Empowerment Mechanism and Governance of Data Elements for Enterprise Incremental Innovation

Wei Feng*, Yuwen Ye
Accounting Institute, Hainan Vocational University of Science and Technology, Haikou, Hainan, China
**Corresponding Author*

Abstract: As the core production resource in the digital economy era, data elements are fundamentally transforming the organizational logic and evolutionary pathways of corporate innovation. Grounded in innovation management and data element theory, this study systematically elucidates the theoretical rationale and operational mechanisms through which data elements empower incremental innovation. Specifically, data elements reduce R&D trial-and-error costs via knowledge codification and experiential accumulation, guide improvement directions through precise supply-demand matching, and catalyze combinatorial innovation via cross-domain knowledge integration, thereby establishing multidimensional empowerment pathways for incremental innovation. Concurrently, the deep integration of data elements introduces governance challenges including opaque innovation processes, ambiguous intellectual property demarcation, and algorithmic bias lock-in, necessitating collaborative governance approaches at corporate, market, and institutional levels.

Keywords: Data Element; Incremental Innovation; Empowerment Mechanism; Governance Path

1. Introduction

In the digital era, the global economic landscape is undergoing profound transformations. Data has evolved from a byproduct of economic activities to a key production factor alongside land, labor, capital, and technology, profoundly influencing corporate innovation models and development strategies [1]. Incremental innovation, which maintains core business operations while continuously improving existing products, technologies, and processes, is characterized by low risk, minimal investment, and rapid returns. It serves as the primary approach for sustainable development and a critical safeguard for enterprises to adapt to dynamic market environments and sustain competitive advantages [2].With the continuous improvement of digital infrastructure and maturation of data processing technologies, data elements have permeated every aspect of incremental innovation, including product development, manufacturing, marketing, and after-sales services, becoming a driving force for corporate innovation. Existing research has made productive explorations into the relationship between data elements and innovation: Some studies examine the macro-level impact of data element market development on regional innovation capabilities, finding that data trading platforms significantly boost corporate innovation output [3]; others analyze micro-level effects of data element application on R&D decisions, confirming that data elements enhance innovation capacity through resource optimization and alleviating financing constraints [4]. However, current research predominantly treats corporate innovation as homogeneous outputs, with limited differentiation in the distinct mechanisms underlying various types of innovative activities. Therefore, this study, based on theories of innovation management and factor economics, explores the enabling mechanism of data factors in corporate incremental innovation, identifies key obstacles in the enabling process, and constructs a scientifically sound governance pathway. This not only enriches research on the relationship between data factors and corporate innovation but also holds significant practical implications for enterprises to fully leverage the value of data factors and drive sustainable incremental innovation.

2. Theoretical Basis

2.1 Theories Related to Data Elements

Compared to traditional production factors like labor and capital, data exhibits distinct characteristics including non-rivalry, zero marginal cost, and positive externalities [5]. Non-rivalry allows multiple entities to simultaneously utilize the same data without diminishing its value, creating significant economies of scale. Zero marginal cost means the additional cost of replicating and distributing data is negligible once generated, enabling widespread circulation and reuse. Positive externalities manifest through knowledge spillovers during data accumulation and application — by processing data, enterprises not only enhance production efficiency but also uncover unexpected knowledge connections that spark new innovations. From an innovation perspective, the value realization of data requires a transformation chain from "data" to "information" and then to "knowledge." Raw data records objective facts without processing; when contextualized and analyzed, it becomes meaningful information; and when integrated with existing knowledge systems, it internalizes into corporate cognitive frameworks and problem-solving capabilities, ultimately becoming knowledge capital that drives innovation [6]. This transformation depends on corporate data governance capabilities, algorithmic model effectiveness, and institutionalized organizational learning. Data's significance to innovation also lies in its "meta-production factor" nature: while contributing to value creation, it fundamentally optimizes the allocation efficiency of other production factors. In R&D activities, data enables enterprises to more accurately identify technical bottlenecks, more efficiently screen experimental protocols, and more scientifically evaluate innovation risks. This role as an "enabler" distinguishes data elements from traditional production factors, transforming them into a "multiplier" for innovation activities [7].

2.2 Theories of Incremental Innovation

Incremental innovation is fundamentally a process of knowledge accumulation and continuous improvement. Unlike disruptive innovation that relies on paradigm-shifting scientific breakthroughs, incremental innovation builds upon existing technological frameworks. By marginally optimizing product design, manufacturing processes, and user experience, it achieves sustained enhancement of innovation performance [8]. This model holds three critical importance for enterprises: First, incremental innovation constitutes the predominant form of innovation activities for most companies, particularly for technology-following enterprises where continuous improvement often represents a more practical and feasible path. Second, incremental innovation exhibits cumulative effects — long-term incremental improvements may trigger qualitative changes, laying the groundwork for disruptive innovation. Third, incremental innovation directly addresses market demands and user experiences, making its outcomes more commercially viable and fostering a virtuous cycle of innovation investment [9]. From a knowledge management perspective, the core challenge of incremental innovation lies in transforming fragmented, tacit experiential knowledge into systematic, inheritable organizational knowledge. Traditional experience-driven innovation heavily relies on individual insights and "learning by doing" among R&D personnel, resulting in inefficient knowledge transfer and potential knowledge gaps due to staff turnover. Moreover, experience-driven improvements are often constrained by subjective judgments of R&D teams, making it difficult to comprehensively capture evolving market demands and technological trends. These limitations inherently constrain incremental innovation while simultaneously creating value opportunities for data-driven interventions [10].

3. The Mechanism of Data Elements Empowering Gradual Innovation

Based on the above theoretical analysis, data elements form multidimensional empowerment for incremental innovation through three pathways: knowledge manifestation and experience accumulation, supply-demand matching and precision improvement, as well as cross-border integration and combined innovation.

3.1 Knowledge Manifestation and Experience Accumulation

The primary obstacle to incremental innovation lies in the trial-and-error costs of R&D processes. Traditional product improvements often rely on physical experiments and prototype testing, where each design change requires completing the full "design-manufacture-test-analysis" cycle

— a time-consuming and costly process. More critically, experimental data remains scattered across engineers' records, failing to form systematic knowledge accumulation and leading to widespread "reinventing the wheel" phenomena. The deep integration of data elements offers new possibilities and implementation pathways to effectively break through current R&D bottlenecks. By systematically cleaning, structurally integrating, and refining knowledge graph construction from extensive historical data accumulated through long-term R&D practices, enterprises can transform fragmented, implicit experiential knowledge into explicit, reusable knowledge assets. This process also consolidates previously isolated data resources into systematic, interconnected knowledge systems. The most direct benefit of knowledge explication manifests in significantly improved R&D efficiency. When R&D teams face new product iterations or technical optimization tasks, they no longer need to rely entirely on personal experience or trial-and-error exploration from scratch. Instead, they can leverage established knowledge graph systems to efficiently retrieve and utilize similar cases from past projects as decision support. This approach allows them to fully adopt effective models from successful past practices while identifying and avoiding lessons from previous failures, thereby substantially reducing R&D process uncertainties, enhancing innovation precision, and improving the efficiency of technology transfer.

3.2 Supply-Demand Matching and Precision Improvement

Another core challenge in incremental innovation lies in determining improvement directions. Traditional product enhancements often rely on R&D teams 'subjective judgments about market demands, which risks creating disconnects from actual user needs — performance metrics deemed crucial by developers may not address real user pain points, while heavily invested technical parameters might struggle to create market differentiation. The application of data elements offers new solutions. By integrating and analyzing user behavior data, product operation data, and after-sales feedback, companies can gain precise market insights and allocate innovation resources to areas with the highest marginal returns. This mechanism relies on two types of data synergy: external market data (including user search records, reviews, and complaints) helps identify performance gaps and improvement opportunities, while internal product data (such as sensor-collected operational parameters, fault logs, and maintenance records) enables pinpointing technical root causes and optimization potential. The deep integration of supply-demand data provides enterprises with real-time market feedback-driven insights, driving a complete shift from traditional subjective improvement models to data-driven iterative optimization mechanisms. This transformation not only enhances the scientific rigor and accuracy of decision-making but also significantly boosts enterprises' responsiveness to market changes and competitiveness. Notably, effective operation of supply-demand matching mechanisms requires addressing constraints related to data sovereignty and privacy protection. Data sharing between different entities often faces legal risks and commercial barriers, making it difficult for enterprises to directly access customers' core operational data. Technologies like federated learning and privacy-preserving computation provide viable solutions for cross-domain collaborative modeling while safeguarding data sovereignty. These technological breakthroughs are expanding the application boundaries of supply-demand matching mechanisms, extending data-driven precision improvements from internal corporate operations to collaborative levels across industrial chains.

3.3 Cross-border Integration and Combination Innovation

While incremental innovation focuses on continuous improvement within existing frameworks, this doesn't mean opportunities are confined to single technical domains. In fact, many critical product iterations emerge from the marginal recombination of knowledge across different fields. The unique value of data lies in its ability to break down barriers between knowledge modules, drive cross-disciplinary integration, and foster compound innovation. The mechanism of cross-boundary integration operates through two dimensions: First, knowledge convergence driven by data flow. When data from different fields converges on a single platform, previously isolated information fragments may form unexpected connections, sparking new innovative ideas. Second, cross-disciplinary collaboration supported by data platforms. Incremental innovation often requires multidisciplinary knowledge synergy, yet traditional organizational models lack effective knowledge-sharing mechanisms among researchers with different professional backgrounds. By establishing shared data infrastructure, researchers from various fields can collaborate in the same digital space, transforming their specialized knowledge into reusable data modules. This collaborative model preserves the depth of professional specialization while expanding the breadth of knowledge integration, opening up new possibilities for incremental innovation. From the perspective of innovation output, the combinatorial innovation driven by cross-boundary integration mechanisms exhibits two key characteristics. Firstly, such innovations typically manifest as "micro-breakthroughs" – not disruptive technological revolutions, but rather marginal performance enhancements achieved through the recombination of diverse knowledge modules. Secondly, these innovations demonstrate cumulative effects, where each cross-boundary integration may generate new knowledge modules for subsequent combinations, forming a continuous positive feedback loop.

These three mechanisms operate not in isolation but are interwoven and synergistic. The knowledge manifestation and experience accumulation mechanism establishes a reusable and calculable knowledge base for enterprises. The supply-demand matching and precision improvement mechanism guides enterprises to allocate innovation resources toward high-value improvement initiatives. Meanwhile, the cross-border integration and combined innovation mechanism expands the exploration space for innovative opportunities.

4. Governance Challenges of Data Elements Embedded in Innovation Process

The deep integration of data elements into corporate innovation activities not only enhances efficiency but also presents a series of governance challenges. These challenges stem from both the inherent economic attributes of data elements and the complex interactions between data application and innovation processes. Identifying and addressing these challenges is essential to fully leverage the empowering effects of data elements and mitigate potential risks.

4.1 Black-Boxing of Innovation Process and the Dilemma of Explainability

The data-driven R&D paradigm is transforming the observability and explainability of innovation processes. In traditional experience-driven development, engineers maintain clear understanding of product improvement logic chains — from problem identification and root cause analysis to solution design — each step grounded in comprehensible expertise. However, when machine learning models deeply intervene in R&D decision-making, the landscape shifts: while models may uncover correlations from massive datasets that humans struggle to interpret and generate optimization plans, their inherent "black-box" nature makes decision-making processes difficult to explain and validate. This explainability dilemma poses multiple challenges for innovation management: First, when R&D decision-making bases lack sufficient understanding, companies weaken their control over innovation direction, potentially falling into blind reliance on algorithms. Second, when innovation outcomes stem from "black-box" model outputs, knowledge accumulation effectiveness diminishes — engineers may obtain optimized formulations or designs without truly understanding causal relationships, making it challenging to transfer such knowledge to other application scenarios. Third, when innovation processes lack explainability, evaluating and auditing innovation outcomes becomes difficult, potentially masking risks caused by algorithmic biases or data quality issues.

4.2 The Blurring of the Definition of Intellectual Property

The introduction of data elements is challenging traditional intellectual property frameworks. The outcomes of incremental innovation often represent cumulative marginal improvements rather than disruptive technological breakthroughs, which inherently face difficulties in definition and protection under conventional IP systems. Data-driven innovation further exacerbates this dilemma: First, attribution of innovation contributions remains ambiguous. When innovation results stem from integrated analysis of multiple data sources, or when algorithmic model training involves contributions from numerous historical cases, it becomes challenging to delineate the innovative contribution shares of different entities. Second, the boundary between data training and intellectual property infringement remains blurred. If a company uses publicly available data to train a model that generates technical solutions similar to existing patents, or if the training data contains outputs of copyrighted works, it may constitute infringement. Third, the intellectual property attributes of data-driven innovation outcomes remain unclear. Whether algorithm-generated recipes or model-recommended design proposals possess patentability is questionable, and it remains uncertain whether the rights belong to algorithm developers, data providers, or application enterprises.

4.3 Algorithmic Bias and the Risk of Technological Lock-In

Data-driven innovation is inherently value-laden. The biases embedded in training datasets can be amplified by algorithms, leading to systematic deviations in innovation trajectories. For instance, if historical R&D data predominantly reflects solutions for specific problem types, models trained on such data may tend to "trench" into existing paths while overlooking potentially more valuable innovation directions. This bias could trap enterprises in technological lock-in — a state where they appear to make continuous improvements but are actually confined to suboptimal technical trajectories. When corporate R&D decisions increasingly rely on data analysis results and algorithmically recommended solutions are repeatedly validated, companies may develop path dependence on existing technical approaches, missing critical transformation windows. More alarmingly, data-driven optimization often pursues local optima, causing enterprises to overlook fundamental paradigm shifts in marginal improvements through "micro-innovations," ultimately falling into the "innovator's dilemma."

4.4 The Tension between Data Security and Trade Secret Protection

The empowerment of innovation through data elements often requires data circulation and sharing, yet this creates inherent tension with trade secret protection. While cross-departmental and cross-enterprise data integration can generate greater innovation value, the open sharing of core data may increase risks of trade secret leakage. Balancing data value realization with corporate asset protection has become the core challenge in data governance. This tension is particularly prominent in industrial chain collaborative innovation scenarios: data sharing between upstream and downstream enterprises helps optimize product design and improve system efficiency, but such shared data may contain sensitive business information that could undermine competitive advantages if leaked. Although privacy-preserving technologies like multi-party secure computation provide effective solutions to mitigate the tension between data privacy protection and value utilization, their current maturity still needs improvement, and high deployment and maintenance costs in practical applications limit large-scale adoption. More crucially, relying solely on technical solutions is insufficient. Technical approaches must be closely integrated with institutional arrangements and governance mechanisms, including clearly defining data sharing scopes and boundaries, reasonably setting usage permissions for different entities, and establishing transparent accountability and traceability mechanisms. Only through dual safeguards of technology and institutional frameworks can we establish a secure, trustworthy, and efficient data circulation and collaboration environment.

5. Path Selection for Data Governance

To address these governance challenges, a systematic data governance framework should be established at the enterprise, market, and institutional levels, fostering a collaborative governance model involving multiple stakeholders.

5.1 Building a Responsible Data Innovation System

From an enterprise perspective, the core mission of data governance lies in establishing a responsible data innovation ecosystem that ensures ethical compliance, risk control, and sustainable value creation. Specifically, companies should enhance governance mechanisms through the following approaches: First, implement a data quality management system. Data quality forms the foundation of data-driven innovation, as low-quality inputs inevitably yield misleading outputs. Enterprises must establish standardized workflows for data collection, cleaning, labeling, and updating to ensure R&D decision-making data is accurate, complete, and timely. Additionally, compliance checks on data sources should be conducted to avoid using infringing or non-compliant data. Second, strengthen algorithmic explainability. For algorithm models deeply involved in R&D decisions, companies should implement explainability evaluation mechanisms to ensure the logical chain of critical decisions can be understood and verified. For models with insufficient explainability but proven value, manual review mechanisms should be established to treat algorithmic outputs as decision references rather than substitutes. Third, improve intellectual property management. To address challenges in defining intellectual property boundaries, enterprises should develop data-driven innovation IP management processes. This involves prudent evaluation of algorithmic innovations, clear attribution of contributions among stakeholders, and prevention of IP disputes through contractual agreements and technical protections. Fourth, implement a data security classification system. Tailored security measures should be applied based on data sensitivity levels and value tiers. For core trade secrets, the scope of disclosure should be strictly restricted; for shareable data, technical measures such as desensitization and anonymization should be employed to mitigate the risk of leakage.

5.2 Cultivating a Standardized and Orderly Data Element Market

From a market perspective, the core mission of data governance lies in cultivating a standardized and orderly data factor market to create a conducive environment for data-driven innovation. Market governance encompasses three key aspects: First, enhancing the infrastructure for data trading and circulation. Data trading platforms serve as the core vehicle for market-oriented allocation of data factors. They should effectively fulfill functions such as data ownership confirmation, valuation and pricing, transaction matching, and compliance review. Platforms need to establish standardized data interfaces and trading rules to reduce transaction costs. Simultaneously, a credit evaluation mechanism for both parties should be established to prevent fraud and breach of contract risks in data transactions. Second, fostering a specialized data service ecosystem. The realization of data factor value relies on professional data processing and analysis capabilities. Encouraging the development of specialized services like data cleaning, annotation, analysis, and visualization will help form a collaborative data service ecosystem, lowering the threshold for enterprises to utilize data. Finally, exploring industry-specific data sharing mechanisms. To meet the needs of collaborative innovation across industrial chains, establishing industry-based data sharing alliances or data spaces through standardized interfaces and trusted environments can gradually break through bottlenecks in enterprise data integration. The establishment of industry data sharing mechanisms must address the "free-rider" problem by designing reasonable contribution and reward mechanisms to incentivize member enterprises to actively participate in data sharing.

5.3 Building an Inclusive and Prudent Governance Framework

From an institutional perspective, the core mission of data governance lies in establishing an inclusive and prudent governance framework to provide stable institutional expectations for data-driven innovation. First, it is essential to improve the data property rights system, as data entitlements form the foundation for data circulation and value distribution. Building upon the established "three rights separation" framework (separation of data resource ownership, data processing and usage rights, and data product operation rights), the next step involves refining rights boundaries in specific scenarios and clarifying the rights and obligations of different stakeholders across data collection, processing, trading, and application stages. Second, a tiered and categorized data supervision system should be established. Different types and application scenarios of data face distinct risk characteristics, requiring differentiated regulatory requirements. Sensitive data involving national security and public interests should be strictly controlled; general commercial data should rely more on market competition and industry self-regulation; personal data should promote compliant usage while protecting individual rights. Third, the data security legal framework needs improvement. Under the basic legal framework of the Data Security Law and Personal Information Protection Law, supporting regulations should be formulated for specific data-driven innovation scenarios, clarifying legal application rules for cross-border data flows, data training and intellectual property, algorithm accountability, and other hot topics. Fourth, a dynamic adjustment mechanism should be established. Given the rapid iteration of data technologies and continuous emergence of innovative applications, the data governance system must maintain sufficient flexibility and adaptability. Regular evaluations and dynamic adjustments should be implemented to optimize governance rules based on technological advancements and practical feedback, avoiding institutional rigidity that hinders innovation.

6. Conclusion

This study systematically investigates the enabling mechanisms and governance pathways of data elements in corporate incremental innovation based on theories such as data element theory and incremental innovation theory. The conclusions drawn are as follows: First, data elements exhibit significant enabling effects on incremental innovation, primarily through three core mechanisms: knowledge manifestation and experience accumulation, supply-demand matching and precision improvement, and cross-border integration and combined innovation. These three interconnected mechanisms form a comprehensive enabling system. Second, the application of data elements in incremental innovation faces multiple practical challenges, including the "black box" nature of innovation processes and interpretability dilemmas, ambiguous intellectual property definitions, risks of algorithmic bias and technological lock-in, as well as tensions between data security and trade secret protection. These challenges constrain the full realization of data elements' enabling potential. Third, to address existing issues, multi-dimensional governance approaches such as establishing a responsible data innovation framework, cultivating a standardized data element market, and creating an inclusive yet prudent governance structure can effectively resolve current problems and maximize the value of data elements in driving corporate incremental innovation.

This study focuses on the overall enabling mechanism and governance pathways of data elements for enterprise incremental innovation, but does not delve into the differences in enabling effects and governance paths across industries or firm sizes. Future research could conduct heterogeneity analysis to enhance the specificity and applicability of the research conclusions.

Acknowledgments

This work was supported by the Hainan Provincial Social Science Fund (HNSK(YB)25-12) and the Key Projects of Hainan Vocational University of Science and Technology (HKKY2025-ZD-09).

References

[1] Jiang L S, Hu X Y, Deng W. Data Elements and the Development of New Quality Productivity in Enterprises. Industrial Economics Review, 1-35 [2026-03-10].

[2] Li H B, Li G. Multiple institutional logics of "incremental innovation" in traditional resource-based agriculture: A case study of the natural rubber industry. China Rural Economy, 2025, (10):115-139.

[3] Li C Y, Zhang S, Wang M. Impact of data factor market construction on enterprise innovation. Scientific Research Management, 1-17 [2026-03-10].

[4] Li X, Gao D Y. How Data Elements Facilitate Breakthroughs in Key Core Technologies of Enterprises. Journal of Shanxi University of Finance and Economics, 2024, 46(12):94-105.

[5] Zhang C, Jiang T Y. Can Data Be Turned into Gold? — A Study on the Impact of Data Elements on the Development of New Quality Productivity. Research World, 2025, (12):39-51. DOI: 10.13778/j.cnki.11-3705/c.2025.12.004.

[6] Ren B P, Chen J W. A New Paradigm of Deep Integration between the Real Economy and Digital Economy. Journal of Xi'an University of Finance and Economics, 2026, 39(01):1-11. DOI: 10.19 331/j.cnki.jxufe. 2026.01.001.

[7] Li Y X, Wei D, Sun X H. "Strengthening Foundations with Data" and "Riding the Wave of Multiplier Effects": A Study on Empowering Modern Industrial Systems with Data Elements. Economic Horizons, 2025, (02):82-96.

[8] Chan W, Lau C, Wong H.Incremental innovation of IAQ management in hotels: Specific framework for processes and activities. International Journal of

Hospitality Management, 2026, 133, 104491-104491.
[9] Alqahtani F, Selviaridis K, Stevenson M. How incentive alignment along the supply chain fosters incremental innovation: evidence from defence performance-based contracts. International Journal of Operations & Production Management, 2025, 45(6):1250-1275.
[10] Zhou H, Yang Y. How Does Knowledge Coupling Affect Firm's Incremental Innovation? The Moderating Effects of Government Support Policies. Discrete Dynamics in Nature and Society, 2021, 2021.