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A Study on the Mechanism for Realizing the Value of Data Elements in Intelligent Management Scenarios

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ABSTRACT: *As data solidifies its status as a fundamental factor of production, the primary corporate hurdle has pivoted from sheer volume accumulation to contextualized value extraction. Adopting a dual perspective of cost reduction and efficiency enhancement, this paper explores the mechanisms through which data elements realize their value across procurement, production, and marketing processes via a comparative case analysis of JD.com (an integrated self-operated model) and Alibaba (a platform-ecosystem model). The analysis unpacks a consistent trajectory for data value morphogenesis: progressing beyond disjointed information capture, through algorithmic synthesis and alignment, toward tangible operational outcomes. Specifically, the procurement phase dissipates information barriers to achieve cost control via demand forecasting; the production phase leverages real-time sensing and C2M reverse customization to optimize resource allocation; and the marketing phase enhances conversion rates and ROI via demand insight and full-funnel attribution. The comparative analysis further reveals a fundamental divergence: the data value of self-operated e-commerce permeates the physical supply chain, whereas that of platform-based e-commerce centers on ecosystem matching. The sustained operation of this cyclical mechanism relies on three critical safeguards—a foundational infrastructure anchored by data mid-ends, technological support driven by algorithmic iteration, and institutional security ensuring data ownership. By delineating how distinct business models dictate data application pathways, this study offers a contextualized theoretical framework, assisting enterprises in translating abstract data strategies into concrete competitive advantages while navigating the trade-offs between technological empowerment and institutional compliance.*

Keywords: *E-commerce intelligent management; Data elements; Value realization mechanism; Cost reduction and efficiency enhancement; Data collaboration*

INTRODUCTION

1.1 Research Background and Problem

With data now entrenched as a fundamental factor of production, the primary corporate hurdle has pivoted from sheer volume accumulation to contextualized value extraction. While data-driven intelligent management has emerged as a crucial pathway for digital transformation (Zhang Lei et al., 2023), the value of data elements does not inherently exist upon collection. Although existing literature extensively documents the macro-economic impact of data factors, micro-level empirical studies on how data specifically alters operational workflows within distinct business architectures remain scarce. Under conventional paradigms, internal information silos breed prohibitive communication and coordination costs between departments, manifesting as severe transaction impediments. Externally, search efficiency remains chronically low. Confronted by rapidly shifting market demands, enterprises simultaneously lack the acute insight and resource reconfiguration capabilities required to adapt. The unique attributes of data elements—replicability, shareability, and diminishing marginal costs—endow them with the potential to resolve these pain points. Viewed through the Resource-Based View (RBV), the unique business data accumulated by an enterprise, when integrated with other factors, can form a “hard-to-imitate” and “irreplaceable” intelligent management self-reinforcing circuit, constructing a sustained competitive advantage. Consequently, how to effectively activate and release the value of data elements within specific intelligent management scenarios has become an urgent practical imperative.

1.2 Significance and Objectives

Theoretically, this study extends the contextualized research on data element value realization by shifting focus from macro-level market allocation to the micro-mechanisms within specific operational scenarios. By elucidating the dual pathways of cost reduction and efficiency enhancement across procurement, production, and marketing, it enriches the micro-foundations of data value transformation. Furthermore, it revitalizes traditional management theories for the digital economy; rather than merely applying TCT, DCT, and RBV as static labels, this research demonstrates how data elements actively operationalize these theories—deconstructing information barriers to lower transaction costs, acting as sensory and reconfiguration nodes to empower dynamic capabilities, and forging inimitable strategic loops to secure competitive advantage. This study contributes to existing literature in three ways. At the conceptual level, we propose a dual-driven framework of “cost reduction and efficiency enhancement,” which challenges the prevailing singular focus on efficiency and systematically demonstrates how data elements function differently across operational processes. Methodologically, rather than describing data applications in isolation, we distill a universal pathway—advancing beyond fragmented collection, through algorithmic matching, to concrete realization—thereby delineating the dynamic black box of data evolving from a raw resource to core competitiveness. Theoretically, this research integrates TCT, DCT, and RBV to explain not merely that data creates value, but precisely how it reduces transaction bottlenecks, enables agile reconfiguration, and constructs sustained competitive barriers within intelligent management scenarios.

Practically, this research transcends abstract data strategies by mapping a concrete end-to-end continuum from disjointed collection to algorithmic matching and value realization. It provides actionable blueprints for digital transformation, reminding enterprises that sustainable data value requires balancing technological empowerment with institutional compliance to avoid the pitfalls of "data silos" or "algorithmic failures."

Taking intelligent management scenarios as the research context, this study aims to achieve three objectives: (1) to clarify the essential connotation and adaptation logic of data element value transformation, answering why data can create value in intelligent management; (2) to analyze the specific mechanisms of data elements across procurement, production, and marketing, revealing how data achieves "cost reduction" and "efficiency enhancement"; and (3) to extract the infrastructure, technical, and institutional conditions that guarantee the sustained operation of data value transformation.

1.3 Methodology and Case Selection

This paper aims to answer the mechanistic question of "how data creates value," which belongs to exploratory and explanatory research, making the comparative case study method appropriate. Selecting JD.com and Alibaba as core comparative cases is predicated on their strong theoretical comparability and typicality. JD.com represents the "integration of production, supply, and sales" asset-heavy self-operated e-commerce, where data value permeates the full-link continuum; conversely, Alibaba represents the "platform ecosystem" asset-light e-commerce, where data value focuses on marketing insights and supply-demand matching. Comparing these two divergent models more comprehensively reveals the value realization mechanisms under different e-commerce architectures, enhancing the external validity and theoretical universality of the conclusions.To ensure analytical rigor, data sources include enterprise annual financial reports, officially released white papers, authoritative media reports, and existing academic literature.

1.4 Analysis Framework: A Tripartite Integration of TCT, DCT, and RBV

To decipher the micro-mechanisms of data value transformation, this study synthesizes TCT, DCT, and RBV into an integrated analytical framework. Drawing on Coase (1937) and Williamson (1985), the "cost reduction" logic posits that information asymmetry under traditional models induces prohibitive internal and external transaction costs; data elements eradicate these barriers through collection and algorithmic matching, thereby alleviating transaction inertia. According to dynamic capability theory (Teece et al., 1997), the "efficiency enhancement" logic elucidates how data elements operationalize the "perceive-capture-reconfigure" process of dynamic capabilities—serving as real-time sensors for opportunity identification and reconfiguration bases for agile response. Grounded in Barney (1991), the competitive advantage logic further deduces that the VRIN characteristics (valuable, rare, inimitable, non-substitutable) of a data closed loop construct sustained strategic barriers. By mapping the universal pathway of "disjointed collection—algorithmic matching—concrete realization" onto this tripartite theoretical foundation, the framework provides a robust lens for subsequent mechanism analysis.

MECHANISMS OF DATA ELEMENT VALUE REALIZATION ACROSS BUSINESS PROCESSES

As shown in Fig 1, the three major business processes—procurement, production, and marketing—form a cross-domain collaborative data continuum. The procurement phase is dominated by cost reduction logic, the production phase by efficiency enhancement logic, and the marketing phase represents the dual coupling of both logics. This section delineates how data elements function across these distinct operational processes to realize value.

2.1 The Cost-Driven Mechanism in Procurement

Driven by the limitations of experience-based procurement, JD.com leveraged data elements to fundamentally restructure its inventory management. Within legacy operational paradigms, procurement judgments are overwhelmingly steered by buyer heuristics, leaving firms exposed to demand volatility. Such reactive posturing demands bloated safety buffers—which, interpreted through a TCT lens, constitute prohibitive preventative friction born of information opacity.

Dissipating these internal information barriers required JD.com to implement an intelligent procurement system; this architecture automatically captures and integrates historical sales data, seasonal fluctuations, and real-time front-end orders. Rather than merely aggregating data, the system deploys machine learning algorithms to dynamically adjust demand forecasts and generate actionable procurement suggestions. This transforms inventory management from passive remediation to proactive planning. By executing procurement strictly based on algorithmic forecasting—automatically initiating orders when demand is predicted to rise and postponing them during anticipated downturns—the system effectively avoids the capital occupation of over-procurement and the production stagnation of under-procurement.

Consequently, this data-driven continuum significantly curtails the transaction costs stemming from uncertainty, reducing JD.com's inventory turnover days from 60 to 25 and cutting capital occupation costs by 30% (Liu & Liu, 2023). To address the limitations of siloed departmental communication, data integration serves as the catalyst for eliminating coordination bottlenecks. In conventional setups, information lags between procurement, production, and sales frequently result in material backlogs or operational delays, manifesting as high internal transaction costs. By real-time capturing of sales orders, production scheduling, and in-transit inventory data, JD.com's platform synchronizes multi-source information to automatically evaluate the matching degree between scheduling and material requirements. This seamless data flow achieves automatic cross-departmental instruction transmission, eradicating manual coordination overhead and drastically minimizing internal transaction costs. Empirically, following this data integration, JD.com shortened its procurement response time from 3 days to 4 hours, with abnormal procurement incidents caused by information asymmetry decreasing by 60% (JD.com Group, 2022).

Constrained by limited channels and qualitative judgments, traditional supplier sourcing is notoriously time-consuming and labor-intensive. Anchored in the logic of alleviating information asymmetry, data elements substantially reduce external search costs. By collecting multi-dimensional data on supplier capacity, quality, delivery, and credit, algorithms comprehensively analyze and generate granular supplier profiles, automatically matching filtering conditions. This enables enterprises to precisely lock in candidate suppliers and dynamically warn of potential risks, substantially reducing external search costs and default risks. JD.com's supplier management system exemplifies this, having shortened the sourcing cycle from 4 weeks to 1 week while achieving automated warnings for quality risks.

2.2 The Efficiency-Driven Mechanism in Production

Confronted with the explosive and volatile order volumes characteristic of self-operated e-commerce—far exceeding the rhythms of traditional retail—JD.com faced severe challenges in synchronizing back-end production scheduling with warehousing operations. Under conventional siloed management, the inherent lag in information transfer between the front-end and the physical supply chain frequently caused operational impediments and missed delivery windows.

To neutralize these operational impediments, the company transitioned to a seamless, data-driven production-sales nexus. Anchored in the "perception capability" of Dynamic Capability Theory (DCT), e-commerce enterprises must acutely identify real-time supply chain anomalies to survive. JD.com actualized this by deploying sensors and RFID tags across its production workshops and intelligent warehousing facilities (e.g., Asia No. 1). These technologies continuously stream real-time data regarding equipment status, production progress, inventory levels, and front-end order inflows. Rather than merely accumulating data, the Industrial Internet of Things and e-commerce platform mid-end dock this information in real time, dynamically comparing order growth rates against warehousing throughput thresholds. When order volumes surge toward capacity limits, the system autonomously triggers alerts to production management—prompting immediate flexible scheduling adjustments or pre-delivery strategies to avert bottlenecks.

This data-empowered perceptual architecture effectively eliminated the lag inherent in traditional models. Empirically, it shortened the response time for sudden orders from hours to mere minutes and drastically curtailed the rates of unsold goods and stockouts caused by production-sales disconnection. Historically, product development and process settings under the e-commerce model heavily relied on suppliers' experiential judgments, lacking real-time grasp of consumer feedback. To pivot from "experiential trial-and-error" to "data-driven optimization," data elements provide a new path for e-commerce reverse customization (C2M). Driven by the "capture capability" of DCT, enterprises must seize optimization opportunities hidden within consumer feedback. By real-time collection of user review data, return reason tags, customer service records, and after-sales repair data, systems can detect abnormal increases in return or negative review rates. Algorithms then automatically retrieve this feedback text, extract quality defect keywords using NLP technology, and compare them with production-end process parameter records to recommend adjustment schemes. This creates a self-reinforcing optimization mechanism based on consumer feedback. For instance, when JD.com's C2M system detected an abnormally elevated complaint rate regarding "loud noise" for a home appliance, the algorithm automatically retrieved production records, located the parameter deviation in the motor installation process, and recommended adding shock pads or adjusting speed. This mechanism reduced the return rate from 5.2% to 1.5% and shortened the process improvement cycle from months to within a week.

During major e-commerce promotions, the effective integration of production and warehousing resources is a prerequisite for ensuring efficient delivery. Moving beyond "static estimation," data elements promote the transition toward "dynamic optimization." Empowered by the "reconfiguration capability" of DCT, enterprises dynamically reallocate production-warehouse resources in response to order peak changes. By real-time collection of pre-sale order data, regional warehousing capacity ratios, supplier capacity status, and logistics data, the system automatically generates resource allocation plans for "production scheduling advancement + cross-regional transfer." This seamlessly connects production instructions with warehousing inbound operations, automatically prioritizing urgent orders for production and allocating them to the nearest warehouse. JD.com's intelligent scheduling system exemplifies this, having increased its production-warehouse resource turnover rate by over 30% during major promotions and reduced shipping delays caused by resource mismatch by 55%.

2.3 The Cost-Efficiency Coupling Mechanism in Marketing

The marketing link serves as a core hub in the cross-industry data circulation system, featuring the distinctive dual synergy of cost cutting and efficiency elevation. Different from the procurement stage that centers on transaction cost control and the production stage targeting dynamic capability improvement, the marketing stage applies data resources to improve operational efficiency such as demand perception and boost economic benefits represented by full-link effect attribution simultaneously.

Constrained by conventional marketing's dependence on retrospective research and intuitive buyer experience, organizations frequently fail to anticipate market shifts. Data elements propel a paradigm shift—moving from reactive consumer search to algorithmic proactive delivery. Integrating the perception logic of DCT with the cost-reduction logic of TCT, this mechanism reduces trial-and-error costs. By integrating multi-dimensional behavioral data—such as browsing, search, favorites, purchase records, and social media discussions—NLP and machine learning mine data to identify demand characteristics and consumption trends. This guides new product selection and development based on data insights, enhancing the success rate of new products. Alibaba's recommendation system dynamically matched associated products based on real-time behavior, increasing the click-through rate by 120% and conversion rate by 80% (Alibaba Group, 2022). Compared to Alibaba's cross-category association recommendations based on the platform ecosystem, JD.com's recommendation system focuses more on deep supplementation and replacement recommendations for self-operated categories, with both achieving second-level intent matching.

With continuously rising customer acquisition costs, improving traffic conversion rates has become the core objective. By real-time recording and retention of each user's complete behavioral trajectory data, systems generate exclusive product recommendation lists based on collaborative filtering and deep learning models, achieving second-level matching. This dynamic matching of intent lowers user search costs and improves page click-through rates, traffic conversion rates, and average order value. Both Alibaba and JD.com achieved a dual enhancement of sales efficiency and user experience by dynamically adjusting recommended content in real time according to the user's current behavior.

Limited by traditional budget allocation that relies on fixed proportions, enterprises often suffer from inefficient marketing spend. Data elements deconstruct this rigidity by enabling real-time tracking of conversion effects, thereby shifting budget allocation from an "experience-driven" gamble to a "performance-driven" science. Integrating the reconfiguration logic of DCT with the strategic resource perspective of RBV, this mechanism transforms raw funnel data into strategic agility. By continuously tracking full-funnel conversion data across every marketing touchpoint, the system calculates critical metrics like customer acquisition cost and channel conversion rates. When expenditures breach predefined thresholds, algorithms autonomously generate rebalancing plans, dynamically divesting from underperforming channels and doubling down on high-efficiency ones.

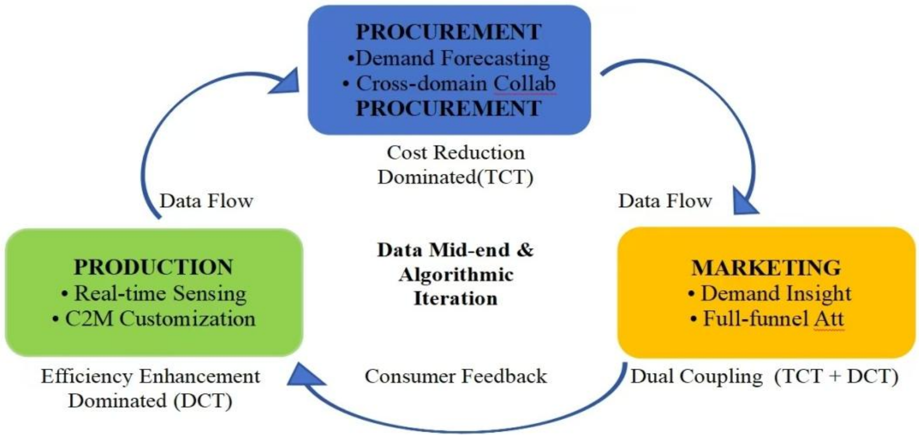

Fig 1. The Coupling Mechanism of Data Value across Procurement, Production, and Marketing

This figure illustrates the cross-domain collaborative data continuum within intelligent management scenarios. The cyclical ecosystem demonstrates how data flows across the three core business processes, driven by the central engine of the data mid-end and algorithmic iteration. The peripheral labels denote the primary value orientation of each phase: the procurement phase (blue) is dominated by cost reduction logic (TCT), the production phase (green) is dominated by efficiency enhancement logic (DCT), and the marketing phase (orange) represents the dual coupling of both logics. Arrows indicate the direction of data feedback and resource reallocation.

DIVERGENT LOGICS: SELF-OPERATED VS. PLATFORM-ECOSYSTEM MODELS

While the mechanisms across procurement, production, and marketing delineate a universal trajectory for data value, the strategic terminus of this reconfiguration fractures along the lines of business models, exposing a fundamental divergence between platform and self-operated architectures. The comparative analysis further reveals that this divergence manifests in distinct pathways: the data value of self-operated e-commerce permeates the physical supply chain, whereas that of platform-based e-commerce centers on ecosystem matching.

3.1 The Penetrating Logic of the Physical Supply Chain (JD.com)

JD.com’s self-operated model extends the attribution boundary far beyond the shopping cart. By integrating front-end marketing data with back-end warehousing and after-sales returns, JD.com emphasizes “brand-performance integration” to precisely calculate the final net profit ROI generated by distinct traffic sources. This underscores that in integrated self-operated models, data value permeates the physical supply chain via a penetrating mechanism. Data flows seamlessly from consumer demand forecasting straight through to inventory control, production scheduling, and final logistics delivery, optimizing for full-link physical profitability and protecting the irreplaceability of end-to-end data assets.

3.2 The Radiating Logic of Ecosystem Matching (Alibaba)

Conversely, Alibaba’s attribution analysis system prioritizes optimizing channel traffic allocation—dynamically adjusting budgets to lower overall acquisition costs by 25% and boosting marketing ROI by 60%. In the platform-ecosystem model, data value operates through a radiating matching mechanism within the network. Rather than penetrating a physical backend, data acts as a node radiating outward to connect third-party sellers, logistics providers, and consumers. The primary optimization target shifts from physical profitability to ecosystem matching efficiency and traffic flow, leveraging cross-category associations and real-time behavioral matching to maximize platform-level transaction volume.

3.3 Comparative Synthesis and Strategic Implications

As illustrated in Fig 2 and systematically summarized in Table 1, the divergence in data value logic between integrated self-operated and platform-ecosystem models is clearly visualized. The central dichotomy lies between asset-heavy physical integration and asset-light ecosystem orchestration. Self-operated e-commerce drives data value deep into the physical supply chain for full-link optimization, whereas platform-based e-commerce leverages data primarily for ecosystem matching and traffic efficiency. This divergence dictates not only how enterprises deploy algorithms but also how they construct their strategic barriers—whether through the VRIN characteristics of a closed-loop physical data continuum (RBV) or the network effects of platform matchmaking.

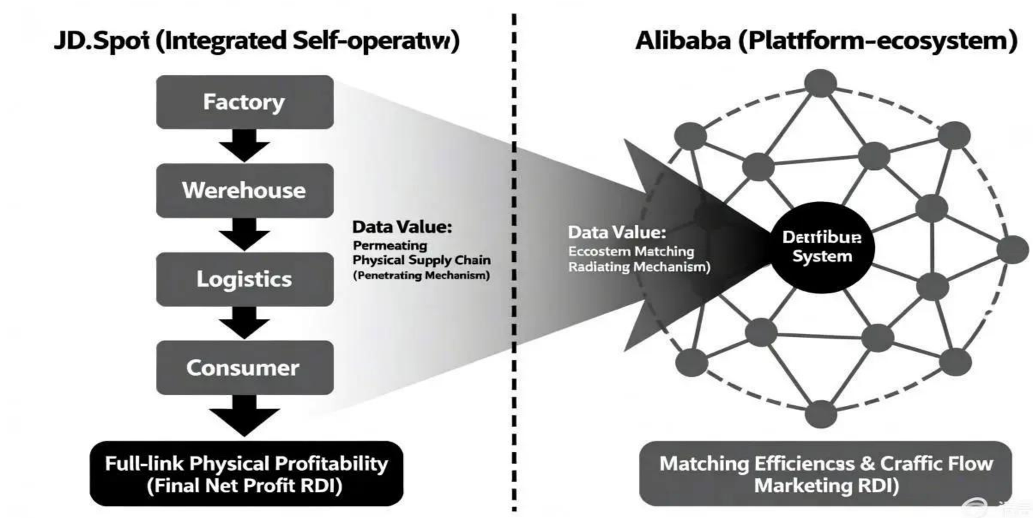

Fig 2. Divergent Data Value Logics: Self-operated vs. Platform-ecosystem Models

This figure visualizes the fundamental divergence in data application pathways dictated by distinct business models. The left section depicts the integrated self-operated model (e.g., JD.com), where data value permeates the physical supply chain via a penetrating mechanism, ultimately optimizing for full-link physical profitability (Final Net Profit ROI). The right section depicts the platform-ecosystem model (e.g., Alibaba), where data value operates through a radiating matching mechanism within the network, primarily optimizing for matching efficiency and traffic flow (Marketing ROI). The central dashed line emphasizes the architectural dichotomy between asset-heavy physical integration and asset-light ecosystem orchestration.

Table 1. Comparative Analysis of Data Value Realization Mechanisms between JD.com and Alibaba

Business Process	Core Mechanism	Theoretical Lens	JD.com (Self-operated) Evidences	Alibaba (Platform-ecosystem) Evidences
Procurement	Inventory Cost Control	TCT (Cost Reduction)	Turnover days: 60→25; Capital costs -30%	N/A (Asset-light model)
Procurement	Process Optimization	TCT (Internal friction)	Response time: 3 days→4 hours; Abnormal incidents -60%	N/A (Asset-light model)
Production	Production-warehouse Sensing	DCT (Perception)	Response time for sudden orders: Hours→Minutes	N/A (No physical backend)
Production	C2M Reverse Customization	DCT (Capture)	Return rate: 5.2%→1.5%; Cycle: Months→Week	Platform-level trend insights for vendors
Marketing	Demand Insight & Matching	DCT+TCT	Deep supplementation recommendations (Second-level)	Cross-category association (CTR +120%, CVR +80%)
Marketing	ROI Optimization	DCT+RBV	Final Net Profit ROI (Brand-performance integration)	Marketing ROI +60% (Channel traffic allocation)

SAFEGUARD MECHANISM FOR DATA ELEMENT VALORIZATION

Regardless of the model—penetrating or radiating—the sustained operation of the cyclical mechanism outlined above cannot rely on technology alone. It demands a tripartite safeguard of foundational infrastructure, continuous algorithmic iteration, and rigid institutional security.

4.1 Foundational Infrastructure: Data Mid-ends and Quality

Information encapsulation—commonly manifesting as disjointed data repositories—generates profound coordination overhead and inter-departmental bottlenecks during data acquisition. Architecting a data mid-end directly confronts this issue, neutralizing structural partitions to alleviate transaction friction. JD.com and Alibaba's early practices both validated this necessity and its solutions. JD.com built a data mid-end to integrate data from various business systems, while Alibaba constructed the "OneData" mid-end system, unifying norms and standards across the group. These two different e-commerce models jointly demonstrate that building a data mid-end is a prerequisite for the effective operation of intelligent procurement and marketing systems.

4.2 Technological Support: Algorithmic Iteration

Enterprises must possess the agility to continuously adapt to environmental changes, and algorithmic models are not a one-time solution but a continuous technical carrier for maintaining dynamic capabilities. JD.com's demand forecasting model established an iteration mechanism, retraining monthly with the latest data, keeping the forecast accuracy above 80%. Similarly, Alibaba established a continuous iteration mechanism for marketing recommendation algorithms, where deep learning models require real-time retraining based on traffic characteristic changes during major promotions. This indicates that whether for self-operated supply chains or platform ecosystems, the continuous evolution of algorithms is the core technical safeguard for sustaining enterprise dynamic capabilities.

4.3 Institutional Security: Data Ownership and Privacy

Data governance and privacy mechanisms protect the strategic "inimitability" and "scarcity" of the data continuum. If data rights are unclear, internal friction will hinder value release; if privacy protection is inadequate, strategic assets will lose their core competitive value. JD.com formulated enterprise data management measures alongside its mid-end, while Alibaba adopted technical and management measures to ensure data security, passing data security management certifications. Only with user trust can data-driven precision marketing continue to thrive, which ultimately protects the irreplaceability of an enterprise's data assets.

CONCLUSION, LIMITATIONS, AND PROSPECTS

5.1 Research Conclusions

Synthesizing the operational realities of JD.com and Alibaba, this analysis establishes that data element value morphogenesis is rarely automatic; rather, it hinges upon a consistent cyclical pathway—advancing beyond disjointed information capture, via algorithmic synthesis, toward tangible operational outcomes. The study highlights that this pathway is context-dependent. The three major business processes—procurement, production, and marketing—form a cross-domain collaborative data continuum, yet their value emphases diverge fundamentally based on business models. Self-operated e-commerce drives data value deep into the physical supply chain for full-link optimization, whereas platform-based e-commerce leverages data primarily for ecosystem matching and traffic efficiency. Regardless of the model, the sustained operation of this mechanism cannot rely on technology alone; it demands a tripartite safeguard of foundational infrastructure (data mid-ends), continuous algorithmic iteration, and rigid institutional security. Ultimately, integrating TCT, DCT, and RBV elucidates the internal logic of this transformation: data simultaneously reduces transaction impediments, empowers dynamic reconfiguration, and fortifies strategic inimitability.

5.2 Research Limitations

This study acknowledges several boundaries. The theoretical comparability of JD.com and Alibaba provides robust analytical depth, yet the sheer scale and resource abundance of these industry leaders may limit direct applicability to small and medium-sized enterprises (SMEs) facing distinct constraints. Methodologically, while relying on secondary public materials ensures breadth, it may not fully capture micro-level organizational bottlenecks during data integration. Furthermore, the qualitative nature of this research offers rich mechanistic insights but lacks the quantitative verification needed to precisely measure the marginal financial impact of specific data elements.

5.3 Future Prospects

Building on these limitations, future research should prioritize investigating "lightweight" and agile data value realization mechanisms tailored for SMEs. Additionally, as generative AI and large language models rapidly permeate the enterprise sector, exploring how these technologies reshape the "processing and matching" phase of the data value chain presents a critical frontier. Finally, deepening the exploration of multimodal data integration and the governance of human-machine collaborative decision-making will be essential for advancing intelligent management from automated efficiency toward true cognitive synergy.

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