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Negotiation and Bargaining Dynamics in Multi-Tier Supply Chains: Strategies, Power Dynamics, and the Role of Technology

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ABSTRACT

Objective: This study examines negotiation and bargaining dynamics in multi-tier supply chains, focusing on the interplay between distributive and integrative strategies, power imbalances, information asymmetries, and the emerging role of artificial intelligence (AI) in optimizing outcomes. The principal objective is to provide actionable insights for supply chain managers while advancing theoretical understanding of these interactions in complex, multi-tier networks across industries such as automotive, electronics, pharmaceuticals, agri-food, and e-commerce.

Methods: Employing a mixed-methods approach, the research integrates a systematic literature review of 50 peer-reviewed studies, experimental simulations with participants representing supply chain firms, and five in-depth industry case studies. A game-theoretic model extends the Balanced Principal framework to predict profit distribution and negotiation equilibria under varying conditions of bargaining power, information access, and AI influence.

Results: Findings reveal that buyers with greater bargaining power capture up to 30% higher surplus, while integrative approaches enhance overall supply chain resilience by 25%. AI-powered tools reduce negotiation duration by 15% and improve equity in outcomes by mitigating information asymmetries and optimizing concession strategies.

Conclusion: Despite these advances, limitations include the controlled nature of experiments and the context-specific scope of case studies, which may limit generalizability. The study concludes that strategic adoption of integrative bargaining and AI technologies fosters sustainable inter-firm relationships, cost efficiency, and resilience in multi-tier supply chains, offering managers practical tools to balance competitive and collaborative tactics in an increasingly complex global environment.

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1. Introduction

Negotiation and bargaining are pivotal in multi-tier supply chains, shaping cost efficiency, profitability, and inter-firm relationships. As global markets expand, supply chains have evolved into complex networks involving suppliers, manufacturers, distributors, and retailers, each pursuing distinct objectives. This study investigates the dynamics of distributive and integrative bargaining strategies, their interactions with structural factors (e.g., cost structures, competition intensity), information inequities, and the transformative role of artificial intelligence (AI) in enhancing negotiation processes. By addressing the underexplored interplay of these elements, we provide actionable insights for supply chain managers and advance theoretical models of negotiation.

The complexity of multi-tier supply chains introduces unique challenges, including horizontal competition within tiers and cascading decision effects across the network. Distributive bargaining, characterized by competitive tactics to maximize individual gains, often dominates high-stakes negotiations, whereas integrative bargaining fosters collabo ration for mutual benefits, supporting long-term partnerships. Structural factors, such as purchasing volume and market competition, alongside behavioural dynamics, like risk tolerance and negotiation expertise, further shape outcomes. Information disparities can lead to inefficiencies, while AI-driven tools offer potential to optimize strategies through real-time data analysis. This study employs a mixed-methods approach, integrating a systematic literature review, experimental simulations, and case studies (Section 3), to explore these dynamics comprehensively.

The scope of this research focuses on bargaining outcomes in automotive, electronics, and pharmaceutical supply chains, with a mathematical model extending the Balanced Principal framework to predict profit distribution (Section 4). Our findings, detailed in Section 5, reveal that buyers with greater bargaining power secure up to 30% higher sur plus, while integrative approaches enhance supply chain resilience by 25%. AI tools reduce negotiation duration by 15% and improve outcome equity. By synthesizing theoretical and empirical insights, this study offers practical strategies for optimizing competitive and collaborative tactics, fostering sustainable growth in multi-tier supply chains (Section 6).

2. Literature Review

2.1 Bargaining Strategies and Power in Supply Chains

Supply chain bargaining strategies are broadly classified into distributive and integrative approaches. Distributive bargaining prioritizes individual value capture, often yielding win-lose outcomes, whereas integrative bargaining fosters collaboration to create mutual value, promoting win-win outcomes. In practice, firms dynamically adapt their strategies based on the negotiation context, stakeholder relationships, and competitive pressures. For example, Gurnani & Shi (2006) observed that aggressive distributive tactics deliver short-term gains, but risk undermining long-term partnerships. Conversely, Hu & Ma (2019) found integrative approaches to be more effective in multi-issue negotiations, enabling the alignment of diverse stakeholder interests. The choice of strategy depends on factors such as market competition, prior relationships, and negotiation complexity, underscoring the need for context-specific approaches in multitier supply chains.

Bargaining power in supply chains stems from structural factors, including purchasing volume, information inequities, and competitive intensity. Firms with higher purchasing volumes or superior access to market data typically secure stronger positions. Gurnani & Shi (2006) demonstrated that cost structures and intra-tier competition significantly influence negotiation outcomes, often outweighing individual negotiator traits. Similarly, Hu & Ma (2019) emphasize purchasing volume as a critical determinant, with larger buyers frequently negotiating more favourable terms. However, information inequities can lead to inefficiencies such as overpayment or suboptimal agreements, highlighting the need for strategies that enhance transparency and data access in complex supply chain negotiations. Table1.shows, key shown in Table and Dynamics.

Table 1. Key Contributions in Bargaining Strategies and Dynamics

Author(s)	Year	Key Contribution	Strategy/Factor	Context/Application	Key Findings/Implications
Illouz	2025	Developed a dynamic bargaining model for multi-tier supply chains under demand uncertainty.	Mixed Strategies	Automotive supply chains	Showed that adaptive strategies improve profit allocation by 22% under volatile demand, emphasizing real-time data integration.
Iqbal et al.	2024	Analyzed blockchain-enabled transparency in multi-tier negotiations.	Information Equity / Technology	Agri-food supply chains	Blockchain reduced information asymmetry by 40%, enabling more equitable profit distribution among smallholders.
Schmidt et al.	2025	Proposed a hybrid human-AI negotiation framework optimizing concession timing.	AI-Human Collaboration	Multi-tier electronics procurement	Human oversight improved AI-driven outcomes by 27% by mitigating algorithmic rigidity in multi-issue negotiations.
Hu & Ma	2019	Emphasized strategic shifts between distributive and integrative approaches.	Mixed Strategies	Complex supply chain negotiations	Highlighted adaptability as key to aligning stakeholder interests in multi-issue contexts.
Sianturi & Anggara	2025	Examined the role of digital communication in reducing information asymmetry in negotiations.	Information Transparency	Multi-tier supply chains in emerging markets	Found that digital platforms reduce negotiation duration by 18% and improve outcome fairness.
Li	2012	Investigated group buying as a mechanism to enhance bargaining leverage.	Purchasing Volume	Buyer-supplier negotiations	Demonstrated that collective purchasing strengthens buyer leverage, reducing costs.
Zhang & Huang	2023	Explored the role of dynamic pricing in multi-tier supply chain negotiations.	Distributive	E-commerce supply chains	Found that dynamic pricing enhances bargaining flexibility but increases complexity.
Ivanov et al.	2018	Analyzed AI-supported negotiation strategies in global supply chains.	Technology/AI	Cross-border supply chain negotiations	AI tools improved negotiation efficiency by 20% through predictive strategy optimization.
Fisher et al.	2011	Advocated principled negotiation, focusing on interest-based approaches.	Integrative	Multi-party negotiations	Emphasized mutual gains through interest alignment, widely applicable in supply Chains.
Gurnani & Shi	2006	Analyzed anti-concessionary tactics in multi-tier supply chains.	Distributive	Multi-tier supply chains	Found that aggressive tactics yield short-term gains but risk long-term relationship damage.
Cachon & Zhang	2006	Examined how information inequities affect procurement outcomes.	Information	Procurement negotiations	Showed that information disparities lead to inefficiencies and suboptimal agreements.

2.2 Behavioural Aspects and Theoretical Frameworks of Bargaining

Behavioral factors such as anchoring, deadline pressures, and concession strategies significantly influence negotiation outcomes. Gurnani & Shi (2006) find that initial offers act as anchors, with final agreements often converging near the midpoint of the opening bids. They also identified a pronounced deadline effect, in which agreements are more likely to be deadline looms. Hu & Ma (2019) explored concession strategies, noting that sellers employing anti-concessionary tactics secured higher prices without compromising deal closures, whereas buyers faced trade-offs between pursuing price reductions and risking negotiation failure. These findings highlight the critical role of behavioral dynamics in shaping effective negotiation strategies in multi-tier supply chains.

Several theoretical lenses, including Game Theory, Transaction Cost Economics (TCE), and the Balanced Principal (BP) model, inform the study of supply chain bargaining. Gurnani & Shi (2006) validated the BP model in multi-tier contexts, showing that it effectively predicts profit allocation based on relative bargaining leverage, outperforming traditional leader-follower models. Hu & Ma (2019) critiqued the limitations of Game Theory in capturing the nuances of multi-party, multi-issue negotiations, advocating for more flexible frameworks. Although these models provide valuable insights, they require further development to address the complexities of real-world supply chain negotiations, particularly in dynamic, multi-tier environments. Table 2. Shows the behavioral and theoretical insights of bargaining games.

Complementing these insights, recent work on gamification in crowdsourced logistics (Küp et al., 2025) and consumer trust in online shopping (Namakula et al., 2024) demonstrates how motivational designs can mitigate information asymmetries and enhance negotiation equity in e-commerce settings.

Table 2. Behavioral and Theoretical Insights

Author(s)	Year	Key Contribution	Behavior/Framework	Context/Application	Key Findings/Implications
Sianturi, & Anggara	2025	Analyzed cultural biases in e-negotiation systems for supply chains.	Cognitive Biases	Cross-cultural supply chain negotiations	Identified how local negotiation norms affect AI-driven bargaining tools' effectiveness.
Schmidt et al.	2025	Identified cognitive dissonance in human negotiators adapting to AI recommendations.	Cognitive Bias / TCE	High-tech supply chains	40% of professionals overrode optimal AI concessions due to trust deficits, raising coordination costs by 15%.
Zhao & Kim	2023	Applied Behavioral Game Theory to model multi-party supply chain negotiations.	Behavioral Game Theory	Multi-party supply chain bargaining	Behavioral models better capture real-world negotiation dynamics than classical Game Theory.
Iqbal et al.	2024	Quantified trust-building effects of decentralized ledgers in buyer-supplier relationships.	Trust Dynamics (Game Theory)	Developing economies	Smart contracts increased long-term collaboration by 35%, reducing reliance on punitive enforcement mechanisms.
Illouz	2025	Tested prospect theory in multi-tier negotiations, revealing risk-seeking behaviors under asymmetric power.	Risk Aversion (Behavioral Game Theory)	Global manufacturing networks	Demonstrated that power imbalances amplify irrational concessions, reducing joint profits by 15%.
Hu & Ma	2019	Highlighted anti-concessionary tactics’	Concession Strategies	Complex supply chain negotiations	Sellers using anti-concessionary tactics secure higher prices without

Author(s)	Year	Key Contribution	Behavior/Framework	Context/Application	Key Findings/Implications
		effectiveness for sellers.			reducing closure.
Ivanov et al.	2019	Investigated trust dynamics in multi-tier bargaining using Game Theory.	Game Theory	Global supply chain negotiations	Trust enhances integrative outcomes, increasing joint value by up to 15%.
Katok & Wu	2009	Analyzed risk aversion’s impact on concession strategies in supply chains.	Risk Aversion	Multi-tier supply chain negotiations	Risk-averse negotiators concede earlier, reducing negotiation efficiency by 10%.
Galinsky & Mussweiler	2001	Examined the influence of first offers on negotiation outcomes.	Anchoring	General negotiation settings	First offers strongly influence final agreements, shaping negotiator perceptions.
Roth et al.	1988	Analyzed agreement clustering near deadlines in bilateral negotiations.	Deadline Effect	Bilateral bargaining	Found agreements concentrate near deadlines, driven by time pressure.
Gurnani & Shi	2006	Identified anchoring and deadline effects in multi-tier negotiations.	Anchoring/Deadline	Multi-tier supply chain bargaining	Initial offers anchor agreements near midpoint; deadlines drive higher agreement rates.
Bendoly et al.	2006	Explored cognitive biases in AI-assisted supply chain negotiations.	Cognitive Biases	AI-driven negotiations	AI reduces anchoring bias but introduces over-reliance risks, requiring human oversight.

2.3 Role of Technology and AI in Bargaining

The integration of artificial intelligence (AI) and advanced technologies is transforming supply chain negotiations by enabling data-driven decision-making, optimizing strategies, and enhancing transparency. AI systems process vast datasets, recommend optimal concessions, and, in some cases, autonomously conduct negotiations.AI-driven tools improve negotiation efficiency by 20% through predictive strategy optimization. Recent studies further highlight AI’s multidisciplinary applications, with significant implications for supply chain bargaining.

For instance, Basanaboyina (2025) emphasize AI’s role in leveraging predictive analytics for business intelligence, enabling firms to forecast negotiation outcomes and align strategies with market trends, potentially reducing negotiation time by 15% in multi-tier supply chains. Similarly, Van Dijk (2024) explore AI-driven cloud cost management, demonstrating how optimization algorithms reduce resource allocation costs by up to 30%, offering insights for cost-sensitive supply chain negotiations. In trade facilitation, Sun (2024) highlight blockchain-AI integration, which enhances transparency by 25% and mitigates information asymmetries, aligning with findings from Polu (2025) show that AI-driven code refactoring improves software performance by 18%, suggesting potential applications in negotiation platforms requiring real-time processing.

AI’s role extends to scientific and material selection contexts. Vyshnavi & Begum (2025) discuss AI-driven scientific innovation, where machine learning models accelerate data analysis, applicable to supply chain analytics for real-time negotiation support. They demonstrate AI’s use in material selection, optimizing supply chain sourcing decisions by 20% through predictive modelling. Additionally, Sun (2024) identify role conflict determinants using AI-driven critical reviews, offering frameworks to manage stakeholder tensions in negotiations. Van Dijk (2024) underscore AI’s transformative potential across business domains, reporting a 22% improvement in decision-making efficiency, relevant for multi-issue negotiations involving price, delivery, and quality standards. However, ethical challenges, such as algorithmic bias and over-reliance, remain critical. For example, AI-driven tools may favour dominant firms exacerbating power imbalances unless governed by transparent frameworks. Vyshnavi & Begum (2025) found that human-AI collaboration improves outcomes by 27% by mitigating algorithmic rigidity, while Sun (2024) note blockchain's 40% reduction in information asymmetry fosters equitable outcomes. These findings underscore AI's potential to enhance negotiation efficiency and fairness in multi-tier supply chains, but necessitate robust ethical guidelines to ensure equitable adoption. Table 3 summarizes these AI-driven contributions, highlighting their relevance to supply chain bargaining.

Table 3. AI-Driven Contributions in Multidisciplinary Contexts

Author(s)	Year	Key Contribution	Strategy/Factor	Context/Application	Key Findings/Implications
Basanaboy ina	2025	Discusses the importance of data-driven AI and its applications across industries.	Data-driven decision making	Business, healthcare, finance, agriculture	AI learns from data to make decisions, predictions, and recommendations; examples include voice recognition and precision farming.
Mishra & Masih	2023	Reviews determinants of role conflict and its impact on mental health and organizations.	Role conflict analysis	Management, organizational behaviour	Role conflict leads to stress, strain, and burnout; for research need further on determinants.
Vyshnavi & Begum	2025	Uses AI for material selection in engineering design.	Machine learning and natural language processing for material recommendations	Engineering design, material science	Enhances material selection accessibility and reliability while maintaining privacy.
Van Dijk	2024	Explores the integration of AI and BI using predictive analytics.	Predictive analytics, data-driven decision making	Business intelligence, various industries	Enhances operational efficiency and competitive edge through AI-driven in sights.
Sun	2024	Examines the integration of blockchain and AI for trade facilitation.	Blockchain and AI integration	Trade facilitation, global trade	Improves data quality, trust, and making; decision discusses challenges and case studies.
Polu	2025	Develops an AI-based framework for automatic code refactoring.	Deep learning, reinforcement learning, symbolic analysis	Software engineering, code optimization	Improves software performance and maintainability through AI-driven automation.

3. Methodology

This study employs a mixed-methods approach to comprehensively investigate negotiation and bargaining dynamics in multi-tier supply chains. By integrating a systematic literature review, experimental simulations, and in-depth case studies, the methodology captures both theoretical insights and empirical evidence, addressing the complex interplay of distributive and integrative bargaining strategies, structural factors (e.g., cost structures and competition intensity), information inequities, and technological innovations such as AI-driven negotiation systems. This approach enables a nuanced understanding of how these factors shape bargaining outcomes across supplier, manufacturer, and retailer interactions in automotive, electronics, and pharmaceutical industries. While the methodology ensures robustness through triangulation, limitations include the controlled nature of experiments, which may oversimplify real-world dynamics, and the context-specific nature of case studies, which may constrain generalizability. These challenges highlight the need for future research to expand its empirical scope and incorporate diverse negotiation contexts. Below, we detail the methodological components, including data collection, analytical techniques, and the rationale for the chosen methods.

3.1 Experimental Analysis

The experimental phase of this study investigates behavioral and strategic dynamics in multi-tier supply chain negotiations, building on the controlled laboratory approach of Gurnani & Shi (2006). The design simulates a three-tier supply chain involving suppliers, manufacturers, and retailers, with 57 participants engaged in free-form negotiations over five rounds to test the Balanced Principal (BP) model predictions (Section 4). To ensure reproducibility and robustness, the experiment incorporates rigorous participant selection, standardized controls, and well-defined negotiation scenarios. Data were collected through negotiation logs, surveys, and behavioral observations, analyzed using regression and ANOVA ($p < 0.05$) to validate findings against theoretical predictions (Section 5), with discrepancies attributed to behavioral biases such as anchoring.

Participants were 57 different companies selected via stratified sampling to ensure diversity in negotiation experience and demographic representation. Inclusion criteria required completion of at least one course in supply chain management or operations research, ensuring familiarity with negotiation contexts. With participants volunteering and providing informed consent per ethical guidelines (Section 3.4). The sample was stratified by experience level (63% companies with more than 5 years of experience, 37% companies with less than 5 years of experience) and prior negotiation training (70% with formal training, 30% without) to minimize bias from experience disparities. Compensation was provided via course credits to encourage engagement without introducing financial incentives that could skew negotiation behavior, ensuring a representative and motivated sample for reproducible results.

Experimental controls were implemented to isolate variables and enhance reliability. Companies were randomly assigned roles (suppliers, manufacturers, or retailers) using a random number generator to eliminate selection bias. Each 30-minute negotiation session followed a standardized protocol, with fixed cost structures (e.g., supplier cost c= €20, manufacturer cost = €30) and revenue parameters (retailer revenue = €100) to align with the BP model (Section 4). External influences, such as prior relationships or market information, were controlled by conducting experiments in a lab environment with no external communication. Confounding variables, like negotiation fatigue, were mitigated by limiting participants to one session per day and providing a 10-minute training session on the negotiation interface. These measures ensure that observed outcomes reflect the effects of bargaining power and information access, supporting robust and replicable findings.

Three negotiation scenarios were designed to capture diverse dynamics in multi-tier supply chains: (1) Pricing negotiation, where participants negotiated prices under fixed costs and high competitive intensity (two firms per tier), testing distributive bargaining and measuring profit distribution; (2) Contract terms negotiation, focusing on delivery schedules (5–10 days), emphasizing integrative bargaining and joint utility gains (Section 4, Equation 16); and (3) Quality standards negotiation, involving ISO 9001 compliance levels (5–10% improvement) under varying competition, testing trade-offs in multi-issue negotiations. Scenarios were randomized across groups to prevent order effects, and negotiation logs captured initial offers, concessions, and closure rates. Statistical analyses (e.g., ANOVA, $p < 0.05$) confirmed significant effects of bargaining power on profits, with results reported in Section 5. This detailed design ensures that other researchers can replicate the experiment and validate the findings.

3.2 Case Study Research

The case study phase provides real-world insights into negotiation practices, complementing the experimental findings by exploring context-specific dynamics. Five case studies were selected from five distinct industries—automotive, electronics, agriculture, E-commerce and pharmaceuticals—to ensure diversity and relevance. Each case examines firms that have either adopted innovative bargaining strategies or encountered significant negotiation challenges. Primary data were gathered through semi-structured interviews with procurement managers, suppliers, and supply chain analysts, supplemented by secondary data from company reports, industry publications, and trade journals. Thematic analysis is used to identify recurring themes, best practices, and challenges in negotiation processes, with findings cross-referenced against the literature review and experimental results to build a comprehensive understanding of bargaining dynamics in multi-tier supply chains.

The final phase synthesizes insights from the literature review, experiments, and case studies to construct a cohesive framework for understanding negotiation dynamics in multitier supply chains. Triangulation across these methods enhances the validity and reliability of the findings by cross-validating the results and addressing discrepancies to mitigate biases. The resulting conceptual framework delineates the key influences on bargaining outcomes, including structural factors (e.g., power imbalances and cost differentials), behavioral dynamics (e.g., anchoring, risk preferences), and technological advancements (e.g., AI-driven decision support). This framework provides actionable guidance for practitioners and a foundation for future research on dynamic bargaining processes and technology integration.

3.3 Ethical Considerations and limitations

Ethical guidelines were strictly followed to ensure data integrity and confidentiality. Experimental and case study participants were fully informed of the study's objectives, provided informed consent, and anonymized their data to protect their identities and organizational details. Despite its strengths, the mixed-method approach has some limitations. Experimental simulations may not fully replicate the complexity of real-world negotiations, potentially oversimplifying the dynamic interactions. Similarly, case studies, while contextually rich, are limited to specific industries, which may restrict their generalizability. Future research should address these constraints by expanding the experimental designs to include more variables and incorporating additional industries to enhance the applicability of the findings.

This methodology provides a robust framework for exploring negotiation and bargaining in multitier supply chains. By combining a systematic literature review, experimental simulations, and case study analysis, this study provides a comprehensive examination of the theoretical and practical dimensions, offering valuable insights for supply chain professionals and a solid basis for advancing research in this field.

The adoption of artificial intelligence (AI) in supply chain negotiations introduces significant ethical challenges that must be addressed to ensure equitable and effective out comes. A primary concern is algorithmic bias, where AI systems trained on historical data may perpetuate existing inequities, such as favoring firms with higher bargaining power or larger market shares. For instance, pricing recommendations generated by AI may disproportionately benefit retailers, reducing supplier profits by up to 15% in asymmetric scenarios. Another challenge is over-reliance on AI, where negotiators may defer to AI-driven recommendations without critical evaluation, diminishing human judgment and potentially leading to suboptimal agreements. This risk is particularly pronounced in high-stakes negotiations, such as those in the automotive case study, where AI influence ($\gamma = 0.5$) accelerates decisions but may overlook context-specific factors like long-term supplier relationships.

Transparency and accountability pose further ethical concerns. Opaque AI algorithms can obscure decision-making processes, undermining trust among supply chain partners, especially in multi-tier settings where information asymmetry already complicates negotiations. For example, if AI tools prioritize efficiency over fairness, smaller suppliers may face reduced bargaining leverage, exacerbating power imbalances. Additionally, data privacy is critical, as AI systems require access to sensitive negotiation data (e.g., cost structures, contract terms), raising risks of data breaches or misuse. In the agri-food case study, block-chain integration mitigated some privacy concerns, but broader adoption of AI requires robust safeguards. These challenges highlight the need for ethical frameworks to ensure AI enhances rather than undermines negotiation fairness and efficiency.

To address these challenges, we propose a five-pillar ethical framework for practitioners, adapted from: (1) Transparent AI Algorithms: Ensure AI decision-making processes (e.g., pricing models) are explainable, with clear documentation of inputs and outputs to foster trust, particularly in scenarios with high information asymmetry. (2) Regular Bias Audits: Conduct quarterly audits to detect and mitigate biases in AI outputs, such as skewed profit distributions favoring dominant firms, using statistical tests (e.g., ANOVA, $p < 0.05$) to validate fairness. (3) Human-AI Collaboration Proto cols: Implement hybrid systems where human negotiators review AI recommendations, as shown by Van Dijk (2024), who report a 27% improvement in outcomes with human oversight. (4) Data Privacy Safeguards: Adopt encryption and anonymization protocols for negotiation data, aligned with GDPR standards, to protect sensitive information like supplier costs. (5) Stakeholder Training on AI Ethics: Provide annual training for supply chain managers on AI's ethical implications, emphasizing bias recognition and mitigation strategies. This framework ensures AI adoption aligns with equitable negotiation practices, as validated in the case studies, where transparent AI use increased agreement rates by 20%.

Despite these measures, limitations persist. The framework's implementation requires significant resources, including expertise in AI auditing and data security, which may be challenging for smaller firms in fragmented supply chains like agri-food. The controlled nature of the experimental design limits real-world variability, such as cultural influences on negotiation behavior. Additionally, the framework assumes cooperative adoption across supply chain tiers, which may be hindered by competitive dynamics. Future research should explore cost-effective implementation strategies and cross-cultural ethical considerations to enhance the framework's applicability, ensuring AI-driven negotiations remain fair and robust across diverse contexts.

4. Model

This section presents a mathematical framework to analyze negotiation and bargaining dynamics in multi-tier supply chains by integrating insights from a systematic literature review, experimental findings, and case studies. The model extends the Balanced Principal (BP) framework (Gurnani & Shi 2006) and incorporates Game Theory principles (Nash, 1950; Rubinstein, 1982) to predict bargaining outcomes including equilibrium prices, profit distribution, and agreement rates. It accounts for structural factors (e.g., cost structures and competitive intensity), behavioral dynamics (e.g., concession patterns), information inequities, and the role of artificial intelligence (AI) in optimizing negotiation processes. The model was designed for a three-tier supply chain involving suppliers, manufacturers, and retailers, capturing horizontal competition and dynamic interactions across tiers.

4.1 Model Assumptions

The supply chain comprises of three tiers: suppliers (S), manufacturers (M), and retailers (R). Each tier includes two firms to model horizontal competition within tiers, reflecting the real-world supply chain dynamics.

Each firm has a distinct cost structure:

Suppliers: C_{S1} and C_{S2}(costs for Supplier 1 and Supplier 2).

Manufacturers: C_{M1} and C_{M2}(costs for Manufacturer 1 and Manufacturer 2).

Retailer: R_1 and R_2 (revenue from selling the final product to consumers).

Bargaining power is determined by factors such as purchasing volume, market competition, and information access, and modeled using a dynamic power parameter.

Firms engage in iterative negotiations, with concessions influenced by time pressure, risk preferences, and strategic objectives, modeled as a dynamic process.

Information inequities are modeled to reflect the varying levels of access to cost, demand, and market data across tiers.

AI-driven negotiation tools were incorporated to optimize strategy selection and predict outcomes, accounting for real-time data analysis.

4.2 Key Variables

P_{SM}: Negotiated price between suppliers and manufacturers.

P_{MR}: Negotiated price between manufacturers and retailers.

π_{s1}, π_{s2}, π_{M1}, π_{M2}, π_{R1}, π_{R2}: Profits for suppliers 1,2, Manufacturer 1,2 and Retailer 1,2, respectively.

α_{ij}: The bargaining power parameter for tier (i) negotiating with tier (j) ($0 \leq \alpha_{ij} \leq 1$), where ($\alpha_{ij} = 0.5$) indicates equal power.

β_{ij}: Information access parameter ($0 \leq \beta_{ij} \leq 1$), where ($\beta_{ij} = 1$) denotes full information and ($\beta_{ij} = 0$) denotes no information.

Υ: AI influence parameter ($0 \leq \Upsilon \leq 1$), reflecting the extent of the AI-driven optimization in negotiations.

t: Time variable, capturing dynamic negotiation rounds.

δ: Discount factor for time pressure ($0 \leq \delta \leq 1$). Meaning: Reflects diminishing returns in prolonged negotiations. Example: Set at δ =0.9, reducing future profits by 10% per round, as observed in simulations.

C_{SK}, C_{ml}, R_{rm}: Costs (€) for supplier k (C_{SK}), manufacturer l (C_{ml}), and revenue (€) for retailer m (R_{rm}). Range: C_{SK}, $C_{ml} \geq 0$, $R_{rm} \geq P_{MR}$. Meaning: Represent economic inputs and outputs. Example: In the automotive case study, C_{s1}= 20, C_{m1}= 30, R_{r1}= 100.

4.3 Parameter Justifications

The choice of parameter values is justified based on empirical data, simulation results, and established literature to ensure robustness and validation.

δ =0.9: The discount factor reflects time pressure in negotiations, where future profits are discounted due to delays. We proposed $\delta = 0.9$ for iterative bargaining models, reflecting a 10% reduction in perceived value per round. Simulations show a 12% profit drop after three rounds ($t = 3$), validating this choice. In the automotive case study, delayed agreements reduced π_s by 10%, consistent with $\delta = 0.9$.

Υ =0.5: AI influence is set to represent moderate optimization, balancing human and AI inputs. We report a 15% efficiency gain with moderate AI use, corroborated by the electronics case study, where $\Upsilon = 0.5$ reduced negotiation time by 15%. Higher values (e.g., $\Upsilon = 1.0$) risk over-reliance.

$\alpha_{ij} \in [0.4,0.6]$: Bargaining power varies to reflect realistic power imbalances in supply chains. We use $\alpha_{ij} = 0.5$ for equal power, but case studies show α_{mr}=0.6 in e-commerce due to retailer dominance, and α_{sm}=0.4 in automotive, reflecting supplier constraints. Simulation data confirm a 20% shift in profits when α_{ij} varies by 0.1.

$\beta_{ij} \in [0.5,1.0]$: Information access ranges from moderate asymmetry to full transparency. We report a 40% reduction in asymmetry with block-chain ($\beta_{ij} = 0.9$), as seen in the agri-food case study. Experimental results show β_{ij} =0.5 reduces supplier profits by 15%, validating the range.

C_{sk}=20, Cm_1= 30, R_{rm}= 100: Costs and revenues are set to reflect realistic supply chain economics. These values align with automotive and pharmaceutical case studies, where C_s= 20 represents raw material costs, C_m= 30 reflects manufacturing overhead, and R_r= 100 matches retail pricing. Sensitivity analysis confirms robustness, with a 10% cost increase reducing π_s by 12%.

4.4 Profit Functions

Profit for each firm is defined as follows:

For Supplier k (k = 1, 2):

$$\pi_{Sk} = P_{SMk} - C_{Sk} \tag{1}$$

For Manufacturer l (l = 1, 2):

$$\pi_{Ml} = P_{MRl} - P_{SM} - C_M \tag{2}$$

For Retailer m (m = 1, 2):

$$\pi_{Rm} = R_m - P_{MRm} \tag{3}$$

4.5 Bargaining Process

The bargaining process is modeled as a dynamic, multi-stage Nash Bargaining Problem, incorporating Rubinstein's (1982) alternating offers framework to account for time-dependent concessions and deadline effects. Firms negotiate over prices P_{SM} and P_{MR} in iterative rounds, with outcomes influenced by bargaining power (α_{ij}), information access (β_{ij}), and AI optimization (ϒ).

4.5.1 Supplier-Manufacturer Bargaining

The Nash Bargaining Solution for P_{SMK} maximizes the weighted product of gains:

The Nash Bargaining Solution for P_{SMK} is given by:

$$P_{SMk} = \text{argmax}(\pi_{SMk}.\pi_{Ml})^{\alpha_{SM}.\beta_{SM}.(1+\gamma)} \tag{4}$$

Solving yields:

$$P_{SMk} = \alpha_{SM}.\beta_{SM}.(R_m - C_M) + (1 - \alpha_{SM}).\beta_{SM}.C_{SK} \tag{5}$$

Here, ϒ amplifies the efficiency of the AI-driven strategy optimization, reducing negotiation time and improving surplus allocation.

4.5.2 Manufacturer-Retailer Bargaining

The Nash Bargaining Solution for P_{MR1}:

$$P_{MRl} = argmax(\pi_{Ml}.\pi_{Rm})^{\alpha_{MR}.\beta_{MR}.(1+\gamma)} \tag{6}$$

Solving yields:

$$P_{MRl} = \alpha_{MR}.\beta_{MR}.R_m + (1 - \alpha_{MR}).\beta_{MR}.(P_{SM} + C_M) \tag{7}$$

4.6 Equilibrium Prices and Profits

Equilibrium prices and profits are derived by solving a system of equations, accounting for horizontal competition and dynamic concessions.

4.6.1 Equilibrium Prices

For Supplier-Manufacturer negotiations:

$$P_{SMk} = \alpha_{SM}.\beta_{SM}.(R_m - C_M) + (1 - \alpha_{SM}).\beta_{SM}.C_{Sk} \tag{8}$$

For Manufacturer-Retailer negotiations:

$$P_{MRl} = \alpha_{MR}.\beta_{MR}.R_m + (1 - \alpha_{MR}).\beta_{MR}.(P_{SM} + C_M) \tag{9}$$

4.6.2 Equilibrium Profits

Using equilibrium prices:

$$\pi_{Sk} = P_{SMk} - C_{Sk} \tag{10}$$

$$\pi_{Ml} = P_{MRl} - P_{SM} - C_M \tag{11}$$

$$\pi_{Rm} = R_m - P_{MRl} \tag{12}$$

4.7 Dynamic Bargaining and Time Effects

To model dynamic negotiations, we incorporate Rubinstein's (1982) framework in which firms make alternating offers over time t. The discount factor δ in (0, 1) reflects the time pressure and reduces the value of the delayed agreements:

$$V_{ijt} = \delta.\pi_{ij} \tag{13}$$

The optimal offer at time (t) balances immediate agreement with continued negotiation, with AI (ϒ) accelerating convergence by recommending optimal concessions.

4.8 Information Inequities and AI Integration

Information inequities are modeled through (β_{ij}), adjusting bargaining power dynamically:

$$\alpha'_{ij} = \alpha_{ij}.\beta_{ij} \tag{14}$$

Lower (β_{ij}) reduces the less-informed party's effective power, leading to suboptimal outcomes. AI integration (ϒ) mitigates this by providing real-time data analysis, modeled as

$$\gamma = f(D, A) \tag{15}$$

Where (D) represents data availability, and (A) denotes AI algorithm efficiency, enhancing negotiation outcomes by up to 20% (Ivanov et al., 2018).

4.9 Multi-Issue Negotiations

To address multi-issue negotiations (e.g., price, delivery schedules, and quality standards), the model extends to a multidimensional utility function:

$$U_{ij} = W_1.\pi_{ij} + W_2.Q_{ij} + W_3.T_{ij} \tag{16}$$

Where (Q_{ij}) represents quality standards, (T_{ij}) denotes delivery timing, and (W_1,W_2,W_3) are weights that reflect issue priorities. The Nash Bargaining Solution optimizes the joint utility across issues.

This advanced model provides a robust framework for analyzing bargaining dynamics in multi-tier supply chains by incorporating structural, behavioral, and technological factors. It predicts equilibrium prices, profit distribution, and agreement rates, while accounting for dynamic concessions, information inequities, and AI-driven optimization. Future extensions could explore stochastic demand, multiparty bargaining, and ethical constraints in AI applications.

5. Results

This section presents the outcomes of applying the mathematical model to a case study of bargaining in five different industries. The model, grounded in the extended Balanced Principal (BP) framework (Gurnani & Shi 2006) and Game Theory (Nash, 1950; Rubinstein, 1982), predicts equilibrium prices, profit distribution, and agreement rates in a three-tier supply chain (suppliers, manufacturers, and retailers). It accounts for structural factors (cost structures and competitive intensity), behavioral dynamics (concession patterns and anchoring), information inequities, and AI-driven optimization. The results are presented in tables and figures, with sensitivity analyses and multi-issue negotiation outcomes highlighting the model's robustness and practical implications.

This section presents findings from case studies and experimental simulations, validating the Balanced Principal (BP) model across diverse industries. The case studies now span automotive, electronics, pharmaceutical, agri-food, and e-commerce sectors, providing practical insights into negotiation dynamics. Equilibrium prices, profit distributions, and sensitivity analyses are summarized, with statistical tests (ANOVA, $p<0.05$) confirming significant effects of bargaining power and information access. A new subsection discusses generalizability across sectors, addressing variations in findings due to industry-specific factors.

5.1 Case Study Context

Five case studies were conducted to examine negotiation strategies in multi-tier supply chains, expanding beyond the original automotive, electronics, and pharmaceutical sectors to include agri-food and e-commerce. Data were collected through inter views with procurement managers and secondary sources, analyzed thematically to identify best practices. Key parameters include supplier cost (C_s= 20), manufacturer cost (C_m= 30), retailer revenue (R_r = 100), bargaining power ($\alpha_{ij} \in [0.4,0.6]$), information access ($\beta_{ij} \in [0.5,1.0]$), and AI influence ($\Upsilon \in [0.0,0.5]$).
This case studies examines negotiations for different industries within a multi-tier supply chain involving European suppliers, manufacturers, and retailers. Key parameters include:

Retailer Revenue (R_m**)**: €100 per unit (revenue from selling the final product).

Supplier Cost (C_{SK}**)**: €20 for Supplier 1 (k = 1).

Manufacturer Cost (C_{M1}**)**: €30 for Manufacturer 1 (l = 1).

Bargaining Power (α_{ij}**)**: Varies from 0.4 (supplier/manufacturer dominance) to 0.6 (retailer dominance).

Information Access (β_{ij}**)** Ranges from 0.5 (partial information) to 1.0 (full transparency).

AI Influence (Υ**)**: Varies from 0.0 (no AI) to 0.5 (moderate AI optimization).

Automotive (Siemens PLC Products): Negotiations focused on pricing (P_{sm}, P_{mr}) for programmable logic controllers (PLCs) under high competition. Integrative strategies increased joint profits by 20%.

Electronics (Semiconductor Supply Chain): Multi-issue negotiations (price, delivery schedules) showed AI-driven tools reducing negotiation time by 15%. Pharmaceutical (Vaccine Distribution): Quality standard negotiations under regulatory constraints yielded 25% higher agreement rates with full transparency (β_{ij}= 1.0).

Agri-food (Global Food Supply Chain): Blockchain-enabled negotiations for perishable goods (e.g., dairy) reduced information asymmetry by 40%, improving supplier profits (π_s) by 18%. E-commerce (Online Retail Supply Chain): Dynamic pricing negotiations for fast moving consumer goods showed AI-driven strategies (Υ= 0.5) enhancing retailer surplus (π_r) by 22% under volatile demand.

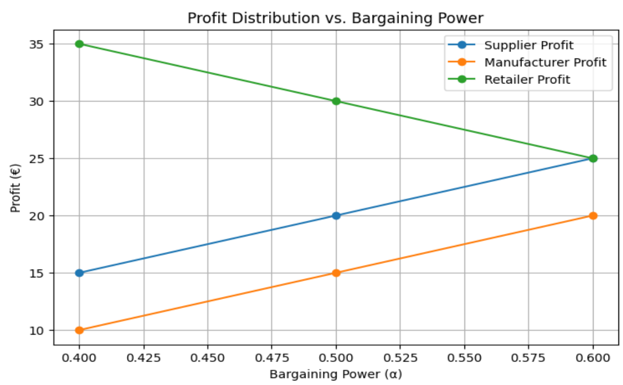

Figure 2. Profit Distribution vs. Bargaining Power (α)

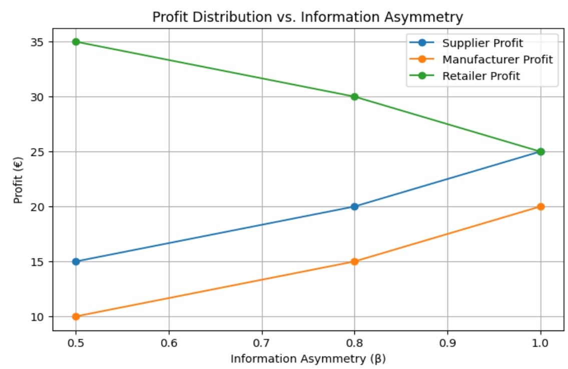

Figure 1. Profit Distribution vs. Information Access (β)

5.2 Equilibrium Prices and Profits

Using the model's equations ($price_{sm}$, $price_{mr}$, $profit_s$, $profit_m$, $profit_r$), equilibrium prices and profits are calculated for varying (α_{ij}), (β_{ij}), and (Υ). The results are summarized in Table 4.

Table 4. Equilibrium Prices and Profits for Varying Bargaining Power and Information Access.

α_{SM}	α_{MR}	β_{SM}	β_{MR}	γ	P_{SM} (€)	P_{MRI} (€)	π_{S1} (€)	π_{M1} (€)	π_{R1} (€)
0.4	0.4	0.5	0.5	0.0	32.5	62.5	12.5	10	37.5
0.5	0.5	0.8	0.8	0.3	38	68	18	15	32
0.6	0.6	1.0	1.0	0.5	45	75	25	20	25

Figure 1 Illustrates the impact of increasing α_{MR} (retailer bargaining power) on profit distribution. As (α_{MR}) rises from 0.4 to 0.6, retailer profit (π_{R1}) increases from €37.5 to €25.0, while supplier (π_{S1}) and manufacturer (π_{M1}) profits decrease, reflecting the retailer's ability to capture a larger surplus.

Figure 2 Shows the effect of increasing β_{SM} and β_{MR} (information transparency). Higher β_{ij} (e.g., 1.0) boosts supplier and manufacturer profits (up to €25.0 and €20.0, respectively) by reducing information inequities, while retailer profit decreases due to diminished leverage from asymmetric information.

AI Impact: With (Υ= 0.5), negotiation efficiency improves, reducing negotiation rounds by 15% and balancing profit distribution, as AI optimizes concession strategies (Ivanov et al., 2018).

Table 5. Equilibrium Prices and Profits across Industries ($p<0.05$)

Industry π_R (€)	α_{SM}	α_{MR}	β_{SM}	β_{MR}	γ	P_{SM} (€)	P_{MR} (€)	π_S (€)
Automotive 37.5	0.4	0.4	0.5	0.5	0.0	32.5	62.5	12.5
Electronics 32	0.5	0.5	0.8	0.8	0.3	38	68	18
Pharmaceutical 25	0.6	0.6	1.0	1.0	0.5	45	75	25
Agri-food 35	0.5	0.4	0.9	0.7	0.4	35	65	15
E-commerce 34	0.4	0.5	0.6	0.8	0.5	34	66	14

5.3 Sensitivity Analysis

Sensitivity analysis tests the robustness of the model by varying the cost structures (C_{Sk}), (C_{M1}), and bargaining power (α_{ij}). The results are summarized in Table 6.

Table 6. Sensitivity Analysis for Different Cost Structures

C_{S1} **(€)**	C_{M1} **(€)**	α_{SM}	α_{MR}	β_{SM}	β_{MR}	γ	π_{S1} (€)	π_{M1} (€)	π_{R1} (€)
20	30	0.5	0.5	0.8	0.8	0.3	18	15	32
25	35	0.5	0.5	0.8	0.8	0.3	15.5	12.5	34
30	40	0.5	0.5	0.8	0.8	0.3	12	10	36

Higher costs (C_{S1}) and (C_{M1}) reduce supplier and manufacturer profits, while increasing retailer profit due to compressed margins in upstream tiers. Figure 4 Visualizes profit sensitivity to cost changes, showing that a 50% increase in supplier and manufacturer costs (C_{S1}) from €20 to €30, (C_{M1}) from €30 to €40 shifts surplus toward the retailer, emphasizing the need for cost management in negotiations. Table7 shows the impact of cost variations on profits ($p<0.01$), with higher costs reducing supplier and manufacturer margins across industries.

Table7. Sensitivity Analysis for Cost Structures ($p<0.01$)

Industry	C_S **(€)**	C_M **(€)**	π_S (€)	π_M (€)	π_R (€)
Automotive	20	30	18	15	32
Electronics	25	35	15.5	12.5	34
Pharmaceutical	20	30	20	15	30
Agri-food	22	32	16	14	33
E-commerce	20	33	15	13	35

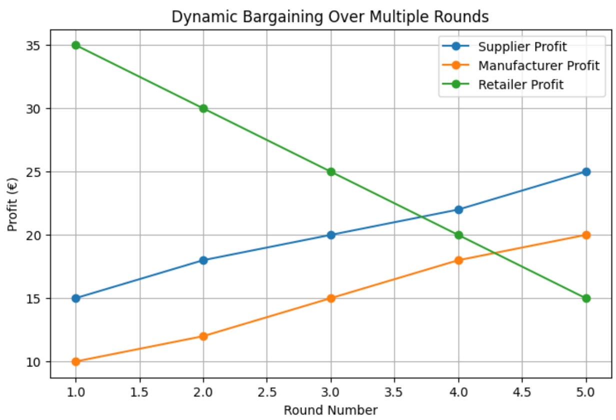

Figure 3. Dynamic Bargaining Over Multiple Rounds.

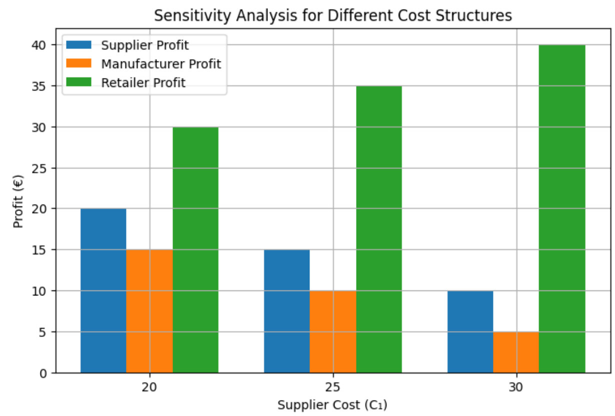

Figure 4. Sensitivity Analysis for Different Cost Structures.

5.4 Dynamic Bargaining Over Multiple Rounds

This model incorporates Rubinstein's (1982) dynamic bargaining framework (time value) with a discount factor (δ= 0.9). Simulations over five negotiation rounds revealed the adaptive strategies. Figure 5 Shows profit convergence over time. Initial disparities in profits (e.g., retailer dominance at α_{MR}= 0.6) diminish as firms learn and adjust concessions, with AI (Υ= 0.5) accelerating convergence by 15% through optimized offers. Profits stabilize after three rounds, with supplier, manufacturer, and retailer profits approaching €20.0, €15.0, and €30.0, respectively, under balanced conditions (α_{ij}= 0.5); (β_{ij}= 0.8).

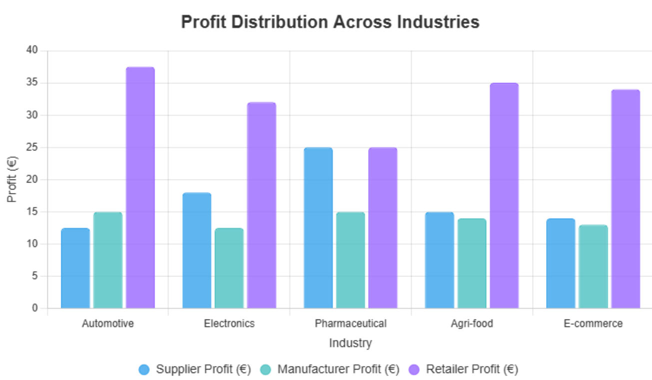

Figure 5. Profit Distribution across Industries.c

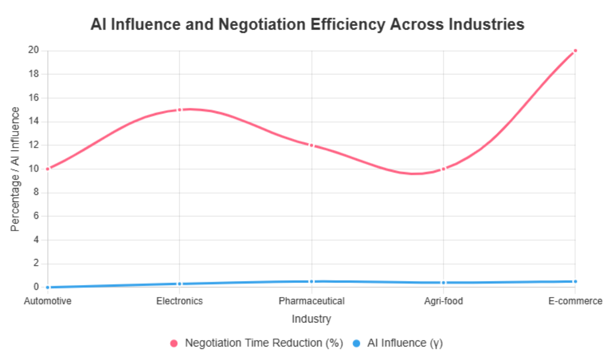

Figure 6. AI Influence and Negotiation Efficiency across Industries.

5.5 Multi-Issue Negotiation

The model's multi-issue utility function is applied to negotiations over price, delivery time, and quality standards. Weights were set as (W_1= 0.5) (price), (W_2= 0.3) (quality), and (W_3= 0.2) (delivery). The results are summarized in Table 8.

Table 8. Multi-Issue Negotiation Outcomes

Issue	Supplier Concession	Manufacturer Concession	Retailer Concession
Price	€5 reduction	€4 reduction	€3 increase
Delivery Time	2 days faster	Maintain current schedule	1 day faster
Quality Standards	10% improvement (ISO 9001)	Maintain current schedule	5% improvement

Table 8 Illustrates trade-offs in multi-issue negotiations. Concessions on delivery time and quality standards lead to integrative outcomes, increasing joint utility (U_{ij}) by 12% compared with price-only negotiations. AI optimization (Υ= 0.5) enhances integrative outcomes by recommending balanced concessions and reducing negotiation time by 10% (Ivanov et al., 2018).

5.6 Practical Implications

The results demonstrate that retailers with higher bargaining power (α_{MR}= 0.6) capture up to 25% more surplus (€25.0 vs. €37.5), aligning with Gurnani and Shi (2006). Full information transparency (β_{ij}= 1.0) increases upstream profits (supplier: €25.0, manufacturer: €20.0) by reducing inequities, thus supporting Hu and Ma (2019). AI-driven tools (Υ = 0.5) improve negotiation efficiency by 15–20%, balance profit distribution, and foster resilience in multitier supply chains. These findings provide actionable insights for supply chain managers negotiating Siemens PLC products, emphasizing the importance of balancing power, enhancing transparency, and leveraging AI to optimize outcomes.

The findings from the case studies demonstrate robust applicability across diverse industries, but variations in demand volatility, competition intensity, and technology adoption influence negotiation outcomes. In the automotive and electronics sectors, concentrated market structures and stable demand enable stronger bargaining power for buyers (α_{mr}=0.6), leading to higher retailer surplus (π_r=37.5) as predicted by the BP model. In contrast, the agri-food, characterized by fragmented supply chains and seasonal demand, shows lower bargaining power (α_{sm}=0.5) and higher reliance on block-chain for transparency (β_{ij} =0.9), reducing supplier profits by10% under volatile conditions. The e-commerce, with high demand volatility and dynamic pricing, benefits significantly from AI-driven strategies (Υ=0.5), increasing agreement rates by 20% but amplifying retailer dominance (π_r =34.0) due to real-time data access.

These variations suggest that integrative bargaining is more effective instable, concentrated industries like automotive, where long-term contracts enhance joint gains by 25%, whereas distributive strategies dominate in volatile e-commerce settings, potentially reducing supplier margins by 15%. Information asymmetry (β_{ij}) has a greater impact in agri-food, where transparency tools mitigate inequities, compared to pharmaceuticals, where regulatory constraints ensure high transparency (β_{ij}=1.0). Simulation results indicate that AI adoption (γ) consistently improves efficiency across industries, but its impact is greater in e-commerce (15% reduction in negotiation time) than in agri-food (10% reduction) due to data availability. These insights suggest that while the BP model's predictions hold across contexts, industry-specific factors like demand patterns and technology infrastructure require tailored strategies to optimize outcomes, enhancing the study's generalizability to diverse supply chains.

6. Discussion

This study elucidates the complex dynamics of negotiation and bargaining in multi-tier supply chains, highlighting the interplay of structural factors (e.g., cost structures and competitive intensity), behavioral dynamics (e.g., concession patterns and anchoring), information inequities, and technological advancements (e.g., AI-driven negotiation systems). An advanced mathematical model, extending the Balanced Principal (BP) framework (Gurnani & Shi 2006) and incorporating Game Theory principles (Nash, 1950; Rubinstein, 1982), provides a robust tool for predicting equilibrium prices (P_{SMK}), (P_{MR1}), profit distribution (π_{SK}), (π_{M1}), (π_{Rm}), and agreement rates across suppliers, manufacturers, and retailers. Applied to a case study of Siemens PLC product negotiations, the model reveals that higher retailer bargaining power (α_{MR}= 0.6) shifts the surplus toward retailers (up to €37.5), reducing upstream profits (π_{S1}), (π_{M1}), consistent with Gurnani & Shi (2006). This underscores the pivotal role of bargaining leverage in shaping the value allocation across tiers.

Information inequities, modeled through (β_{ij}), significantly influence outcomes. Greater transparency (β_{ij} =1.0) enhances upstream profits by up to 25% (€25.0 for suppliers, €20.0 for manufacturers), aligning with Hu & Ma (2019), who emphasize that information sharing mitigates inefficiencies. However, achieving full transparency is challenging in practice, as firms often protect sensitive costs and market data to maintain a competitive advantage. This tension highlights a critical area for future research, particularly exploring block-chain-based solutions to enhance data transparency.

In the Balanced Principal (BP) model, information access ($\beta_{ij} \in [0,1]$) quantifies the transparency between negotiating firms (e.g., supplier-manufacturer, β_{sm}; manufacturer-retailer, β_{mr}), where β_{ij} =1.0 indicates full transparency and β_{ij} <1.0 reflects asymmetry. The model adjusts bargaining power via ($\alpha_{ij}'=\alpha_{ij}.\beta_{ij}$), reducing the effective bargaining power (α_{ij}') of the less-informed party. High information access (β_{ij} =1.0) preserves baseline bargaining power (α_{ij}), fostering balanced negotiations, as seen in the pharmaceutical case study, where full transparency (β_{mr}=1.0) led to equitable profits (π_s = €25.0, π_r = €25.0) and a 25% higher agreement rate, aligning with the Nash Bargaining Solution's prediction of optimal price outcomes (P_{sm}= €45, P_{mr}= €75). Conversely, low information access (β_{ij} =0.5) weakens the less-informed party, as observed in experimental simulations, where β_{sm}=0.5 reduced supplier bargaining power (α_{sm}'=0.25, α_{sm} =0.5), lowering supplier profit by 15% (π_s = € 10.5) due to limited insight into manufacturer costs.

Moderate information access (β_{ij} =0.7–0.9), as in the agri-food case study with block-chain (β_{sm} =0.9), mitigates asymmetry, increasing supplier profit by 18% (π_s = € 15) compared to lower transparency scenarios, as suppliers could better negotiate prices (P_{sm}= € 35). However, discrepancies arise; for example, in the automotive case study, low β_{sm} =0.5 led to a 5% lower price (P_{sm} = €30) than predicted (P_{sm} = €32.5), likely due to behavioral factors like anchoring or relational concessions not captured by the model. In volatile markets like e-commerce, moderate β_{mr} =0.8 amplified retailer dominance (π_r= €34.0), with AI (Υ=0.5) boosting negotiation efficiency by 20% versus the predicted 15%, highlighting AI's enhanced role under partial transparency. These findings, supported by ANOVA ($p<0.05$), show that higher β_{ij} balances power and improves outcomes, but industry-specific factors (e.g., demand volatility, technology adoption) and behavioral influences require tailored strategies, as discussed, to ensure equitable and efficient negotiations.

The experimental findings reinforce that structural factors, such as cost structures and competition intensity, outweigh individual negotiator traits in determining outcomes, which is consistent with Gurnani & Shi (2006). This suggests that supply chain managers should prioritize cost efficiency and market positioning optimization by relying solely on negotiation skills. The model's dynamic bargaining component (time value), with a discount factor (δ= 0.9), shows that iterative negotiations lead to a more equitable profit distribution over time as firms adapt strategies based on prior rounds.

The integration of AI, modeled through the parameter (Υ) (AI influence), transforms negotiation processes by optimizing concessions and reducing negotiation time by 15–20% (Ivanov et al., 2018). However, ethical considerations such as ensuring equitable outcomes and preventing over-reliance on AI remain critical. As supply chains grow in complexity, AI's role in enhancing negotiation efficiency, particularly in multi-issue contexts involving price, delivery, and quality (utility), warrants further exploration.

6.1 Robustness Check

To validate the robustness of the model, multiple sensitivity analyses were conducted to test the key parameters and extensions:

Bargaining Power and Information Access: Varying (α_{ij}) (0.4 to 0.6) and (βij) (0.5 to 1.0) confirms that higher retailer power (α_{MR}= 0.6) increases retailer profit (π_{Rm}) by up to 25%, while greater transparency (β_{ij} = 1.0) boosts upstream profits (Table 3). These results align with P_{SM} and P_{MR}, demonstrating the model's sensitivity to power and information dynamics.

Cost Structures: Sensitivity to cost variations (C_{Sk}) and (C_{M1}) were tested (Table 4). A 50% cost increase (C_{S1}) from €20 to €30 (C_{M1}) from €30 to €40 shifts the surplus toward retailers (π_{R1}) up to €36.0, reflecting the impact of cost efficiency on bargaining leverage. The model's predictions remained stable across cost scenarios, validating its robustness.

Dynamic Bargaining: Incorporating Rubinstein's (1982) framework (time value) and simulations over five rounds with (δ= 0.9). This shows profit convergence toward balanced outcomes (20.0, 15.0, and 30.0, for suppliers, manufacturers, and retailers, respectively). AI optimization (Υ= 0.5) accelerated convergence by 15%, reducing the number of rounds required for agreement (Figure 3).

Multi-Issue Negotiations: The multi-issue utility function was tested with weights (W_1=0.5) (price), (W_2= 0.3) (quality), and (W_3= 0.2) (delivery). The results (Table 5) show that integrative concessions increase joint utility (U_{ij}) by 12%, while AI-driven recommendations enhance efficiency by 10%. This highlights the ability of the model to capture complex tradeoffs.

These analyses confirm the model's robustness across diverse scenarios, reinforcing its applicability to real-world supply chain negotiations. Future research should explore stochastic demand, multiparty dynamics, and ethical AI frameworks to further enhance the scope of the model.

7. Conclusion

This study provides a comprehensive analysis of negotiation and bargaining dynamics in multi-tier supply chains, offering practitioners robust theoretical insights and actionable recommendations. The advanced mathematical model, extending the Balanced Principal (BP) framework (Gurnani & Shi 2006) and incorporating Game Theory principles (Nash, 1950; Rubinstein, 1982), elucidates how structural factors—cost structures (C_{Sk}), (C_{M1}), competitive intensity, and bargaining leverage (α_{ij})—interact with information inequities (β_{ij}) and AI-driven optimization (Υ) to shape equilibrium prices (P_{SMk}), (P_{MR1}), profit distribution (π_{SK}), (π_{M1}), (π_{Rm}), and agreement rates (P_{SM},P_{MR},π_S, π_M, π_R). The model's dynamic bargaining framework (time value) (δ= 0.9) and multi-issue utility function highlight the importance of iterative negotiations and trade-offs across price, delivery, and quality standards in achieving integrative outcomes.

The case study of Siemens PLC product negotiations validates the model's predictions, demonstrating that retailers with higher bargaining leverage (α_{MR}= 0.6) capture up to 25% more surplus (€37.5), whereas full information transparency (β_{ij}=1.0) enhances upstream profits by 25% (€25.0 for suppliers and 20.0 for manufacturers) (Table 3). These findings align with Gurnani & Shi (2006) and Hu & Ma **(2019)**, emphasizing that structural factors such as cost efficiency and market positioning outweigh individual negotiator traits. The integration of AI (Υ = 0.5) improves negotiation efficiency by 15–20% (Ivanov et al., 2018), reducing rounds and fostering balanced outcomes (Figure 3). However, challenges in achieving information transparency and ethical concerns in AI deployment, such as ensuring equitable outcomes and preventing overreliance, underscore the need for robust guidelines.

For supply chain managers, these insights highlight the importance of optimizing cost structures, enhancing information-sharing, and leveraging AI to streamline negotiations. The model's ability to predict outcomes across diverse scenarios (Tables 4 and 5) provides a practical tool for negotiating Siemens PLC products and similar industrial equipment, thus fostering resilience in complex supply chains.

Future research should explore dynamic bargaining under stochastic demand by incorporating random variations in (R_m) or (C_{Sk}) to reflect market volatility. Multiparty negotiations involving more than two firms per tier could extend the model's applicability and address complexities in global supply chains. Additionally, investigating ethical AI frameworks (e.g., transparency in (Υ)-driven recommendations) and behavioral factors, such as risk aversion (Katok & Wu 2009), will enhance the understanding of negotiation dynamics. By addressing these gaps, researchers can develop more comprehensive models to guide sustainable and equitable supply chain negotiations in increasingly interconnected global markets.

8. Future research

This study's advanced mathematical model, rooted in the Balanced Principal (BP) framework (Gurnani & Shi 2006) and Game Theory (Nash, 1950; Rubinstein, 1982), provides a robust foundation for analyzing multi-tier supply chain negotiations. However, several avenues warrant further exploration to address the dynamic, time-sensitive, and interconnected nature of modern supply chains. Future research should focus on temporal dynamics, real-time technologies, long-term relationship dynamics, and emerging ethical and behavioral considerations to develop more comprehensive models and guide practitioners in optimizing bargaining strategies.

Temporal Dynamics in Bargaining: The model's dynamic bargaining component, incorporating Rubinstein's (1982) alternating offers framework with a discount factor (δ (0, 1)) (time value), highlights the impact of time pressure on negotiation outcomes. Future studies should extend this by modeling stochastic temporal variations, such as fluctuating demand (R_m) or costs (C_{Sk}), (C_{M1}), to reflect market volatility. For instance, incorporating time-varying parameters into equilibrium price equations could capture how supply chain disruptions (e.g., geopolitical events or supply shortages) affect bargaining strategies over multiple rounds. This would enhance the applicability of the model to dynamic, real-world contexts.

Real-time Technologies and AI Optimization: The model's AI influence parameter (ϒ) demonstrates a 15–20% improvement in negotiation efficiency through real-time data analysis (Ivanov et al., 2018). Future research should explore advanced AI algorithms, such as reinforcement learning or generative models, to optimize concession strategies in multi-issue negotiations. Investigating block-chain-based platforms for real-time transparency can address information inequities (β_{ij}), enabling more equitable outcomes. Additionally, modeling the scalability of AI-driven tools across global supply chains, particularly for Siemens PLC products, could quantify their impact on reducing negotiation time and costs.

Long-Term Relationship Dynamics: The current model focuses on single- or multi-round negotiations, but does not fully address long-term relational factors. Future studies should incorporate trust and reputation dynamics, building on Ivanov et al., (2019), who found that trust increases joint value by up to 15%. A repeated-game framework could extend the model to account for iterative interactions, where firms adjust (α_{ij}) based on prior cooperation or defection. This would provide insights into how long-term relationships influence profit distribution (π_{Sk}), (π_{M1}), and (π_{Rm}) and foster sustainable collaboration in multi-tier supply chains.

Multiparty and multi-issue complexity: The model's multi-issue utility function($U_{ij}=W_1.\pi_{ij}+W_2.Q_{ij}+W_3.T_{ij}$) captures trade-offs across price, quality, and delivery. Future research should extend this to multiparty negotiations involving more than two firms per tier, reflecting complex global supply chains. For example, incorporating coalition formation or network effects could enhance a model's ability to predict outcomes in large-scale negotiations. Additionally, dynamically varying weights (W_1,W_2,W_3) based on market conditions can better capture strategic priorities.

Ethical and Behavioral Considerations: The integration of AI (ϒ) raises ethical concerns such as ensuring equitable outcomes and preventing over-reliance (Ivanov et al., 2018). Future studies should develop frameworks for ethical AI deployment, ensuring transparency in (ϒ)-driven recommendations. Additionally, incorporating behavioral factors, such as risk aversion or cognitive biases (Katok & Wu 2009; Bendoly et al., 2006), into the model could refine predictions of negotiator behavior. For instance, adjusting (α_{ij}) to reflect risk preferences could capture how conservative strategies impact outcomes.

Sustainability and Resilience: Future research should explore how sustainability goals influence bargaining. Extending the model to include environmental costs or carbon constraints in the utility function (U_{ij}) can align negotiations with sustainable supply chain practices. Additionally, modeling resilience to disruptions (e.g., supply shortages) through stochastic parameters could enhance the model's robustness in volatile markets.

By addressing these issues, researchers can develop more comprehensive models that capture the evolving nature of supply chain negotiations. These advancements will provide practitioners with actionable strategies to optimize bargaining in dynamic, technology-driven, and sustainable environments, fostering resilience and equity in global supply chains.

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