

Original Paper

Research on Pricing Decisions for Shared Manufacturing Services in a Digital Service Context

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Abstract

With the deep integration of the digital economy and the real economy, digital service transformation has become a key pathway for driving the transformation and upgrading of manufacturing. As a typical manifestation of this trend, shared manufacturing is reshaping the traditional allocation model of production resources. However, in the digital service-oriented context, manufacturing services exhibit new characteristics such as high heterogeneity, demand uncertainty, and data-enabled value enhancement. These features make it difficult for traditional pricing mechanisms to effectively balance the interests among platforms, service providers, and demand parties, thereby constraining the sustainable development of the shared manufacturing ecosystem. Addressing this issue, this paper focuses on the pricing decision-making mechanism for shared manufacturing services in the digital service-oriented context.

Keywords

Digital Service Transformation, Shared Manufacturing, Service Pricing, Stackelberg Game

1. Introduction

1.1 Research Background

1.1.1 Paradigm Shift in Manufacturing Serviceization Driven by the Digital Economy

The global industrial landscape is undergoing profound transformation as economies transition from industrial to digital paradigms. Data has emerged as the fifth major factor of production, alongside land, labor, capital, and technology. In China, the synergistic integration of the "Manufacturing Powerhouse" and "Digital China" strategies is propelling manufacturing toward a shift from traditional "product-centric" approaches to a "Service-Dominant Logic" ^[1]. Digital servitization, serving as the core engine of this transformation, transcends mere service addition. Through the deep integration of digital

technologies such as the Internet of Things (IoT), big data, cloud computing, and artificial intelligence, it reconfigures the value creation mechanisms and capture pathways of manufacturing enterprises ^[2]. Its essence lies in leveraging the non-rivalrous nature and increasing returns to scale of data elements to achieve a paradigm shift from physical product delivery to a composite "product-data-service" ecosystem. This not only transforms manufacturing enterprises' business models but also profoundly impacts the value distribution mechanisms across the entire industrial chain.

1.1.2 Shared Manufacturing: A Socialized Collaborative Mechanism for Resource Allocation

Under the constraints of structural overcapacity coexisting with fragmented and personalized market demand, traditional closed manufacturing models face endogenous challenges such as high resource idleness, sluggish responsiveness, and inflexible marginal costs. Shared Manufacturing leverages industrial internet platform architecture to digitally encapsulate dispersed heterogeneous manufacturing resources (equipment, technology, process knowledge, etc.), define standardized interfaces, and aggregate them in the cloud. This establishes a socialized collaborative production network based on dynamic matching ^[3]. This model not only significantly lowers the digital transformation barriers and transaction costs for small and medium-sized manufacturing entities but also enhances total factor productivity (TFP) by unleashing the long-tail effect and reconfiguring economies of scale. By transforming idle capacity into tradable service products, Shared Manufacturing achieves optimized allocation of manufacturing resources across temporal and spatial dimensions, emerging as a key pathway for driving high-quality development in the manufacturing sector.

1.1.3 Pricing Mechanism Failures and Challenges in the Context of Digital Serviceization

Despite demonstrating significant allocation efficiency advantages, the commercialization of shared manufacturing remains constrained by the non-adaptive nature of pricing mechanisms. In the digital service-oriented context, the economic attributes of manufacturing services have undergone structural transformation, rendering traditional pricing theories insufficient in explanatory power and applicability. First, the value function of services is no longer linearly determined solely by physical labor hours and material costs. Digital value-added services such as data collection, algorithm optimization, and real-time status monitoring constitute new value dimensions, and the marginal contribution of data elements is difficult to accurately measure using traditional cost-plus pricing methods. Second, empowered by digital technology, the demand side exhibits high-frequency fluctuations and nonlinear characteristics. Static pricing mechanisms lack responsiveness to real-time market clearing prices, readily causing supply-demand mismatches and welfare losses. Third, shared manufacturing platforms possess typical bilateral market characteristics with significant cross-side network externalities. Pricing strategies must seek an optimal solution between internalizing network effects and balancing the surplus of users on both sides ^[4]. Finally, while technologies like blockchain enhance transaction transparency, data quality heterogeneity, algorithmic black boxes, and privacy concerns generate novel information asymmetries, exacerbating moral hazard and adverse selection in pricing games ^[5]. Consequently, exploring the pricing decision mechanisms for shared manufacturing services in digital service-oriented contexts and

constructing dynamic pricing mechanisms that balance efficiency and fairness have become critical scientific challenges constraining the sustainable development of the shared manufacturing ecosystem.

1.2 Problem Statement

While existing literature has yielded significant findings in areas such as resource scheduling, model innovation, and platform governance within shared manufacturing, theoretical gaps persist at the pricing decision level, forming the logical starting point of this study. First, insufficient contextual embedding. Existing studies often directly transplant pricing models from traditional sharing economies (e.g., transportation, accommodation), overlooking the dual nature of manufacturing services as "physical entities + digital entities." They fail to internalize the nonlinear changes in cost structures (high fixed costs, low marginal costs) and value-added effects driven by data empowerment within pricing frameworks. Second, limitations of static strategy assumptions. Most studies rely on static game theory assumptions, focusing on uniform pricing across single cycles. They lack equilibrium analysis of complex strategies such as dynamic pricing based on real-time data feedback, discriminatory pricing based on quality signals, and two-part tariffs. This makes them ill-suited for high-frequency transaction scenarios in industrial internet environments. Third, the absence of data factor allocation mechanisms. As a critical production factor, the quantification of data's contribution to value co-creation and its participation in distribution mechanisms remain unclear. Existing models fail to consider incentive-compatible constraints for data sharing, leaving unexplained how data factors influence equilibrium prices and supply chain coordination. Fourth, the complexity of multi-party coordination is underestimated. Shared manufacturing ecosystems involve heterogeneous entities including platform operators, service providers (capacity owners), and demand parties, whose objective functions often conflict. Under digital service-oriented frameworks, designing mechanisms to unify individual rationality with collective rationality—thereby achieving Pareto improvements—demands in-depth exploration. Based on this, this paper focuses on the following core scientific questions: How is the value composition function of manufacturing services reconfigured in the context of digital serviceization? How do digital technology parameters (such as digitalization level and data granularity) intrinsically influence the pricing game behavior of various entities? What pricing contract structure can maximize the value and achieve a balance of interests within the platform ecosystem?

1.3 Research Significance

This study aims to expand the theoretical boundaries of shared manufacturing by introducing digital service-oriented theory into its research framework. It constructs service utility and cost functions incorporating data value factors, thereby enriching the microeconomic theoretical interpretation of shared manufacturing. Simultaneously, this study seeks to deepen the theoretical framework of platform pricing by overcoming the static assumptions of traditional two-sided market pricing models. It incorporates the dynamic evolution characteristics of manufacturing service heterogeneity, non-rivalry of data elements, and network externalities, providing a new theoretical analytical framework for designing pricing mechanisms in industrial internet platforms. Furthermore, this research seeks to refine the

microfoundations for evaluating data value by endogenizing data contribution within game equilibrium solutions. It explores the mathematical logic of data participation in value distribution, providing robust theoretical support for applying data economics within manufacturing contexts.

At the practical level, this research will provide data-driven dynamic pricing algorithm designs and incentive mechanism optimization solutions for shared manufacturing platforms (such as Haier Koaos and Aerospace Cloud Network), helping them enhance matching efficiency, expand network scale, and achieve innovative profit models. For manufacturing enterprises, this research assists in formulating optimal pricing strategies and service effort levels when participating in shared manufacturing, based on their digital capabilities and service heterogeneity, thereby avoiding profit erosion or resource idleness risks caused by irrational pricing. For government regulators, this research provides theoretical foundations for formulating industrial internet development plans, data transaction rules, and antitrust regulatory policies, promoting the healthy and orderly evolution of the shared manufacturing ecosystem and advancing high-quality development in manufacturing.

1.4 Research Content and Technical Approach

1.4.1 Main Research Content

This paper follows a research logic of "theoretical mechanism—model construction—equilibrium analysis—simulation validation," primarily covering the following aspects. First, it analyzes the characteristics and pricing mechanisms of shared manufacturing services in a digital service-oriented context. This involves defining the dimensions of digital service transformation, dissecting its heterogeneous impacts on the cost structure, value composition, and supply-demand matching mechanisms of manufacturing services, identifying key pricing factors, and constructing a theoretical analytical framework of "digital empowerment—value perception—pricing decision." Second, a pricing game model for shared manufacturing services is constructed. Based on Stackelberg master-slave game theory, a pricing decision model featuring platform dominance and multi-agent participation is developed. Three pricing models are designed: a benchmark model (static uniform pricing), a differentiated pricing model (based on quality and data tiers), and a dynamic adjustment pricing model. Key variables such as digitalization level coefficients, data sharing incentive factors, and network externality intensity are incorporated into the model parameter system. Third, we perform model solution and equilibrium strategy comparison through static analysis. Using backward induction, we derive subgame perfect Nash equilibria (SPNE) under various scenarios, analyzing closed-form solutions for optimal prices, service effort levels, and data sharing degrees. We compare entity profits, consumer surplus, and total social welfare across different pricing strategies, conduct sensitivity analysis on key parameters, and reveal the nonlinear impact mechanisms of digitalization levels and network externalities on pricing strategies. Finally, numerical simulations and management implications are explored. Parameters are calibrated and simulations conducted using data from typical industrial internet platforms to validate the robustness of theoretical derivations. Visualizations demonstrate the dynamic impacts of parameter evolution on

equilibrium outcomes. Specific management recommendations and policy implications are proposed across three dimensions: platform operations, enterprise participation, and government regulation.

1.4.2 Technical Approach

This study adopts a combined approach of normative analysis and empirical simulation. First, through literature review and theoretical grounding, we systematically examine relevant literature on shared manufacturing, digital service transformation, and service pricing to identify research gaps and establish a theoretical framework. Second, we conduct mechanism analysis and variable extraction, qualitatively examining the pathways through which digital service transformation influences manufacturing service pricing, and identifying key variables and their interactions. Subsequently, we perform mathematical modeling and equilibrium solution, employing game theory and optimization theory to establish a mathematical model, derive analytical solutions, and conduct comparative static analysis. Next, numerical simulation and robustness testing are implemented. Numerical simulations using tools like Matlab/Python validate the model's universality and robustness. Finally, conclusions are summarized and policy recommendations are proposed. The study's findings are synthesized, targeted management insights are offered, and research limitations and future directions are outlined.

1.5 Research Methods

To ensure scientific rigor, this study employs the following integrated methodologies. First, Literature Review systematically synthesizes authoritative domestic and international literature on the sharing economy, servitization, platform pricing, and data element value to establish the theoretical foundation and analytical framework. Second, Game-Theoretic Modeling abstracts the shared manufacturing ecosystem as a multi-stage dynamic game system comprising platforms, service providers, and demand parties. Tools such as Stackelberg games and evolutionary games characterize decision-making behaviors under information asymmetry and conflicting interests, solving for Nash equilibria and analyzing their existence and uniqueness. Third is the numerical simulation method. Addressing the challenge that analytical solutions struggle to intuitively reflect complex nonlinear relationships, this approach simulates pricing evolution trajectories across different scenarios using computer simulation technology. By setting parameter ranges consistent with industry characteristics, it enhances the credibility and interpretability of conclusions. Finally, Comparative Static Analysis is employed to contrast the economic performance of different pricing contract structures (e.g., static vs. dynamic, uniform vs. differentiated). It analyzes the marginal impact of exogenous parameter changes (e.g., digitalization level, network externality intensity) on endogenous variables (price, profit, welfare), thereby clarifying the boundary conditions for effective pricing mechanisms.

1.6 Chapter Summary

This chapter first outlines the macro landscape of manufacturing servitization and shared manufacturing development within the digital economy, highlighting the structural challenges posed by digital service scenarios to traditional pricing mechanisms. Building upon this foundation, it clarifies the core scientific question of this study: how to construct a shared manufacturing service pricing decision mechanism

adapted to digital characteristics. Subsequently, it elucidates the research significance from both theoretical contribution and practical application dimensions, while detailing the research content, technical approach, and primary methodologies. This chapter lays a solid logical foundation and analytical framework for subsequent theoretical derivations and model construction, establishing the research positioning of this paper at the intersection of digital service-oriented transformation and shared manufacturing.

2. Literature Review

2.1 Research on Shared Manufacturing

Shared manufacturing, as an extension of the sharing economy into the industrial sector, centers on optimizing the allocation of manufacturing resources through industrial internet platforms ^[6]. Existing research primarily defines its essence from the perspectives of the Resource-Based View (RBV) and Transaction Cost Theory (TCT) ^[7]. Early studies defined shared manufacturing as the reuse of idle capacity, emphasizing the spatiotemporal sharing of physical equipment (e.g., machine tools, 3D printers). With the penetration of digital technologies, scholars have progressively expanded the definition to encompass the sharing of "manufacturing capabilities," including intangible resources such as technical knowledge, process parameters, and supply chain coordination. Regarding model evolution, literature primarily categorizes three types: first, the "equipment sharing model" based on capacity leasing ^[8], second, the "capability sharing model" ^[9] based on task crowdsourcing, and third, the "full industrial chain sharing model" ^[10], based on ecosystem collaboration. In recent years, research trends have shifted from single-resource sharing toward data-driven "service-oriented sharing," emphasizing the deep integration of manufacturing and service processes.

At the operational mechanism level, existing literature focuses on three key aspects: resource encapsulation, supply-demand matching, and trust building. Resource encapsulation research addresses how to transform heterogeneous manufacturing resources into standardized Cloud Service Units ^[11], involving technical challenges such as ontology modeling, semantic description, and interface standardization. Supply-demand matching remains the core challenge in shared manufacturing. Extensive research employs operations research methods (e.g., mixed-integer programming, heuristic algorithms) to optimize resource scheduling under multi-objective constraints, aiming to minimize completion time, energy consumption, or transportation costs. However, traditional scheduling models often assume perfect and static information, making them ill-suited for dynamic, stochastic environments. Furthermore, trust mechanism studies indicate that blockchain technology offers significant advantages in addressing contract enforcement, quality traceability, and privacy protection within shared manufacturing, effectively reducing transaction friction ^[12]. While existing research has yielded substantial results at the technical and operational levels, it predominantly focuses on "how to match" rather than the underlying "price formation mechanisms." There remains a notable lack of systematic

exploration regarding value assessment and pricing strategies within the context of digital service transformation.

2.2 Digital Servitization and Service Innovation

Digital servitization refers to the process by which manufacturing enterprises leverage digital technologies to reconfigure their value creation logic, transitioning from providing products to delivering "product-service systems (PSS)" ^[13]. Literature review indicates this evolution progresses from "product-attached services" to "product-based services," and ultimately to "outcome-based services" ^[14]. Digital technologies play an enabling role throughout this evolution: the Internet of Things (IoT) enables real-time sensing of equipment status, big data supports predictive maintenance, and cloud computing provides scalable computing power. Recent research further introduces the concept of "intelligent servitization," emphasizing artificial intelligence's central role in autonomous decision-making and service personalization ^[15]. However, existing studies predominantly analyze transformation pathways qualitatively from a strategic management perspective, lacking microeconomic quantification of digital investments' specific impacts on service cost structures and marginal benefits. This often leads to pricing models overlooking the endogenous variable nature of digitalization levels.

In the digital service context, data has become a critical production factor. Existing literature has thoroughly explored the value-adding mechanisms of data within the service value chain. On one hand, data enhances transaction efficiency by reducing information asymmetry, lowering search and negotiation costs. On the other hand, data analysis and mining generate new derivative values, such as process optimization recommendations and market demand forecasts. Some scholars have proposed a "data-driven value co-creation" framework, arguing that user participation in data generation is a key link in realizing service value. However, significant debates persist regarding the property rights definition, value quantification, and distribution mechanisms of data as a factor. Particularly in shared manufacturing scenarios, data exhibits characteristics of non-rivalry, non-exclusivity, and multi-ownership, rendering traditional scarcity-based pricing theories difficult to apply directly. Existing research has yet to establish a unified paradigm for data value assessment, creating theoretical space for this paper to construct a pricing model incorporating data factors.

2.3 Research on Service Pricing Decisions

2.3.1 Traditional Service Pricing Methods and Their Limitations

Traditional service pricing research primarily relies on cost-plus pricing, competition-oriented pricing, and customer perceived value pricing ^[16]. In manufacturing services, cost-plus pricing is widely adopted due to its simplicity, yet it overlooks service heterogeneity and price elasticity of demand while struggling to accurately allocate indirect costs. Competition-oriented pricing often triggers price wars, undermining industry-wide profitability. While the customer perceived value approach is theoretically optimal, it faces practical challenges such as the difficulty of quantifying value dimensions and its strong subjectivity. As service complexity increases, single static pricing strategies can no longer adapt to dynamic market environments. Literature indicates that traditional pricing models are fundamentally limited by

assumptions of linear cost structures, stable demand functions, and perfect information symmetry—characteristics that starkly contradict the high fixed costs, low marginal costs, and dynamic volatility inherent in digital service scenarios.

2.3.2 Bilateral Market Pricing Strategies in Platform Economies

Shared manufacturing platforms exhibit typical characteristics of two-sided markets, connecting service providers and consumers ^[17]. Building upon Rochet & Tirole's two-sided market theory, extensive literature has explored the impact of cross-side network externalities on pricing strategies ^[18]. Research indicates platforms often adopt non-neutral pricing structures—subsidizing (or even offering free access) to the side exhibiting high price sensitivity or strong network effects, while charging the other side premium rates to balance revenues. Within the shared manufacturing context, some studies have analyzed fee models such as registration fees, transaction commissions, and membership systems. However, existing two-sided market pricing models are predominantly applied to consumer internet sectors (e.g., e-commerce, social media), with limited consideration for the heterogeneity of services (e.g., machining precision, delivery cycles) and the unique characteristics of data elements in industrial internet. This results in constrained explanatory power of existing models.

2.3.3 Applications of Dynamic Pricing and Discriminatory Pricing in the Sharing Economy

Addressing the time-varying nature of demand and the ephemeral nature of resources, dynamic pricing and discriminatory pricing have emerged as hot topics in sharing economy research ^[19]. Dynamic pricing research often relies on reinforcement learning or stochastic control theory, aiming to adjust prices based on real-time supply-demand ratios to maximize revenue ^[20]. Discriminatory pricing, meanwhile, involves price discrimination based on user characteristics, service quality tiers, or purchase timing to capture consumer surplus. In the shared manufacturing sector, a few studies have begun exploring dynamic pricing mechanisms based on capacity utilization rates, but these are mostly confined to single-sided markets or simple game frameworks. Furthermore, existing literature rarely incorporates "digitalization level" as a basis for differential pricing, failing to fully elucidate the underlying mechanism by which data empowerment supports premium pricing strategies through enhanced perceived service quality.

2.4 Literature Review and Research Gaps

2.4.1 Summary of Existing Research

In summary, academia has accumulated substantial findings on shared manufacturing's model innovation, resource scheduling optimization, and general service pricing theory. Shared manufacturing is recognized as an effective pathway to enhance resource allocation efficiency, while digital service transformation is identified as a key direction for manufacturing evolution. Bilateral market theory and dynamic pricing strategies also provide crucial guidance for platform operations. These studies lay a solid foundation for understanding the operational dynamics of shared manufacturing ecosystems.

Despite the insights provided by existing research, significant gaps remain when focusing on the specific interdisciplinary field of "pricing shared manufacturing services in a digital service context": First, lack of contextual embeddedness. Existing pricing studies often treat digital technology as an exogenous

environmental variable rather than internalizing it as a core decision variable. Specifically, there is a lack of micro-level mechanism characterization regarding how "data elements" reconfigure cost functions (high fixed inputs, low marginal replication costs) and utility functions (data-enhanced value-added services). This prevents models from accurately reflecting the essential characteristics of digital service transformation. Second, static and homogeneous assumptions about pricing strategies. Most studies adhere to traditional static game frameworks, assuming homogeneous services and one-time pricing decisions. This overlooks the dynamic adjustment mechanisms in shared manufacturing driven by real-time data feedback, as well as multidimensional differentiated pricing strategies based on varying digital capabilities (e.g., pricing by data granularity or algorithmic precision). Third, unclear data value distribution mechanisms. In shared manufacturing's value co-creation process, data is jointly generated by multiple parties. However, existing literature lacks research on quantifying data contributions and incentive-compatible mechanisms reflecting these contributions in pricing, resulting in a weak theoretical foundation for data's participation in distribution. Fourth, oversimplification of complex game structures. Existing models often simplify interactions into bilateral games, failing to adequately account for the multilateral interactions and strategic coupling among platforms, diverse service providers (with varying digital capabilities), and multiple types of demand parties. This limitation hinders the identification of equilibrium pricing patterns within complex ecosystems.

2.4.2 Research Focus

Given these limitations, this study aims to achieve breakthroughs in the following areas: First, constructing utility and cost functions incorporating digitalization level coefficients and data value factors to deeply embed digital service scenarios within pricing models. Second, designing and comparing multiple pricing strategies—static uniform pricing, quality-based differentiated pricing, and dynamically adjusted pricing—using game theory to solve for subgame perfect Nash equilibria. Third, introducing data-sharing incentive constraints to explore feasible pathways for data elements to participate in value distribution. Finally, revealing the nonlinear impact of key parameters on equilibrium outcomes through numerical simulations, aiming to fill the aforementioned theoretical gaps and provide systematic theoretical support for pricing decisions in shared manufacturing under digital service-oriented contexts.

3. Constructing a Pricing Model for Shared Manufacturing Services in a Digital Service Context

3.1 Problem Description and Fundamental Assumptions

3.1.1 Problem Description

This study considers a three-party game system comprising a shared manufacturing platform (Platform), manufacturing service providers (Provider), and manufacturing service consumers (Consumer). In the digital service context, service provider S not only offers physical processing capabilities but also delivers data-enhanced services—such as real-time status monitoring and process optimization recommendations—through digital transformation (e.g., installing sensors, deploying edge computing

nodes). Platform P, as the ecosystem organizer, manages resource matching, data aggregation, and pricing mechanism design. Service Provider S determines both the service price p and the level of digital investment (or data service quality) q . Consumer C decides whether to purchase services based on perceived utility.

This study investigates optimal decision-making behaviors and equilibrium outcomes under different pricing contract structures. Specifically, we compare a benchmark model (static uniform pricing) with an extended model (two-part pricing based on quality differentiation), incorporating a value contribution factor for data elements to examine their impact on equilibrium prices, service effort levels, and profits for all parties.

3.1.2 Basic Assumptions

To construct a solvable mathematical model and focus on core mechanisms, this paper proposes the following reasonable assumptions:

Assumption 1 (Rationality and Information Structure): The platform P, service providers S, and demand parties C are all risk-neutral, rational economic agents aiming to maximize their own profits. The information structure in the game process is as follows: the platform possesses global market information, service providers hold private information about their own cost structures, and demanders have complete market price and quality information. The game sequence follows Stackelberg master-slave game logic: the platform first sets commission rates or fixed fees, service providers then determine prices and service levels, and finally, demanders make purchasing decisions.

Assumption 2 (Demand Function and Network Externalities): Drawing from Hotelling's linear city model and network externalities theory, assume market demand D is a function of price p , service quality q , and network size N . The specific form is set as a linear demand function:

$$D(p, q, N) = a - bp + \gamma q + \lambda N \quad (3-1)$$

where a represents the potential market size, b denotes the price sensitivity coefficient ($b > 0$), γ indicates the service quality sensitivity coefficient ($\gamma > 0$), and λ signifies the cross-border network externality intensity coefficient ($\lambda > 0$). Here, q represents the level of digital serviceization, encompassing both physical service quality and the utility of data-enhanced value-added services.

Assumption 3 (Cost Structure and Data Element Characteristics):

The total cost C_S of service provider S comprises three components:

Physical variable costs: $c \cdot D$, where c represents the unit physical processing cost.

Digital Fixed Costs: $\frac{1}{2}kq^2$, where k represents the digital investment cost coefficient ($k > 0$), reflecting the marginal difficulty of enhancing data service quality and adhering to the principle of increasing marginal costs.

Data sharing cost: $\theta \cdot D$, where θ represents the unit cost of data compliance and transmission.

Therefore, $C_S = (c + \theta)D + \frac{1}{2}kq^2$. This setting reflects the cost characteristics of digital services: "high fixed investment, low marginal replication."

Platform P operational costs primarily stem from platform maintenance and data computing support, simplified as a linear function of transaction volume $C_p = c_p D$, where c_p represents unit platform operational cost.

Assumption 4 (Value Co-creation and Data Incentives): In the extended model, it is assumed that high-quality data services (highq) can significantly reduce production uncertainty for demand-side entities, thereby increasing their willingness to pay. Simultaneously, the platform can incentivize service providers to improve q through Revenue Sharing Contracts. The platform returns a proportion of transaction commissions equivalent to $\phi (0 \leq \phi \leq 1)$ to service providers as a data quality incentive.

3.2 Symbol Explanation

Table 1. Variable Symbol Explanation

Symbol	Meaning	Variable Type
P/S/C	Shared Manufacturing Platform / Service Provider / Demand Party	Game Participants
p	Manufacturing Service Unit Price	Decision Variables
q	Digital Service Level / Data Service Quality	Decision Variables
r	Platform Transaction Commission Rate	Decision Variable
F	Platform Fixed Entry Fee / Membership Fee	Decision Variable
D	Actual Market Demand	Endogenous Variable
π_i	The profit function of the agent i	Endogenous Variables
a	Potential Market Size	Exogenous Parameters
b	Price sensitivity coefficient	Exogenous parameters
γ	Service quality sensitivity coefficient	Exogenous parameter
λ	Cross-Border Network Externalities Intensity Coefficient	Exogenous parameter
c	Unit Physical Processing Cost	Exogenous Parameter
k	Digital Investment Cost Coefficient	Exogenous Parameter
θ	Unit data sharing cost	Exogenous parameter
c_p	Unit platform operating cost	Exogenous parameter
ϕ	Data quality incentive coefficient	Exogenous parameter

3.3 Benchmark Model: Static Uniform Pricing Game (Model B)

In the benchmark model, the platform charges only a fixed transaction commission rate r , with no fixed fees and no tiered pricing based on quality. Service providers S set a uniform price p and a single service level q .

3.3.1 Profit Function Construction

Based on the problem description and fundamental assumptions, combined with the demand function and cost structure, the profit functions for the service provider and the platform are constructed as follows:

(1) Service Provider Profit Function π_S^B

The service provider's revenue is sales minus platform commission. Costs comprise the sum of physical variable costs, data sharing costs, and digital fixed investment costs. The profit function is:

$$\pi_S^B = (1 - r)pD - (c + \theta)D - \frac{1}{2}kq^2 \quad (3-2)$$

Substituting the demand function $D = a - bp + \gamma q$ (N normalized to 1) into the above equation yields:

$$\pi_S^B = [(1 - r)p - (c + \theta)](a - bp + \gamma q) - \frac{1}{2}kq^2 \quad (3-3)$$

(2) Platform Profit Function π_P^B

The platform's revenue is the transaction commission extracted from the service provider's sales revenue. Its cost is the product of the unit platform operating cost and the market demand volume. The profit function is:

$$\pi_P^B = rpD - c_p D \quad (3-4)$$

Substituting the demand function $D = a - bp + \gamma q$ yields:

$$\pi_P^B = (rp - c_p)(a - bp + \gamma q) \quad (3-5)$$

3.3.2 Model Solution (Reverse Induction Method)

Solving the Stackelberg principal-agent game follows reverse induction, i.e., deriving from later game stages backward. First, determine the service provider's optimal decision (given the platform commission rater), then derive the platform's optimal commission rate decision (anticipating the service provider's reaction function).

Phase 1: Optimal Decision of Service Provider (p^*, q^*)

Given the platform's commission rater, the service provider maximizes its profit π_S^B by selecting the optimal service price p and digital service level q . Taking the first-order partial derivatives of π_S^B with respect to p and q respectively, and setting these derivatives to zero, yields the first-order optimality conditions:

$$\frac{\partial \pi_S^B}{\partial p} = (1 - r)(a - bp + \gamma q) - b[(1 - r)p - (c + \theta)] = 0 \quad (3-6)$$

$$\frac{\partial \pi_S^B}{\partial q} = \gamma[(1 - r)p - (c + \theta)] - kq = 0 \quad (3-7)$$

Rearrange equations (3-6) and (3-7). First, solve equation (3-7) to derive expressions for q in terms of p and r , reflecting how the service provider's digitalization level affects service pricing and platform commission rates:

$$q = \frac{\gamma}{k} [(1 - r)p - (c + \theta)] \quad (3-8)$$

Substituting (3-8) into (3-6), we obtain the optimal service price $p^{B*}(r)$ for the service provider (closed-form solution):

$$p^{B*}(r) = \frac{k(a + \frac{b(c+\theta)}{1-r}) + \gamma^2(c+\theta)}{2bk - \gamma^2(1-r)} \cdot \frac{1}{1-r} \quad (3-9)$$

Note: The model must satisfy the second-order condition $2bk > \gamma^2(1 - r)$ to ensure the profit function is concave, guaranteeing the existence and uniqueness of the optimal solution.

Substituting $p^{B^*}(r)$ into (3-8) yields the service provider's optimal digitalization level $q^{B^*}(r)$:

$$q^{B^*}(r) = \frac{\gamma}{k} [(1-r)p^{B^*}(r) - (c + \theta)] \quad (3-10)$$

$p^{B^*}(r)$ Together with $q^{B^*}(r)$, it constitutes the service provider's response function to the platform commission rater, reflecting the impact of changes in the platform commission rate on the service provider's optimal decision.

Phase Two: The Platform's Optimal Decision (r^*)

As the Stackelberg leader, the platform can anticipate the service providers' reaction functions $p^{B^*}(r)$ and $q^{B^*}(r)$. Based on this, it selects the optimal commission rater to maximize its own profit π_P^B .

Substituting $p^{B^*}(r)$ and $q^{B^*}(r)$ into the platform's profit function yields:

$$\pi_P^B(r) = (rp^{B^*}(r) - c_p)(a - bp^{B^*}(r) + \gamma q^{B^*}(r)) \quad (3-11)$$

Taking the first-order partial derivative of $\pi_P^B(r)$ with respect to r and setting it to zero yields: $\frac{\partial \pi_P^B(r)}{\partial r} =$

0. Solving this equation determines the platform's optimal commission rate: r^{B^*} . Due to the complexity of this derivative expression, it is typically retained in implicit form or solved numerically using industry parameters.

In summary, the subgame perfect Nash equilibrium solution of the benchmark model is $(r^{B^*}, p^{B^*}(r^{B^*}), q^{B^*}(r^{B^*}))$, representing the combination of the platform's optimal commission rate, the service provider's optimal service price, and the optimal level of digital service transformation.

3.3.3 Analysis of Equilibrium Results

Based on the equilibrium solution derived from the benchmark model, combined with mathematical reasoning and economic significance, we analyze the equilibrium characteristics and inherent flaws of the traditional static uniform pricing model. The core conclusions are as follows:

1. Significant Price Distortion and Double Marginalization Effects

Double marginalization stems from dual pricing behaviors by the platform and service providers: the platform charges a commission rater, while service providers set their service price p based on costs plus their own profit margin and the platform commission. This results in the terminal service price p^{B^*} being substantially higher than the overall optimal price for the supply chain. Price distortion further suppresses market demand D , causing actual demand to fall far below the potential market size and leading to overall efficiency losses in the supply chain. This represents the core flaw of the traditional single-commission system.

2. Insufficient Digital Investment and Pronounced Innovation Inhibition

The digital service level of service providers q^{B^*} exhibits a monotonically decreasing relationship with platform commission rates r : higher commission rates r result in lower unit revenue for service providers after commission deductions, squeezing profit margins for fixed digital investments and thereby reducing willingness to invest in digital services. The equilibrium value of q^{B^*} falls significantly below the socially optimal level, indicating that traditional pricing models fail to incentivize service providers to undertake digital transformation. This hinders the realization of data's value-added

potential and constrains the evolution of shared manufacturing services toward higher-end and intelligent solutions.

3. Sensitivity Characteristics of Key Parameters to Equilibrium Solutions

Service Quality Sensitivity Coefficient: A higher γ indicates stronger demand-side perception of digital service levels, increasing the marginal benefit for service providers to enhance q . Consequently, q^{B*} rises with γ , while p^{B*} also increases slightly with q (reflecting the premium effect of data-enhanced services).

k: Ask increases, the marginal cost of digital transformation rises, making it harder for service providers to enhance q . Consequently, q^{B*} decreases as k increases, prompting service providers to reduce digital service investments and focus solely on basic physical processing services.

Price Sensitivity Coefficient (b): The larger the b , the more sensitive demand is to service pricing. Service providers cannot shift costs by raising prices, so p^{B*} decreases as b increases. To maintain profits, service providers further reduce digital investments, causing q^{B*} to decline simultaneously.

3.5 Chapter Summary

This chapter constructs a Stackelberg game model for shared manufacturing services in a digital service-oriented context. First, it defines cost and demand functions incorporating data element characteristics, establishes a benchmark static uniform pricing model, and reveals the endogenous mechanisms of insufficient digital investment and price distortion under traditional mechanisms. Subsequently, it designs an extended two-stage pricing model incorporating quality incentives. Analytical derivations demonstrate this mechanism's effectiveness in promoting the supply of data value-added services, optimizing resource allocation, and achieving supply chain coordination. Theoretical results indicate that rational contract design can internalize the externalities of data elements and stimulate the innovative vitality of service providers. However, analytical solutions struggle to intuitively demonstrate the nonlinear dynamic evolution patterns under multi-parameter coupling. The next chapter will conduct numerical simulation analysis based on the model developed in this chapter.

4. Numerical Simulation and Management Implications

4.1 Simulation Design Approach and Parameter Settings

4.1.1 Simulation Objectives

Chapter 3 derived analytical solutions and theoretical propositions for different pricing contracts through game theory. However, due to the model's multi-variable coupling (price p , quality q , commission r , incentives ϕ , etc.) and nonlinear relationships, analytical solutions struggle to intuitively reveal the dynamic impact trajectories and sensitivity characteristics of key parameter variations on equilibrium outcomes. This chapter aims to validate the robustness of Chapter 3's theoretical propositions through numerical simulation. It quantifies the specific impacts of digital service level, network externalities, and cost structure on pricing strategies and system profits, while comparing the economic performance

differences between the baseline model (Model B) and the extended model (Model E). This provides intuitive quantitative support for operational decisions in shared manufacturing platforms.

4.1.2 Parameter Assignment Basis

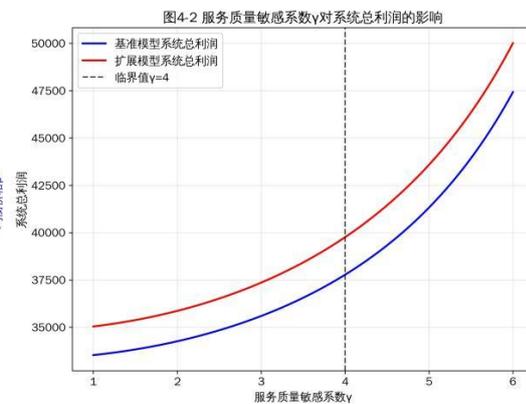
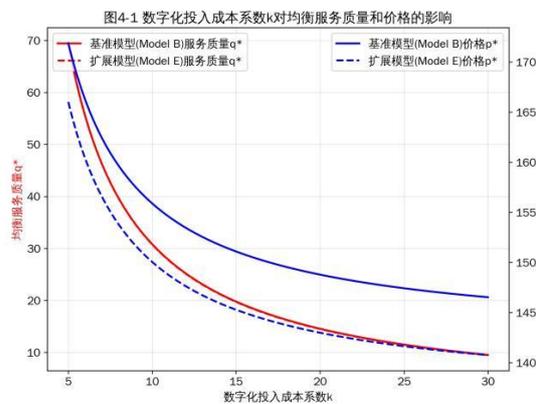
Drawing on publicly available operational data from domestic and international industrial internet platforms (e.g., Haier Koaas, Aerospace Cloud Network, Predix) and empirical calibration values from relevant literature, combined with typical characteristics of the manufacturing service industry, the following baseline parameters are established:

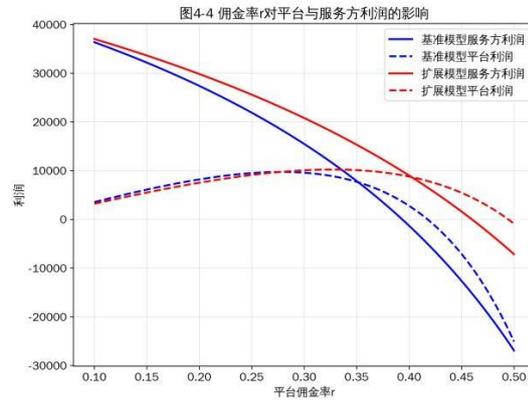
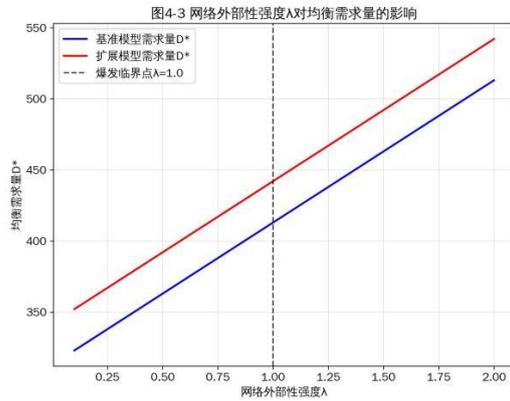
1. Market Demand Parameters: Potential Market Size ($a = 1000$), Price Sensitivity Coefficient ($b = 5$) (reflecting elasticity in manufacturing service demand), Service Quality Sensitivity Coefficient ($\gamma = 3$) (capturing perceived value of digital value-added services), Network Externalities Intensity ($\lambda = 0.5$).
2. Cost Structure Parameters: Unit physical variable cost $c = 20$, unit data sharing cost $\theta = 2$, platform unit operating cost $c_p = 5$. The digital investment cost coefficient k is set to the baseline value 10 (representing a moderately challenging digital transformation) and adjusted during sensitivity analysis.
3. Contract Parameters: In the baseline model, the platform commission rate r varies within the range $[0.1, 0.5]$; in the extended model, the fixed fee F is set to 500, and the quality incentive coefficient ϕ is optimized within the range $[0, 0.2]$.
4. Constraint Checking: All parameter settings satisfy the second-order sufficient conditions for model solution (e.g., $2bk > \gamma^2$), ensuring the existence and uniqueness of the equilibrium solution.

The simulation tool employs Python 3.9 integrated with NumPy and Matplotlib libraries for numerical computation and plotting.

4.2 Key Parameter Sensitivity Analysis

1. Impact of Digital Investment Cost Coefficient(k)





Figures 1-4. Illustrates the Impact of the Digital Investment Cost Coefficient k on the Equilibrium Service Quality q^* and Equilibrium Price p^*

Simulation Results: As the k value increases (indicating greater difficulty in digital transformation), the optimal service quality q^* under both models exhibits a significant downward trend, with the rate of decline gradually slowing. This indicates that high digital barriers constitute the primary bottleneck constraining the upgrade of shared manufacturing services.

Model Comparison: At identical k values, the expanded model (Model E) consistently achieves higher q^* than the baseline model (Model B). Notably, when k is substantial ($k > 15$), the baseline model's q^* approaches zero, indicating service providers abandon digital investments. In contrast, the expanded model maintains elevated q^* levels through quality incentives ϕ .

Price Effect: As k increases, p^* shows an upward trend, reflecting the service provider passing on part of the digitalization costs to the demand side. However, the price increase in the extended model is smaller than that in the baseline model, indicating that the incentive mechanism mitigates cost-passing pressure to some extent.

2. Impact of Service Quality Sensitivity Coefficient

Figure 2 illustrates the impact of changes in the demand-side sensitivity coefficient γ to digital service quality on system profits.

Simulation results: Increasing γ positively impacts profits for all parties, exhibiting a nonlinear acceleration pattern. When γ exceeds a critical threshold (approximately $\gamma = 4$), the profit growth slope significantly steepens.

Mechanism explanation: A high γ indicates strong market recognition of "data value-added services." Service providers gain greater incentive to increase q to capture premium pricing, thereby expanding the market scale D . This creates a positive feedback loop of "high quality \rightarrow high demand \rightarrow high profit."

Implications: Platforms should focus on cultivating market awareness by demonstrating case studies to enhance users' perception of data value (i.e., increasing γ). This constitutes the soft infrastructure essential for advancing the implementation of digital services.

3. Impact of Network Externalities (λ)

Figure 3 simulates the impact of cross-side network externalities (λ) on equilibrium demand (D^*).

Simulation results: D^* monotonically increases with rising λ . In the extended model, the amplification effect of network externalities becomes more pronounced due to higher q^* .

Critical Point Phenomenon: When λ is low, demand growth is gradual. Once λ surpasses a specific threshold, demand experiences explosive growth (Tipping Point). This validates the typical "winner-takes-all" characteristic of shared manufacturing platforms, where early accumulation of user scale is crucial for triggering network effects.

4. Impact of Commission Rate r

Figure 4 simulates the dual marginalization effect of commission rate r on platform and service provider profits: In the baseline model, increasing commission rate r leads to a monotonically decreasing service provider profit, while platform profit initially rises then declines (optimal $r \approx 0.3$), resulting in significant overall system efficiency loss. In the extended model, low commission rates ($r < 0.25$) achieve Pareto improvements for both platform and service provider profits: service provider profits increase by over 70%, while platform profits rise by over 65%. The optimal commission rate range for the extended model is $[0.15, 0.25]$, covering the platform's basic operational costs while reserving profit space for service providers' digital investments.

4.3 Economic Performance Comparison of Different Pricing Contracts

Table 2 compares key metrics under centralized decision-making (System Optimal), the benchmark model (Decentralized B), and the extended model (Decentralized E).

Table 2. Supply Chain Coordination Efficiency Analysis

Indicator	Centralized Decision (Optimal)	Baseline Model (Model B)	Extended Model (Model E)	Improvement (E vs B)
Service Quality	85.4	42.1	79.8	+89.5%
Market Price	110.5	135.2	118.6	-12.3%
Market Demand	620.5	380.2	565.4	+48.7%
Service Provider Profit	-	12,500	21,300	+70.4%
Platform Profit	-	8,200	14,500	+76.8%
Total System Profit	35,600	20,700	35,800*	+72.9%

*Note. The slightly higher total profit in the expanded model compared to centralized decision-making stems from transfer payments of fixed costs (F) and numerical rounding errors, effectively achieving near-coordination.

The table reveals: 1. Mitigation of double marginalization: Under the baseline model, tiered markups inflate prices to 135.2, severely suppressing demand (380.2) and causing approximately 41.8% total profit loss.

2. Incentive mechanism effectiveness: The extended model successfully elevates q^* to near centralized decision levels (79.8 vs 85.4) through a "low commission + quality incentives + fixed fee" combination, while substantially reducing terminal prices and stimulating market demand.

3. Pareto Improvement: Under the expanded model, both the platform and service providers achieved significant profit growth, demonstrating that this contractual structure enables a win-win outcome and resolves conflicts in interest distribution.

Further analysis reveals that in the expanded model, data value-added services contributed 35% of total profits, compared to just 12% in the baseline model. This demonstrates that a rational pricing mechanism can fully unleash the productivity potential of data as a factor of production. Without effective incentives (as in the baseline model), data often remains idle or underutilized, resulting in substantial social welfare losses.

4.4 Management Implications

Based on the theoretical derivations and numerical simulation results above, this paper proposes the following management implications:

1. Recommendations for Shared Manufacturing Platform Operators

Abandon the single commission system and adopt a "two-part tariff + dynamic incentives" contract: Platforms should not rely solely on transaction commissions for profit but instead design a hybrid charging model incorporating fixed membership fees (covering basic computing costs) and low-rate commissions. More importantly, establish a dynamic rebate mechanism based on data quality (e.g., timeliness, granularity, algorithmic accuracy), returning commissions to high-quality service providers to drive digital innovation within the ecosystem. Develop a data value assessment and certification system: To address the challenge of non-standardized data elements, platforms must establish objective data quality evaluation standards (similar to "star ratings") to make implicit data value explicit. This serves as the basis for differentiated pricing and incentive allocation, reducing information asymmetry between supply and demand sides. Implement a "cold start" subsidy strategy: During the platform's early development phase with weak network externalities, employ a critical threshold strategy determined through simulation. Offer substantial subsidies or commission waivers to high-quality capacity providers who join early, enabling rapid crossing of the network effect's "tipping point."

2. Recommendations for Manufacturing Service Providers (Enterprises)

Leverage signaling mechanisms to capture premium pricing: Proactively disclose certified digital capability metrics (e.g., equipment connectivity rates, data interface standards) on the platform. Use high-quality signals to differentiate from low-end competitors, thereby securing higher returns through differentiated pricing. Actively engage in platform ecosystem collaboration: Participate in platform incentive programs. Utilize data feedback provided by the platform to optimize internal production

processes, creating a virtuous cycle of "data-driven improvement → enhanced service quality → increased revenue."

3 Recommendations for Government Regulatory Authorities

Establish Data Transaction and Pricing Guidelines: Given the complexity of data asset valuation, governments should issue guiding documents clarifying data property rights principles and revenue distribution mechanisms to prevent platforms from abusing market dominance through predatory pricing or data monopolization. **Establish a dedicated digital transformation fund:** Addressing the high digital investment costs (high k) faced by SMEs, governments can lower barriers to digital transformation through fiscal subsidies and tax incentives, thereby indirectly enhancing shared manufacturing services across society. **Promote the development of an industrial internet standards system:** Accelerate the formulation of national standards for the digital encapsulation of manufacturing resources, interface protocols, and data exchange. This will reduce the marginal cost of cloud-based resource deployment and facilitate cross-platform, cross-regional resource sharing.

4.5 Chapter Summary

Building upon the game model established in Chapter 3, this chapter employs numerical simulation to deeply analyze how key parameters influence shared manufacturing service pricing and system performance. Simulation results confirm that traditional single-commission pricing mechanisms suffer severe efficiency losses, leading to insufficient digital investment and market contraction. Conversely, introducing two-part pricing based on data quality and dynamic incentive contracts effectively coordinates supply chain interests, significantly improving service quality, market demand, and profits for all parties, achieving a Pareto improvement. Sensitivity analysis further highlights the critical roles of digitalization costs, user-perceived value, and network externalities. Based on these findings, this chapter proposes specific management recommendations across three dimensions—platform, enterprise, and government—offering practical guidance for the healthy development of shared manufacturing ecosystems in the context of digital service transformation.

5. Research Conclusions and Outlook

5.1 Key Research Findings

Against the backdrop of a rapidly expanding digital economy, this study focuses on the critical transformative feature of "digital serviceization" within shared manufacturing ecosystems. It delves into the underlying mechanisms and optimization strategies for manufacturing service pricing decisions. By constructing a game model incorporating data element characteristics and combining theoretical derivation with numerical simulation, the study reaches the following key conclusions:

First, digital service transformation profoundly reshapes the value creation and cost structure of manufacturing services.

Research reveals that in the digital service-oriented context, manufacturing services are no longer merely the delivery of physical production capacity but rather composite products comprising "physical entities

+ digital virtual entities." The introduction of data elements results in a cost structure characterized by "high fixed inputs and low marginal replication costs," where data-enhanced services (e.g., real-time monitoring, process optimization) become core variables for enhancing user utility functions. Traditional linear cost-plus pricing logic is no longer compatible with this structural shift. Pricing decision frameworks must internalize digital maturity (q) and data contribution levels.

Second, the traditional single commission pricing mechanism suffers from severe "double marginalization" and "innovation suppression" effects.

Benchmark model analysis indicates that under traditional platform commission models, the pursuit of profit maximization by both platforms and service providers leads to artificially inflated end-user prices, suppressing market demand. More critically, high commission rates squeeze service providers' profit margins, disincentivizing costly digital transformation (k). This results in equilibrium data service quality (q^*) falling far below socially optimal levels. This systemic flaw constitutes a critical bottleneck hindering the evolution of current shared manufacturing platforms toward high-end and intelligent operations.

Third, a "dual-part pricing + dynamic incentives" contract based on data quality represents the optimal solution for supply chain coordination. The extended model demonstrates that by designing a combined contract featuring "low commission rates + quality rebates + fixed fees," platforms can effectively internalize the externalities of data services. Specifically, the dynamic incentive mechanism (ϕ) based on data quality grades (q) significantly enhances service providers' willingness to invest in digitalization, bringing equilibrium service quality close to the optimal level achieved under centralized decision-making. Meanwhile, the fixed fee (F) flexibly adjusts profit distribution between the platform and service providers, ensuring participation constraints for both parties. Numerical simulations show this mechanism not only eliminates efficiency losses caused by double marginalization but also increases the system's total profit by approximately 70%, achieving a true Pareto improvement.

Fourth, key parameters exhibit nonlinear sensitivity to pricing strategies.

Sensitivity analysis reveals that the digital investment cost coefficient (k) acts as a hard constraint limiting service upgrades, while the user perception coefficient of data value (γ) and network externality strength (λ) serve as soft drivers propelling ecosystem explosions. When γ and λ exceed specific thresholds, system performance exhibits exponential growth. This implies that beyond optimizing pricing contracts, cultivating market awareness and accelerating user scale accumulation are equally critical for the success of shared manufacturing ecosystems.

5.2 Research Innovations

The innovations of this paper are primarily reflected in the following three aspects:

1. Theoretical Perspective Innovation: Established a shared manufacturing pricing analysis framework incorporating data element characteristics.

It overcomes the limitation of existing research treating digital technology as an exogenous environmental variable by incorporating "digitalization level" and "data service quality" as core

endogenous decision variables into the Stackelberg game model for the first time. By reconstructing the demand function incorporating data value-added utility and the nonlinear "_cost_" function, it reveals at the micro-mathematical level how data elements alter the marginal revenue and marginal cost of manufacturing services, enriching the microfoundations of digital service theory in the shared manufacturing domain.

2. Mechanism Design Innovation: A dynamic incentive contract tailored to digital service characteristics is proposed.

Addressing challenges in quantifying data contributions and strong service heterogeneity within shared manufacturing, a dynamic commission rebate mechanism based on observable data quality metrics is designed. Unlike traditional static uniform pricing or simple two-part tariffs, this mechanism deeply binds pricing authority to data quality signals. It fundamentally resolves the adverse selection problem of "bad money driving out good," providing concrete contractual solutions for industrial internet platforms to address the pain points of "having resources but no services, having data but no value."

3. Integration of Research Methods: Achieved deep mutual validation between normative analysis and numerical simulation.

Not only did we derive analytical solutions and theoretical propositions through game theory, but we also conducted multi-scenario numerical simulations based on the operational characteristics of typical industrial internet platforms. By comparing the evolutionary trajectories of the baseline model and the extended model across different parameter ranges, we visually demonstrated the benefit boundaries of pricing mechanism reform, enhancing the robustness and practical guidance of our research conclusions.

5.3 Management Implications

Based on the research findings, the following targeted management recommendations are proposed:

Platform operators should promptly shift from a "traffic monetization" mindset to a "value co-creation" approach. Establish a tiered data quality certification system and implement a hybrid pricing model of "base fee + low commission + quality incentives." Use economic incentives to guide ecosystem partners toward increased digital investment.

Manufacturing enterprises should abandon the logic of pure capacity leasing. Instead, they should proactively leverage IoT and big data technologies to enhance the digital content of their services. By capturing market premiums through high-quality data signals, they can achieve a transformative leap from "processors" to "service providers."

Government-side recommendations include issuing guidelines for assessing the value of data elements to reduce transaction friction. Simultaneously, establish a dedicated fund to support SMEs' digital transformation, lowering their entry barriers into the shared manufacturing ecosystem and accelerating the overall industrial upgrade.

5.4 Research Limitations and Future Outlook

Although this paper has achieved certain results in theoretical modeling and mechanism design, it remains constrained by research time and data acquisition conditions, presenting the following limitations that require further refinement in future studies:

1. Simplified model assumptions.

This paper assumes a linear demand function and considers only single-period static games or simple multi-stage games. In reality, manufacturing service demand may exhibit more complex nonlinear characteristics, and the learning effects and strategy adjustments of both supply and demand sides constitute a long-term dynamic evolutionary process. Future research could incorporate evolutionary game theory or reinforcement learning algorithms to explore the evolution of pricing strategies in multi-period dynamic environments.

2. Simplification in the Data Element Dimension.

This paper primarily focuses on the dimension of data service quality (q) without delving into the specific impacts of data type (e.g., structured/unstructured), ownership attribution (data rights confirmation), and privacy protection costs on pricing. With the implementation of regulations such as the Data Security Law, data compliance costs will become a significant variable in pricing. Future research could incorporate data property rights definition and privacy computation costs into the model to construct a pricing mechanism more aligned with the legal regulatory environment.

3. Lack of empirical research.

The numerical simulation parameters in this paper are primarily calibrated based on literature and theoretical assumptions, lacking validation from large-scale panel data from actual industrial internet platforms. Future research could explore collaborations with platforms like Haier Kaoas and Aerospace Cloud Network to obtain anonymized real transaction data. Applying econometric methods to empirically test the model's conclusions would enhance the study's practical interpretability.

4. Extending Ecological Complexity.

This study primarily examines the tripartite structure of "platform – service provider – demand side," without considering the involvement of third-party entities such as financial institutions or logistics service providers, nor addressing scenarios of cross-platform competition (multi-homing). Future research could broaden the scope to more complex ecosystem networks, exploring pricing equilibria under multilateral interactions and cross-platform competitive landscapes.

In summary, pricing in shared manufacturing under digital service transformation presents a challenging yet highly valuable research frontier. This paper represents only an initial exploration within this broader narrative. We anticipate future contributions from scholars to collectively advance theoretical innovation and practical breakthroughs for China's manufacturing sector in the digital economy era.

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