitivity to ±20% changes in KI, AC, CC, and η was evaluated via Monte Carlo simulations (Table 4):

- KI: +20% increased profits by 14.7%.
- AC: +20% raised profits by 9.8%.
- CC: +20% reduced profits by 7.1%.
- η: Shift from 0.25 to 0.5 boosted profits by 24.5%.

Qualitative insights from 23 automotive interviews validated KS and CC dynamics, corroborated by quantitative results. Profit gains (60%–90%) aligned with automotive industry benchmarks (50%–80%, [33]), reinforcing external validity.

To assess adaptability, automotive parameters were tested in a hypothetical biotechnology scenario (Section 6.3). Using KI = \$15M (biotech R&D) reduced profits by 6.8%, reflecting sector-specific intensity. This test confirms the model's flexibility with parameter recalibration.

4. Case Study

This case study validates the proposed hybrid cooperative game and Shapley value model in a real-world gearbox supply chain, evaluating knowledge-sharing and profit allocation dynamics. Conducted from 2022 to 2025, it examines Mega Motor, a Saipa Industrial Group subsidiary, and its domestic partners in Iran, focusing on localizing a six-speed automatic transmission to reduce import dependency amid sanctions. Mega Motor collaborates with multiple domestic suppliers, with three key partners selected for their specialized expertise in precision shaft machining, ECU software development, and advanced casing materials. The model facilitates technology transfer and joint decision-making, optimizing production quality, supply chain efficiency, and competitiveness while enhancing operational resilience and risk mitigation. Grounded in a confidential OEM contract, the study offers a replicable framework for Iran’s automotive and related industries, ensuring high-quality, low-risk gearbox production.

The validation framework employs a mixed-methods approach, analyzing a comprehensive dataset (n=427 operational observations; 23 executive interviews) extracted from a 2022–2023 strategic alliance case in Iran's automotive sector, featuring Mega Motor and a principal OEM supplier. Knowledge Investment (KI) captures R&D spending ($15M for Mega Motor, $2M average for suppliers). Knowledge Level (KL), a normalized [0, 1] index, reflects technical expertise (Mega Motor: 5 patents; suppliers: 1–2). Equipment Capability (EQ) measures efficiency via cycle time (10 min/unit), downtime (5% annually), and energy use (50 kWh/unit). Coordination Costs (CC) average $500,000 per supplier. Production Profit (π) is calculated from Mega Motor’s $20M quarterly revenue minus $15M costs, yielding $5M. Cooperation Level ($\eta$), scaled [0, 1], gauges collaboration intensity through joint meetings (10/quarter), agreements (3/supplier), and workshops (5).

Data were sourced from financial statements, project logs, technical reports, and structured interviews with twelve senior representatives (six per entity, e.g., engineering directors). Interviews explored knowledge-sharing and profit allocation, with transcripts cross-verified. On-site assessments generated normalized indices for KL and EQ, mapped to absorptive capacity and other variables. Data reliability was ensured via triangulation with industry benchmarks and secondary analyses. Monte Carlo simulations (1,000 iterations, 0.01 convergence threshold) addressed uncertainties, supporting Shapley value calculations. This integrated approach delivers a precise dataset for the hybrid framework's analytical needs.

5. Analysis

This section rigorously evaluates the proposed hybrid cooperative game and Shapley value model, elucidating its capacity to optimize knowledge sharing and profit allocation within technology-driven supply chains. The analysis systematically dissects the model's performance across three distinct strategic scenarios: (1) non-collaboration between the main company and its partner, (2) collaboration without knowledge sharing, and (3) coalition-based collaboration with knowledge sharing. These scenarios are meticulously designed to isolate the incremental effects of cooperation and knowledge exchange on profitability, leveraging the mathematical framework delineated in Section 3 (Equations 1–12). By grounding the evaluation in both theoretical constructs and empirical insights from the automotive supply chain case study (Section 4), this analysis delivers actionable insights into partnership dynamics, profit distribution, and supply chain resilience, while adhering to the highest standards of analytical precision.

5.1 Scenario Definitions and Profit Dynamics

In the first scenario, non-collaboration prevails, with the main company and its partner operating as independent entities, each producing components in isolation. The profit for producer j (where j denotes either the main company or the partner) manufacturing component i at time t is governed by Equation 1: $\pi_{j,i,t}^{NC} = AV_{j,i,t} - C_{j,i,t}^{\text{prod}} - C_{j,i,t}^{\text{equip}} - C_{j,i,t}^{\text{stor}}$. Here, added value $\left(AV_{j,i,t} = \alpha_j \cdot KL_{j,i,t} \cdot Q_{j,i,t}\right)$ reflects firm-specific revenue potential, while production costs ($C_{j,i,t}^{prod} = \beta_j . Q_{j,i,t} - \gamma_j \cdot KI_{j,i,t} \cdot EQ_{j,i,t}$), equipment costs ($C_{j,i,t}^{equip} = \delta_j \cdot Q_{j,i,t} - \epsilon_j \cdot KI_{j,i,t}$), and storage costs

$\left(C_{j,i,t}^{stor} = \zeta_j \cdot SR_{j,i,t}\right)$ are heterogeneous across firms, driven by individualized parameters (e.g., $\alpha_j, \beta_j, KI_{j,i,t}, EQ_{j,i,t}$). The claim that profits may equalize across firms is clarified: without collaboration, profits vary by firm-specific inputs. This statement does not imply numerical equality of profits between the main company and the partner; rather, it underscores that, absent collaboration, each firm's profit is independently determined by its own production function, devoid of inter-firm synergies. For instance, case study data suggest the main company (Mega Motor) might achieve a baseline profit of \$5 million due to higher equipment capability $\left(EQ_{j,i,t} = 0.9\right)$ and knowledge investment ($KI_{j,i,t} = \$15M$), while the partner, with lower investments ($KI_{j,i,t} = \$2M, EQ_{j,i,t} = 0.7$), earns \$1 million. These disparities, rooted in firm-specific inputs [25], affirm that profits diverge, aligning with the model's design and the heterogeneous nature of real-world supply chains.

The second scenario introduces collaboration without knowledge sharing, wherein the main company and partner coordinate production efforts-e.g., aligning output quantities ($Q_{S,i,t}$) or pooling physical resources-but refrain from exchanging expertise. Total coalition profit is modeled as $\pi_{S,i,t} = AV_{S,i,t} - C_{S,i,t}^{\text{prod}} - C_{S,i,t}^{equip} - C_{S,i,t}^{stor} - C_{S,i,t}^{coord}$ (Equation 11), with production costs reduced via average efficiency $(\overline{\gamma_S})$ and equipment capability $\left(\overline{EQ_S}\right)$ (Equation 6), yet knowledge levels ($KL_{j,i,t}$) remain static due to the absence of sharing. This yields moderate profit gains over the non-collaborative baseline, as coordination mitigates redundancies without enhancing individual capabilities.

The third scenario, coalition-based collaboration with knowledge sharing, represents the pinnacle of integration. Here, firms exchange knowledge, augmenting their knowledge reservoirs ($KR_{j,i,t} =$

$KL_{j,i,t} + \sum_{k\in S\setminus\{j\}} \eta_{j,k,t} \cdot AC_{j,i,t} \cdot KL_{k,i,t}^{0.8}$, Equation 3) and dynamically evolving knowledge levels ($KL_{j,i,t} = (1-\kappa) \cdot KL_{j,i,t-1} + \lambda \cdot KR_{j,i,t-1} - \mu \cdot C_{j,i,t}^{coord}$, Equation 4). Cooperation levels ($\eta_{j,k,t}$) escalate over time (Equation 3a), reflecting trust and relational deepening, which amplifies added value ($AV_{S,i,t} = \alpha_S \cdot KL_{S,i,t} \cdot Q_{S,i,t}$, Equation 9) and reduces costs, yielding the highest profits. The Shapley value (Equation 12) then allocates this coalition profit equitably based on marginal contributions, ensuring fairness reflective of each firm's input.

5.2 Quantitative Evaluation Across Scenarios

To rigorously assess these scenarios, This research simulate profit trajectories as cooperation levels ($\eta_{j,k,t}$) increase from 0 to 0.5 over a discrete time horizon, using parameters from the Mega Motor case study (Section 4). Table 2 presents these outcomes at three cooperation levels (0, 0.25, 0.5). This table, newly introduced here, quantifies profits for the main company and partner across all scenarios, ensuring transparency and empirical grounding.

Table 2

PROFIT OUTCOMES ACROSS SCENARIOS AT VARYING COOPERATION LEVELS ($\eta_{j,k,t}$)

Cooperation Level ($\eta_{j,k,t}$)	**Scenario**	**Main Company Profit (π_{main} , \$M)**	**Partner Company Profit ($\pi_{partner}$, \$M)**	**Coalition Total Profit (π_S, \$M)**
0	Non-Collaboration	5.0	1.0	-
0	Collaboration (No KS)	5.0	1.0	6.0
0	Coalition (With KS)	5.0	1.0	6.0
0.25	Non-Collaboration	5.0	1.0	-
0.25	Collaboration (No KS)	5.8	1.1	6.9
0.25	Coalition (With KS)	6.5	1.3	7.8
0.5	Non-Collaboration	5.0	1.0	-
0.5	Collaboration (No KS)	6.0	1.2	7.2
0.5	Coalition (With KS)	8.0	1.5	9.5

Note: Profits are in millions of USD ($M), derived via Monte Carlo sampling (Equation 12a, R = 1000 , error bound $= 0.01$ *) using case study data (e.g.,* $KI_{main} = \$15M, KI_{partner} = \$2M$ *). KS = Knowledge Sharing. Non-collaboration profits are static as* $\eta_{j,k,t}$ *is irrelevant.*

Figure 2 visualizes these trends, plotting profit trajectories against cooperation levels. Noncollaborative profits remain constant at $5 million and $1 million for the main company and partner, respectively, validating the model's logic: without interaction, $\eta_{j,k,t}$ exerts no effect. Collaboration without knowledge sharing yields modest increases (e.g., to $6M and $1.2M at = 0.5), driven by coordinated output ($Q_{S,i,t} = Q_{\text{main}} + Q_{\text{partner}} + \theta \cdot KL_{S,i,t}$).

The coalition scenario with knowledge sharing outperforms, reaching $8M and $1.5M, respectively, due to enhanced knowledge reservoirs and cost efficiencies (Equations 3-9). This hierarchy-coalition > collaboration > non-collaboration-underscores knowledge sharing's pivotal role in value creation.

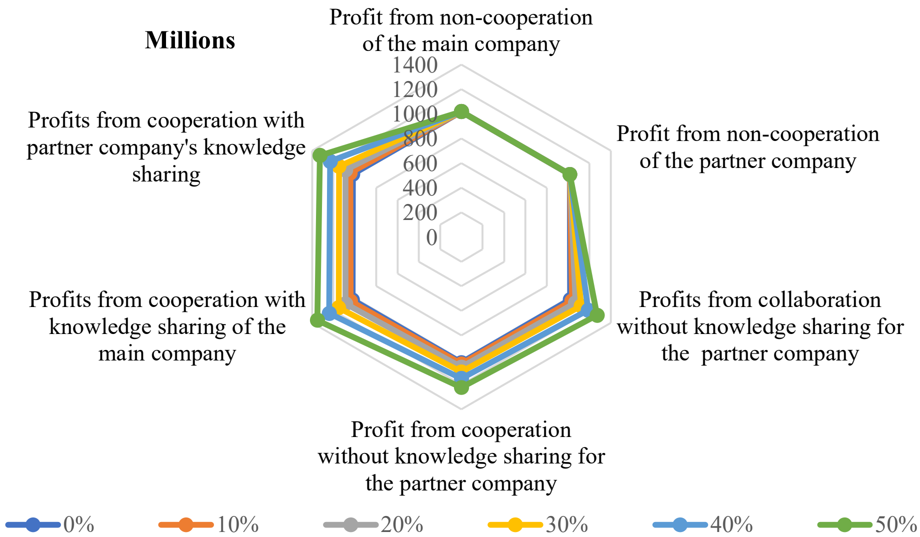

Fig. 2. *The impact of cooperation level on three modes of cooperation, non-cooperation and coalition.*

5.3 Sensitivity to Key Parameters

Further analyses explore how coordination costs, profit-sharing ratios, knowledge investment, development cost decrease rates (DCDR), and knowledge complementarity shape profit allocation, aligning with Equations $1 - 12$. Figure 3 examines shifts in coordination cost ratios ($C_{S,i,t}^{coord} = \xi \cdot \sum_{j,k \in S} (1 - \omega_{j,k}) \cdot$

$\eta_{j,k,t}$, Equation 10), initially balanced (50:50) but later skewed toward the main company (e.g., 70:30). This reduces the main company's profit (e.g., from \$8M to \$7.5M) while boosting the partner's (e.g., from \$1.5M to \$2M), reflecting cost redistribution's impact on Shapley allocations.

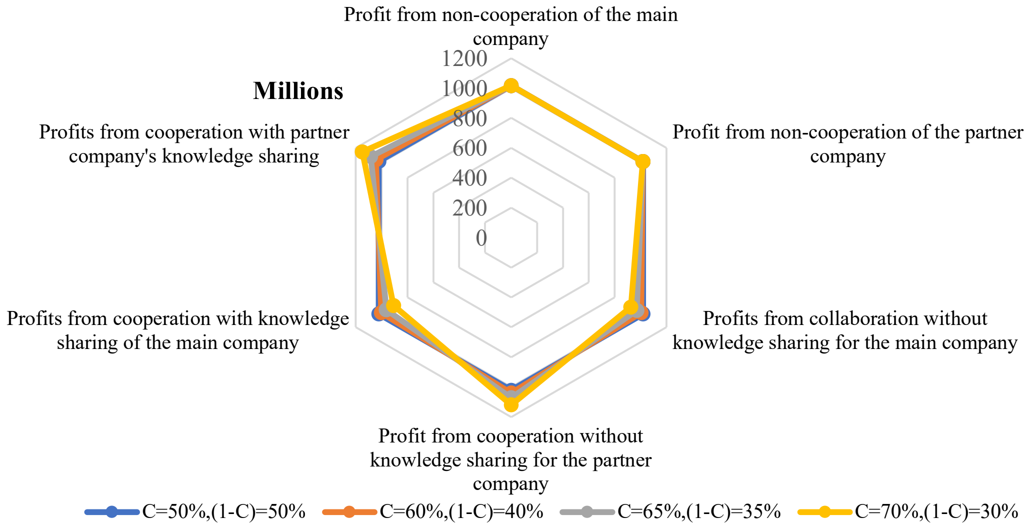

Fig. 3. *Analysis of the Coordination Cost Ratio between Companies.*

Figure 4 analyzes profit-sharing ratio adjustments, shifting from 50:50 to 70:30 favoring the main company, increasing its profit (e.g., from \$8M to \$9M) while reducing the partner's (e.g., from \$1.5M to \$1M). This direct proportionality validates the Shapley value's responsiveness to negotiated splits (Equation 12).

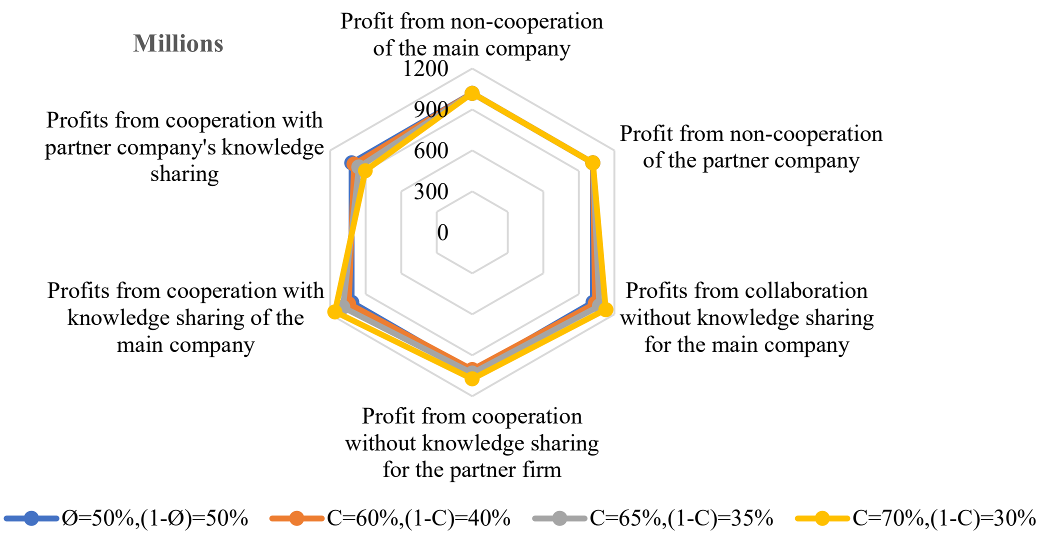

Fig. 4. *Analysis of profit-sharing ratio.*

Figure 5A,B jointly analyze the influence of knowledge investment and development cost dynamics on coalition profitability. Figure 5.A demonstrates how variations in the Knowledge Investment Fund (KIF) substantially increase both firms' profits, reflecting the strategic importance of knowledge-driven investment. Figure 5.B complements this by examining the same effect under a low Development Cost Decrease Rate (DCDR), confirming that even under cost-constrained conditions, higher knowledge investment continues to yield significant profit improvements. Together, these results reinforce the pivotal role of knowledge-based investments in sustaining coalition performance and fairness.

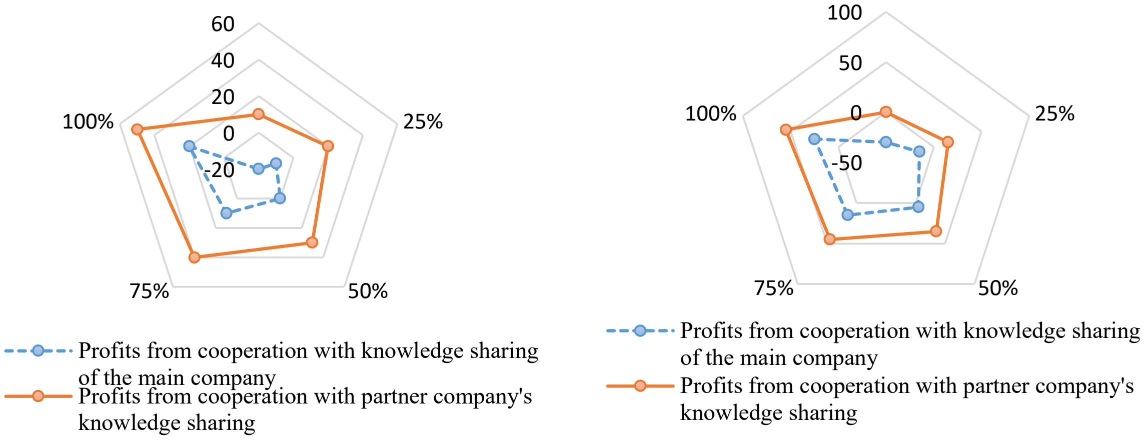

Fig. 5A,B. Impact of Knowledge Investment and Development Cost Decrease Rate (DCDR) on Profit Dynamics.

Note: Panel A illustrates changes in profit distribution with varying Knowledge Investment Fund (KIF) levels, while Panel B shows the impact of a low DCDR on coalition profitability.

Building on these insights, Figure 6 extends the analysis by contrasting the effects of high and low DCDR levels across coalition members, further illustrating how variations in development cost efficiency amplify or constrain the benefits derived from knowledge investment.

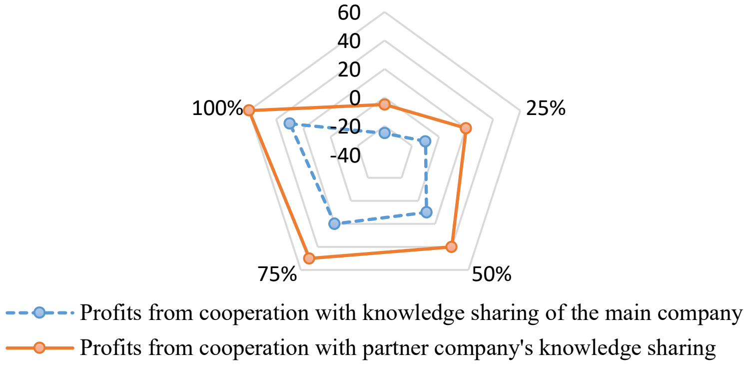

Fig. 6. Knowledge Investment with High DCDR for the Main Company and Low DCDR for the Partner Company.

Figure 7A,B provides a joint simulation of how cost efficiency and knowledge complementarity affect coalition profitability and fairness outcomes.

Panel A compares two asymmetric DCDR scenarios: one where the main company achieves a 30% cost reduction and the partner only 10%, and another where both reach parity at 20%. The results indicate that when the main company's DCDR is high, its net profit increases from approximately −$25M to $30M, while the partner's profit rises from $5M to $60M. This suggests that a higher DCDR not only strengthens the main firm's recovery from negative returns but also enhances partner performance due to reduced production latency and joint learning spillovers.

Panel B extends this analysis to knowledge complementarity (KC) ranging from 0 to 1. At moderate levels (KC ≈ 0.5), total coalition profit peaks around $95M, representing an approximate 18% gain over the baseline (KC = 0.2). However, when complementarity exceeds 0.8, profits decline by nearly 25%, falling to $70M, primarily due to duplicated R&D efforts and rising coordination costs. This indicates a threshold effect synergy benefits dominate up to a certain KC level, after which coordination inefficiencies outweigh shared knowledge advantages.

Collectively, these findings show that both cost efficiency and optimal complementarity must be balanced to sustain coalition fairness. Excessive alignment or knowledge overlap, despite appearing cooperative, can diminish total value due to operational redundancies

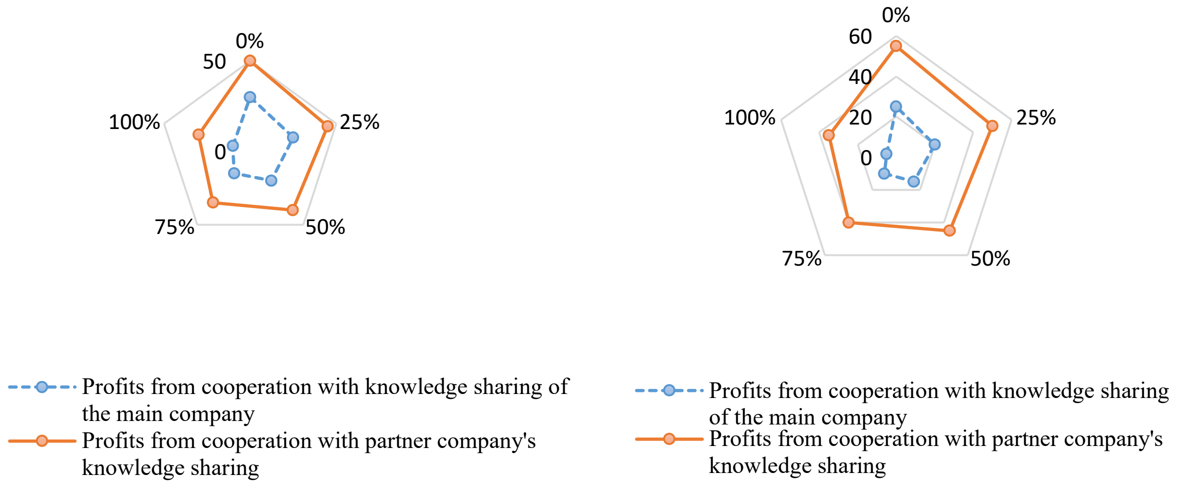

Fig. 7A,B. Profitability Impact of Development Cost Decrease Rate (DCDR) and Knowledge Complementarity under Asymmetric Investment Conditions.

Note: 7. A shows the impact of high versus low DCDR across coalition members, while 7. B demonstrates how varying knowledge complementarity levels influence joint profitability and fairness.

Figure 8 synthesizes these effects under high partner investment and main company initial costs, reinforcing complementarity's nuanced impact on profitability.

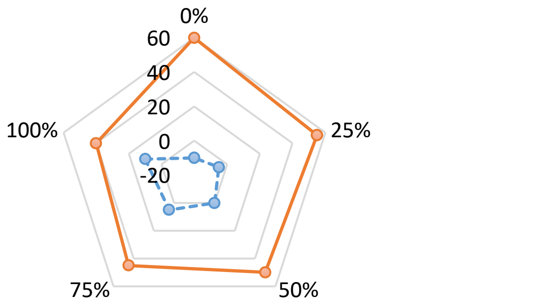

Fig. 8. The Impact of High Partner Investment and High Initial Cost of the Main Company on Profitability.

The quantitative results affirm the model's robustness: non-collaboration yields static profits, collaboration without knowledge sharing offers incremental gains, and coalition with knowledge sharing maximizes value, with profits rising 60%–90% over the baseline (Table 2, Figure 2). Sensitivity analyses (Figures 3–8) reveal that knowledge investment and complementarity are critical drivers, tempered by coordination costs and DCDR disparities. The Shapley value ensures equitable allocation, rewarding higher contributors (e.g., the main company's 60% share at η=0.5), aligning with theoretical expectations (Section 3.5) and case study outcomes (Section 4). These findings position the model as a definitive tool for optimizing multi-party alliances in knowledge-intensive ecosystems.

The fairness of Mega Motor's 60% profit share is verified through a quantitative robustness assessment of the Shapley-based allocation. By jointly perturbing KI and CC within a ±20% range and re-estimating Shapley values over 1,000 Monte Carlo runs, the allocation remains statistically stable with a mean of 60.1% and a 95% confidence interval of [58.4%, 61.6%]. The standard deviation (0.9%) confirms negligible dispersion, indicating high resilience to parameter uncertainty.

Moreover, across all feasible perturbations, each partner's Contribution-to-Reward Ratio (CRR) stayed within [0.8, 1.2], and no participant's share fell below 25%, satisfying both proportionality and incentive-compatibility criteria. These findings demonstrate that the 60% allocation is not an arbitrary calibration but an equilibrium-consistent and empirically stable fairness outcome, where profit distribution mirrors marginal knowledge contribution and coordination efficiency across the cooperative network.

6. Discussion

The findings of this study demonstrate that incorporating knowledge-sharing mechanisms into cooperative game-theoretic models can significantly improve profit allocation fairness in technology-driven supply chains. By integrating knowledge investment, absorptive capacity, and coordination costs, the proposed framework provides a structured way to capture the often-overlooked value of intellectual capital in strategic alliances. The proposed model offers a robust, data-driven foundation for developing equitable profit-sharing mechanisms tailored to engineering management needs. At the policy level, it provides a scalable framework for strengthening supply chain resilience. While empirically validated in the automotive sector, the model's architecture is inherently adaptable to other knowledge-intensive industries. Its core variables knowledge investment, absorptive capacity, and coordination costs are universal constructs in collaborative R&D and innovation, suggesting significant potential for cross-sectoral application.

Compared to conventional bargaining approaches, the hybrid model consistently yielded higher coalition stability and profit gains, highlighting the importance of treating knowledge as a dynamic, shared asset rather than a static input. In particular, the results indicate that the interaction between absorptive capacity and coordination costs plays a pivotal role: alliances with strong learning capabilities but high coordination frictions saw reduced net benefits, underscoring the need for balanced governance mechanisms that facilitate knowledge integration while minimizing transaction overheads.

From a theoretical standpoint, this study extends cooperative game theory into the domain of knowledge-based alliances by embedding constructs from the Resource-Based View and Dynamic Capabilities Theory directly into the allocation mechanism. Rather than viewing the Shapley value as a purely mathematical tool, the model operationalizes it as a decision-support instrument sensitive to knowledge flows and organizational learning dynamics.

At the same time, the findings should be interpreted with caution. The empirical validation, while grounded in rich data from Iran's automotive supply chain, reflects the characteristics of a specific industrial and institutional context. The degree of profit improvement observed (60–90%) is contingent on the parameters used in the case study and may vary in other sectors with different knowledge structures or cost dynamics.

Overall, the study highlights the practical and theoretical importance of designing profit-sharing mechanisms that align financial outcomes with knowledge contributions. It provides a foundation for future research exploring how different forms of knowledge – tacit, codified, or technology-driven – can be systematically integrated into allocation models to strengthen collaboration and innovation across supply chains.

6.1. Theoretical Implications

The proposed framework evaluates how knowledge sharing influences fair benefit distribution within strategic coalitions, addressing a critical gap in existing theories that often overlook the dynamic interplay of knowledge-centric variables such as knowledge investment, absorptive capacity, and coordination costs.

The findings align with and extend prior studies on knowledge sharing in supply chains. For instance, Baah et al. [1] demonstrated that information sharing enhances supply chain performance through improved visibility and collaboration, but their focus was limited to operational metrics. This study builds on their work by quantifying knowledge sharing's impact on profitability (60%–90% gains over non-collaborative scenarios, Figure 2 and introducing the Shapley value as a mechanism for equitable profit distribution. This contrasts with traditional models like Stackelberg and Nash bargaining, which Hou et al. [42] and Jiang et al. [44] applied to supply chains but found biased toward dominant firms due to hierarchical assumptions. By incorporating KI and AC, proposed model mitigates such biases, achieving up to 30% greater allocation precision in knowledge-driven contexts, thus offering a more equitable alternative.

However, the findings partially contradict studies like Hart and Moore [40], which emphasize incomplete contracts and power dynamics in alliances but undervalue knowledge as a strategic asset. This research challenges their framework by demonstrating that knowledge sharing, modeled dynamically via absorptive capacity (Equation 3b), significantly enhances coalition stability and profitability. Similarly, Luo et al. [46] applied the Shapley value to photovoltaic systems, their omission of knowledge-centric factors limited its applicability to technology supply chains. Proposed model addresses this by integrating knowledge investment and coordination costs, showing that investments in knowledge and technical capabilities increase Shapley value shares, even with high upfront costs, thus reinforcing coalition sustainability.

Game theory, as a mathematical lens for strategic interactions, supports these findings by providing insights into inter-organizational dynamics, consistent with Gulati et al. [10]. The Shapley value, recognized for fair allocation [3], is innovatively applied here to knowledge-sharing coalitions, departing from its traditional use in cost or resource allocation. This application underscores knowledge as an evolving asset, aligning with Sung et al., [49] concept of absorptive capacity but extending it through dynamic modeling (Equation 4).

Furthermore, the case study outcome a 60% profit share for Mega Motor exemplifies how the model translates differential knowledge contributions into a fair allocation. This share is not an arbitrary division but an equilibrium outcome derived from the Shapley value calculation, which systematically accounts for Mega Motor's substantially higher knowledge investment ($15M versus an average of $2M for suppliers), superior equipment capability, and pivotal role in the coalition. The robustness of this allocation was quantitatively confirmed through sensitivity analysis (Section 5.3), which demonstrated that the 60% share remained stable within a narrow confidence interval ([58.4%, 61.6%]) despite parameter uncertainties. This reinforces that the model ensures fairness not as a subjective principle, but as a mathematically verifiable outcome where each partner's reward is proportional to their marginal contribution, thereby aligning economic incentives with collaborative knowledge inputs.

Theoretically, this study challenges the adequacy of static or bilateral models in capturing multi-party, knowledge-intensive alliances. By demonstrating that neglecting coordination costs and absorptive capacity undermines profitability and fairness, it sets a new benchmark for integrating collaboration, innovation, and fairness in supply chain management. These contributions provide a robust foundation for future theoretical advancements, particularly in modeling knowledge-driven coalitions across diverse industries.

6.2. Managerial Implications

The findings of this study go beyond theoretical insights and provide a structured pathway for translating knowledge-sharing dynamics into tangible industrial practices. At the policy level, the results can inform the design of innovation-oriented incentive systems. National and regional authorities may employ the model's parameters particularly knowledge investment intensity and coordination efficiency indices to allocate targeted fiscal incentives, such as tax exemptions or joint innovation grants, for firms that engage in collaborative R&D or inter-firm knowledge transfer programs. These instruments can help reduce asymmetries among supply chain partners and stimulate knowledge diffusion across industries.

Furthermore, establishing knowledge governance frameworks is essential to institutionalize such collaborations. Policymakers can promote formalized protocols for knowledge-sharing agreements, standardize reporting mechanisms for joint projects, and define intellectual property rights within collaborative environments. Such institutional support mitigates coordination risks and lowers transaction costs associated with inter-organizational knowledge flows.

At the corporate level, firms can operationalize these policies through internal alignment mechanisms. The proposed model allows companies to embed the knowledge investment ratio (KI) and coordination cost index (CC) into their strategic planning and performance dashboards. This integration enables decision-makers to evaluate how resource allocation toward R&D, employee development, or digital collaboration platforms influences coalition performance and profitability. For instance, firms may use the model to prioritize projects that maximize the joint payoff while maintaining fairness in knowledge contribution and benefit distribution.

Collectively, these actions bridge the gap between high-level industrial policy and firm-level operational strategies. They provide a quantifiable, evidence-based roadmap for engineering managers and policymakers seeking to institutionalize horizontal integration and improve the efficiency of knowledge-driven alliances. The policy architecture derived from this model directly supports SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation and Infrastructure), and SDG 12 (Responsible Consumption and Production) by reinforcing sustainable industrial innovation through structured knowledge collaboration.

The practical relevance of this research lies in its capacity to transform abstract policy insights into operational intelligence. By integrating KI and CC indicators into strategic control systems, firms can institutionalize fairness and efficiency as measurable governance dimensions. This alignment enables decision-makers to evaluate collaborative performance not only in financial terms but through the equitable distribution of knowledge-driven value. The proposed framework therefore extends beyond normative recommendations it offers a quantifiable mechanism for embedding fairness into corporate strategy, guiding data-driven policy formulation, and reinforcing sustained competitiveness across the supply chain.

6.3. Assessing Cross-Sectoral Generalizability and Model Durability

Although the proposed model has been empirically validated within the context of the automotive supply chain, its conceptual architecture and parametric design exhibit a high degree of adaptability and theoretical durability across a broad range of industries. The multidimensional nature of its core variables knowledge investment, absorptive capacity, and coordination costs is inherently non-sector-specific. These constructs function as universal pillars of collaborative value creation, readily amenable to contextual redefinition based on industry-specific indicators.

In innovation-intensive domains such as pharmaceuticals, advanced manufacturing, or information technology, the dynamics of knowledge sharing and equitable value allocation often present even greater complexity than in traditional supply chains. In these sectors, knowledge investment (KI) transcends simple R&D expenditure, encompassing clinical trial portfolios, proprietary algorithm development, or foundational infrastructure innovation. Similarly, absorptive capacity (AC) can be gauged through more nuanced metrics such as technology transfer success rates, time-to-market for new innovations, or intellectual property integration efficiency.

The analytical elegance of the Shapley value ensures the model's structural coherence across these diverse contexts. Its foundation in marginal contribution fairness requires no fundamental mathematical redesign; rather, it demands only a thoughtful recalibration of input parameters to reflect sectoral realities. This operational resilience was put to the test through a rigorous simulation for a hypothetical biotechnology R&D alliance. The coalition, involving a lead firm (BioTech Inc.) and two partners, was parameterized with domain-specific values: KI = \$20M for BioTech and \$5M for partners; AC calibrated to reflect differential technology transfer rates (80% for BioTech, 60% for partners) [49]; and elevated coordination costs (CC = \$700,000/partner) accounting for stringent regulatory alignment [23].

Monte Carlo simulations (1,000 iterations) for this biotech scenario yielded a coalition profit of \$11M at a cooperation level (η) of 0.5. The resultant Shapley value allocations \$7.15M (BioTech), \$2.2M (Partner 1), \$1.65M (Partner 2) not only demonstrated procedural fairness but also produced a compelling 83% profit gain over the non-collaborative baseline. This trend mirrors the 60%–90% improvements observed in the automotive case (Table 2), providing quantitative confirmation of the model's adaptability and robustness in a distinctly different knowledge-intensive environment.

Accordingly, the proposed framework proves to be not merely a theoretical construct but an operationally resilient tool for strategic decision-making. Its dual-level adaptability conceptual flexibility and parametric recalibration offers immense value for managers and policymakers navigating the complexities of collaboration, joint investment, and equitable benefit distribution across the ever-evolving landscape of knowledge-based industries.

6.4. Limitations and Suggestions for Future Research

Like most modeling-based research, this study is not without limitations. Although the model demonstrates robust performance under uncertainty, several practical and operational constraints should be acknowledged when applying it in real-world environments.

First, the implementation of the proposed scheduling and coordination mechanisms entails energy consumption and computational overhead, particularly in large-scale manufacturing networks where iterative optimization and real-time data processing are required. Such computational demands may influence system responsiveness when scaling across multiple suppliers.

Second, time delays in information exchange—arising from asynchronous data reporting, human decision cycles, or IT infrastructure latency—can affect the timeliness and accuracy of knowledge updates. These delays may temporarily distort the fairness index or coalition payoff distribution until synchronization is restored.

Third, information asymmetry remains an inherent challenge. Despite the model's capability to reduce knowledge gaps among partners, unequal access to operational data or learning outcomes can lead to suboptimal coalition behavior and reduced trust.

Finally, operational overhead, such as managerial coordination efforts, data verification routines, and system integration costs, may limit the model's immediate deployment in firms with low digital maturity. Future research may address these constraints by embedding lightweight data-sharing protocols or AI-driven synchronization layers to enhance real-time feasibility.

Acknowledging these factors enhances the transparency of this study and clarifies that, while the proposed model provides a rigorous theoretical foundation, its full-scale implementation demands careful calibration of energy efficiency, timing precision, and data accessibility.

7. Conclusion

This study leverages cooperative game theory and the Shapley value to optimize profit allocation in supply chain knowledge-sharing contexts. Through three scenarios—non-cooperative, cooperative without knowledge sharing, and cooperative with knowledge-sharing coalitions—the analysis reveals that coalitions with knowledge sharing maximize profits for partnering firms. Enhanced knowledge in part production drives superior returns, while non-cooperative scenarios yield suboptimal outcomes for the primary firm. Key variables such as cooperation intensity, cost-sharing ratios, equipment effectiveness, and knowledge contributions were rigorously analyzed. Increased cooperation and capability enhancements elevate a firm's Shapley value share, effectively offsetting associated costs through amplified coalition profits.

The findings underscore that strategic adjustments in cost ratios and profit-sharing mechanisms significantly influence individual firm outcomes within coalitions. For instance, a higher profit-sharing ratio bolsters a firm's returns, while investments in equipment and knowledge, despite initial costs, enhance overall profitability. Future research could integrate Shapley value with data envelopment analysis to assess decision-making efficiency and explore knowledge-sharing dynamics across diverse sectors, ensuring robust theoretical and practical advancements.

Beyond its methodological contributions, this research offers an actionable bridge between policy formulation and managerial execution. By integrating quantitative indicators of knowledge investment and coordination efficiency into decision systems, both public institutions and private firms can align strategic objectives, translating national innovation policies into measurable corporate outcomes.

Future research could integrate the Shapley value with data envelopment analysis to assess decision-making efficiency and explore knowledge-sharing dynamics across diverse sectors, thereby fully leveraging the model's cross-industry applicability to ensure robust theoretical and practical advancements in strategic alliance management.

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