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RESEARCH ARTICLE

Business Intelligence for Big Data-Driven Product Innovation: An Analysis Based on the Subject-Strategy-Process (SSP) Framework*

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Abstract

Artificial intelligence (AI) has reshaped the subject of product innovation and triggered transformations in product innovation strategies and processes. This study proposes a subject-strategy-process (SSP) framework for business intelligence (BI) for big data-driven product innovation through logical deduction, drawing on the theory of big data cooperative assets and an adaptive innovation perspective on enterprise-user interaction. The aim is to explore new mechanisms through which AI influences product innovation in manufacturing. This study indicates three aspects. Firstly, the two-way involvement of humans and AI forms a dual feedback-enhancement mechanism of factor combination and knowledge accumulation. This mechanism drives structural changes in innovation subjects and forms a new foundation for strategic and process transformations in product innovation. Secondly, the alignment between an enterprise's cognitive strategy about AI, competitive strategy, organizational culture, business model, and ecosystem jointly shapes the integrated application of AI in innovation processes. Thirdly, the new features of the big data-driven product innovation process include full-process diffusion from the fuzzy front end, nonlinear iteration of demand-solution pairs, and generative self-testing in intelligent manufacturing. Taken together, the study demonstrates that the SSP framework is well- suited to analyzing the new mechanisms of BI for big data-driven product innovation, which offers a fresh lens for examining the relationship between AI and product innovation.

Keywords artificial intelligence (AI); product innovation; business intelligence (BI); big data cooperative assets; subject-strategy-process (SSP) framework

1 Introduction

ChatGPT was named as one of the journal *Nature*'s top ten figures of 2023, the first nonhuman entity to be included, in recognition of the emerging role of artificial intelligence (AI) large models as new social actors in scientific development. This recognition signals a shift from the era of traditionally structured business intelligence (BI) to an era of AI-driven, unstructured BI. According to the definition of IBM, BI refers to a set of strategies, supported

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by a range of digital technologies that simplify the collection and analysis of information to fully use an enterprise's data assets for better business decision-making. Evidently, AI both relies on and generates big data, making the two inseparable. Accordingly, in this study, AI is conceptualized as representing the big data context or resource base, and the effective utilization of big data signifies the realization of AI applications.

At present, China ranks among the global leaders in AI-driven technological innovation and industrial development. According to the Ministry of Industry and Information Technology of the People's Republic of China, as of June 2022, the scale of China's core AI industry had exceeded 400 billion yuan, with more than 3,000 AI enterprises, second only to the US. AI technologies and industries are enabling enterprises to accelerate digital transformation in manufacturing and advance product innovation at speeds and quality levels far beyond those of the past. As of July 2023, China had established more than 2,500 digital workshops and smart factories at or above Level 2 in smart manufacturing capability maturity. Compared with digital workshops and smart factories at Level 1 maturity, these demonstration factories have, on average, shortened product development cycles by 20.7%, increased production efficiency by 34.8%, and reduced defect rates by 27.4%. In the domain of product innovation, AI assists enterprises in assessing the market potential of new products (Mariani & Nambisan, 2021), supports exploratory and exploitative learning for product innovation, enables rapid product launches (Del Giudice et al., 2021), and facilitates the completion of product innovation while mitigating associated risks.

However, our theoretical understanding remains limited regarding how AI influences the development of BI for product innovation, and which foundational factors are reshaped at the strategic and process levels of product innovation through deep human-AI collaboration. To address this gap, this study proposes a subject-strategy-process (SSP) framework of BI for big data-driven product innovation through logical deduction, drawing on the theory of big data cooperative assets and an adaptive innovation perspective on enterprise-user interaction. This framework is used to explore new mechanisms through which AI affects product innovation, thereby advancing theoretical research on BI for product innovation in the AI era.

2 The SSP Framework for the Mechanisms by Which AI Influences Product Innovation

2.1 Literature Review of the SSP Framework

Based on the representative literature, research on how AI influences product innovation can be summarized along three main lines.

First, the impact of AI on structural changes in innovation subjects. This main research line is explored from three perspectives. The first perspective, grounded in knowledge management and organizational learning, emphasizes the role of AI in recombining data, knowledge, and capital factors. Specifically, Liu et al. (2020) argue that AI accelerates knowledge creation and technology spillovers, enhances learning and absorptive capacities,

and promotes innovation by increasing investment in R&D and talent. At the same time, AI removes physical constraints such as distance, location, and uneven resource distribution, thereby altering patterns of knowledge accumulation. Over time, this process breaks down the boundaries of traditional enterprises and transforms them from closed entities into modular production networks (Davenport, 2018). The second perspective, drawing on social networks, underscores the role of AI in recombining labor factors. Wu et al. (2023) suggest that AI has evolved from a supportive tool for product innovation into a new innovation subject, which works collaboratively with humans for heuristic verification in the product innovation process. Serving as an important complement to traditional experience-based and data-based verification, AI enables a balance between product originality and the heterogeneity of user needs. The third perspective, informed by technology acceptance theory, focuses on the role of AI in recombining management and technology factors, with particular attention to organizational and employees' attitudes toward AI in product innovation. Glikson and Woolley (2020) contend that AI's tangibility, transparency, reliability, and behavioral immediacy are critical to building cognitive trust, while its anthropomorphic qualities significantly influence affective trust. Furthermore, perceived ease of use, perceived usefulness, perceived trust, perceived intelligence, and anthropomorphism are all key factors influencing the adoption of AI in the innovation process (Pillai & Sivathanu, 2020). Collectively, these studies suggest that AI can emerge as a new type of innovation subject that collaborates with humans to reshape combinations of factors and modes of knowledge accumulation. Nevertheless, its integration into the innovation process still faces challenges related to trust, data quality, and system integration.

Second, the impact of AI on strategic transformations in product innovation. This main line of research is also examined from three perspectives. The first perspective, grounded in competitive strategy and organizational culture, investigates the mechanisms through which AI strengthens an organization's capacity to develop its own dynamic capabilities and core competitiveness in product innovation. Enterprises draw on AI technologies to enhance the scalability of innovation processes, as well as to strengthen organizational capabilities for dynamic learning and adaptation, thereby fostering a data-driven organizational culture (Lee et al., 2023; Verganti et al., 2020). The second perspective, from the vantage point of business models and ecosystems, is illustrated by Plantec et al. (2023), who argue that enterprises designing AI-embedded systems primarily rely on knowledge development. Big data and AI technologies are integrated into all stages of new product development, thus creating a feedback-driven and iterative model of product upgrading. Externally, the distributive, editable, and scalable AI enables enterprises to rapidly connect and align with complementary partners, thereby building innovation ecosystems (Shu et al., 2022). The third perspective, in terms of risk management, focuses on the supervision and governance of AI algorithms themselves. Since AI is trained based on historical data, its capacity to address long-term challenges may be diminished. As such, using AI for product innovation requires managing the risks associated with increased bias and preventing discriminatory outcomes in

decision-making (de Sousa et al., 2019; Yang et al., 2021). Moreover, the opacity inherent in AI as a form of machine cognition necessitates adequately addressing the algorithmic results' interpretability, and organizations invest in data governance and infrastructure (Maragno et al., 2023). Taken together, these studies suggest that the cognitive strategy regarding AI in product innovation not only drives internal organizational development but also fosters rapid connections between enterprises and external ecosystems. This enables them to effectively address risks and management challenges associated with AI algorithms.

Third, the impact of AI on transformations in the management of product innovation processes. This research is explored from two main perspectives. The first perspective, grounded in changes to the division of labor in innovation, is exemplified by Hossain et al. (2022), who contend that AI addresses the complexity of product innovation by iteratively executing simple tasks. As a result, human design activities increasingly take the form of meaning-making, which focuses on identifying which problems should or could be solved. For instance, when manufacturing enterprises adopt AI to replace marketing personnel on marketing analytics platforms, they enhance their ability to perceive, seize, and reconfigure markets, thereby gaining sustained competitive advantages. The second perspective focuses on improving the quality and efficiency of innovation processes. Thomassey and Zeng (2018) argue that AI-driven adaptive quality management can address the challenges facing traditional quality management methods, particularly in handling high-dimensional and nonlinear manufacturing data, where AI's contribution to product innovation is evident. For example, the adoption of AI technologies enables automated data collection and asset management and improves the material quality of innovative products while minimizing errors in final product inspection. Empirical evidence indicates that the higher the level of AI development in the industry and region where the enterprise operates, the stronger AI's positive effect on its innovation efficiency. Compared with traditional methods, AI-driven adaptive quality management reduces yield losses by 21.7% (Li et al., 2023; Senoner et al., 2022). In addition, enterprises use external market and user knowledge generated by big data-driven AI to make rational marketing decisions in the downstream phase of product innovation, thereby enhancing their performance (Bag et al., 2021). Collectively, these findings suggest that AI applications exert a profound impact on the management of product innovation processes.

Overall, research on the mechanisms by which AI influences product innovation is characterized by multi-perspective, multidimensional, and multilevel approaches. Yet, the core research agenda has centered on how AI reconstructs various stages of product innovation and enhances efficiency while reducing costs across the entire value chain. Specifically, AI induces structural changes in innovation subjects and drives strategic and process transformations in product innovation. Existing literature on innovation subjects focuses on how AI collaborates with humans in innovation and how AI applications align with data, labor, technology, and capital factors. At the strategic level, studies focus on how the strategic use of AI aligns with competitive strategy, business model innovation,

organizational culture, and ecosystems. At the process level, research examines how AI integrates the idea generation, detailed design and development, and testing and commercialization stages of product innovation, thus enabling dynamic, end-to-end process integration and coordination. Based on these mechanisms, AI applications at the levels of subjects, strategies, and processes are mutually influential and reinforcing. Thus, examining the mechanisms of AI's impact on product innovation from these three levels constitutes one of the theoretical points of consensus in the literature and forms the foundation for the SSP framework proposed in this study.

2.2 Theoretical Foundations and Research Perspectives of the SSP Framework

Academic definitions of AI vary according to research context. In light of the specific context of innovation management and drawing on definitions of AI from technology (Loureiro et al., 2021), process (Liu et al., 2020), and innovation perspectives (Prem, 2019), this study proposes a definition of AI from the standpoint of innovation management: AI refers to a digital ecosystem embedded in an enterprise's strategy and innovation development that enables cross-business, cross-process, and cross-temporal value creation and product innovation. This definition underscores that AI-driven transformations in innovation subjects, strategies, and processes form the foundation of the product innovation mechanism. The product innovation mechanism refers to the structural relationships and modes of operation among various factors in the product innovation process. Two common perspectives are used to characterize product innovation: a technological innovation perspective and a factor recombination perspective. Integrating these two perspectives, this study explores how AI influences the integration of product innovation processes and the transformation of factor recombination patterns, building on the theory of big data cooperative assets, combined with endogenous growth theory and Schumpeter's theory of innovation, and through an adaptive innovation perspective on enterprise-user interaction. In doing so, it characterizes the new mechanisms through which AI influences product innovation.

The structural transformation of innovation subjects brought about by AI is realized through adaptive innovation in enterprise-user interaction. Such adaptive innovation constitutes the mainstream innovation model of the digital economy (Xie, Wu, & Xiao, 2023) and provides the big data foundation on which AI evolves and advances. An examination of the new mechanisms through which AI affects product innovation from the perspective of adaptive innovation in enterprise-user interaction enables a clearer articulation of the origins of these mechanisms and grounds them in the underlying logic of AI's technological progress. Meanwhile, the theory of big data cooperative assets offers important theoretical guidance for understanding the essential characteristics of adaptive innovation in enterprise-user interaction (Xie, Zhang, & Wu, 2023). Firstly, the theory emphasizes that enterprise-user interaction forms the foundation and prerequisite for the existence of big data cooperative assets. Secondly, it underscores the high context-dependence of such assets, noting that the

development of big data, enterprise-user interaction, and actor value co-creation are the three conditions necessary for realizing the value of big data cooperative assets (Xie et al., 2016). In the context of AI applied to product innovation, the data generated through human-AI interaction essentially constitutes big data cooperative assets. Moreover, these assets are not only the outcome of human-AI interaction but also its driving force and foundation. Accordingly, big data cooperative assets are well suited to serve as the theoretical foundation for this study in characterizing the new mechanism through which AI influences product innovation.

With regard to innovation subjects, the new mechanism by which AI affects product innovation primarily operates through feedback-based enhancement generated by the two-way involvement of humans and AI. In the product innovation process, human-AI interaction is central and foundational; two-way involvement in this interaction amplifies an enterprise's technological change effect, labor substitution effect, and knowledge spillover effect (Wang et al., 2023). This not only alters the current modes of combining production factors but also changes the modes of knowledge accumulation. Humans contribute experience and intuitive judgment to product innovation, while AI enables enterprises to achieve more efficient and accurate market insight, user preference analysis, and real-time monitoring of public opinion. In response to both existing and latent needs, AI generates a greater number of commercially viable new solutions, thereby improving innovation efficiency and reinforcing the differentiated competitiveness of innovative products. Through mutual feedback, supplementation, and refinement of ideas between humans and AI, product innovation gains a feedback-based enhancement effect.

In terms of innovation strategies, the new mechanism by which AI affects product innovation primarily operates through process integration enabled by strategic alignment. As different types of innovation are interactive and co-evolutionary, no product innovation occurs in isolation; all require a matching innovation strategy and complementary assets for support. As such, product innovation, AI technologies, and other factors within the organization co-evolve through dynamic interaction. Enterprises must use AI strategically, integrate a cognitive strategy for AI into their organizational strategy, and align these strategies with their competitive strategy, business models, organizational culture, and ecosystems. Only by achieving such alignment can enterprises create value through product and service innovation.

As for the process of innovation, the new mechanism by which AI affects product innovation primarily operates through integrated and dynamic collaboration across the front, middle, and back ends of the process. In the fuzzy front end (FFE) of idea generation, although investment in AI does not significantly alter product structures, it substantially increases the number of trademarks and product patents. For example, investment in AI promotes idea generation in the early stage of product innovation (Babina et al., 2023); by processing large volumes of information within existing knowledge domains, AI systems can rapidly identify latent knowledge, thereby developing or recognizing a wide range of ideas and forming idea networks. In the middle stage of design and development, AI can overcome

the constraints of local knowledge search and draw inspiration from product knowledge across different domains to form product prototype networks. In the later stage of testing and commercialization, AI-driven product innovation can create intelligent product networks in which the functions of products within the network are highly interrelated. Through deep human-AI interactive feedback, these products can conduct self-testing and optimization and generate new ideas in the process that provide potential foundations and directions for the next cycle of product innovation.

2.3 Dimensions, Structures, and Elements of the SSP Framework

The impact of AI on the subjects, strategies, and processes of innovation constitutes the three analytical dimensions of BI for big data-driven product innovation. As a new social actor, AI integrates into organizational activities, introduces new production factor inputs, and forms novel combinations of production factors that drive advances in product innovation. In particular, AI generates a time-space compression effect that enhances product development efficiency (Xie et al., 2020) and triggers fundamental changes in organizational innovation strategies and processes. The interaction among these three dimensions creates an AI ecosystem for product innovation and gives rise to BI for a big data-driven product innovation, within which each dimension contains different combinations of factors. Accordingly, drawing on the theory of big data cooperative assets and the perspective of adaptive change in enterprise-user interaction, this study proposes the SSP analytical framework of BI for big data-driven product innovation to explore the new mechanisms of such intelligence. The framework is illustrated in Figure 1.

As shown in Figure 1, the innovation entities, strategies, and processes interact with each other, forming the operational structure and characteristics of the AI ecosystem in product innovation. These three factors mutually influence one another in a pairwise manner. As for innovation subjects, humans reconfigure AI and other production factors through new combinations, leading to abrupt changes in the mode of knowledge accumulation. The knowledge generated from product innovation is then fed back to humans to enrich the existing product knowledge base. In this feedback-based enhancement, humans and AI establish a mode of deep collaboration and interaction characterized by two-way involvement. In terms of innovation strategies, the cognitive strategy about AI is embedded across the front, middle, and back ends of innovation processes through alignment with competitive strategy, organizational culture, business models, and ecosystems. With regard to innovation processes, deep collaboration and interaction between humans and AI give rise to idea networks, prototype networks, and product networks at the front, middle, and back ends, respectively. These networks achieve integrated and dynamic collaboration through AI-enabled inspiration, bias correction, and self-testing.

It is also evident in Figure 1 that the subjects, strategies, and processes of innovation interact to form the operational structure and characteristics of the AI ecosystem for product

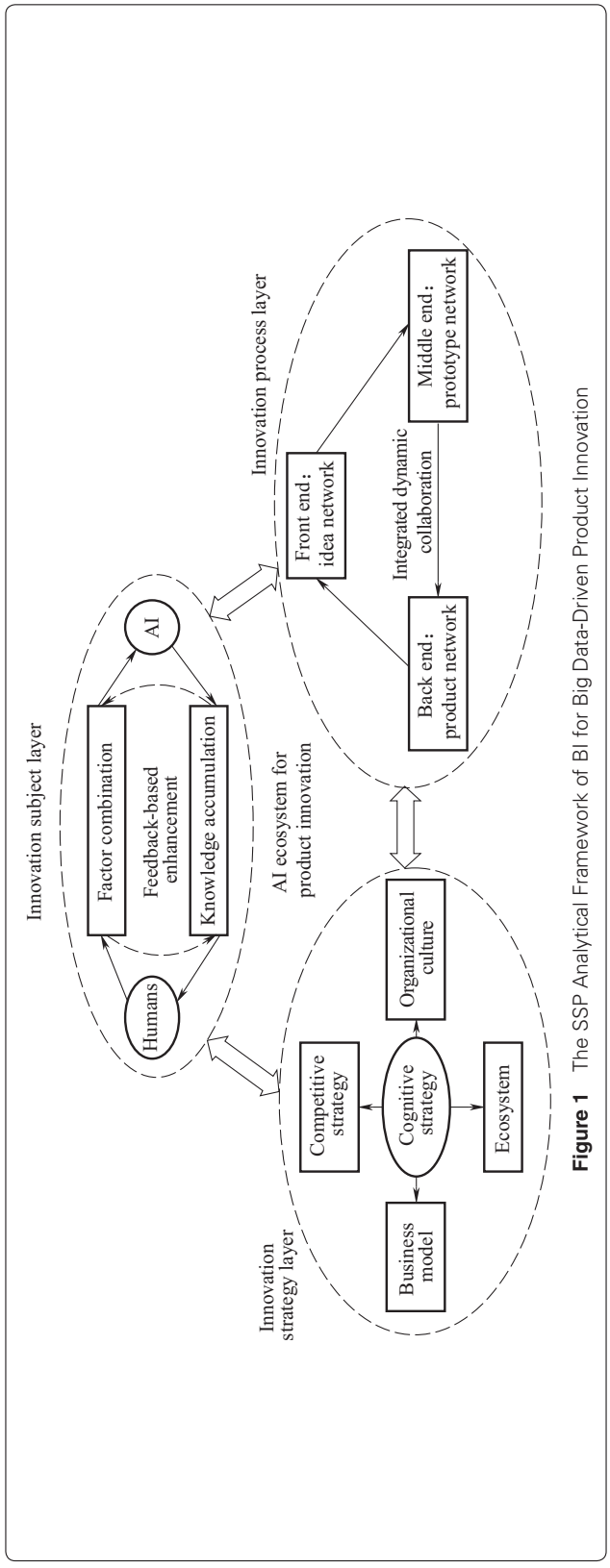

Figure 1 The SSP Analytical Framework of BI for Big Data-Driven Product Innovation

innovation, with each pair influencing one another. Accordingly, the SSP framework can also be regarded as an analytical framework for the AI ecosystem for product innovation. At the level of innovation subjects, factor combination and knowledge accumulation along a feedback-based enhancement path influence innovation strategy, which in turn guides the integration of the front, middle, and back ends at the process level. At this level, collaboration between humans and AI influences the innovation process through the paths of factor combination and knowledge accumulation, giving rise to full-process diffusion from the FFE, nonlinear iteration between demand-solution pairs, and generative self-testing in intelligent manufacturing. These, in turn, support the alignment of cognitive strategy about AI with competitive strategy, organizational culture, business models, and ecosystems at the level of innovation strategies.

First, the two-way influence between innovation subjects and innovation strategies is reflected in two main aspects. Regarding the influence of innovation subjects on innovation strategy, AI, which serves as a reliable and efficient analytical actor in product innovation decision-making, drives the formation of enterprises' cognitive strategy about AI. These cognitive strategies are aligned with competitive strategy, organizational culture, business models, and ecosystems, thereby enabling integration across the front, middle, and back ends of the innovation process. Regarding the influence of innovation strategy on innovation subjects, cognitive strategies about AI endow enterprises with the ability to reason, learn, associate, and solve problems based on existing knowledge, which facilitates a feedback cycle between factor combination and knowledge accumulation. As the intervals between iterations shorten and the number of cycles increases, the human-AI collaboration mechanism produces innovation outcomes with greater stability.

Second, the two-way influence between innovation subjects and innovation processes is also reflected in two major aspects. Regarding the influence of innovation subjects on innovation processes, the human-AI collaboration mechanism in product innovation plays distinct roles across the front, middle, and back ends of the process. At the front end, that is, the stage of product ideation, AI's self-generative capability and its interactive inspiration to humans (Wu et al., 2023) facilitate the rapid generation of diverse idea networks. At the middle end, namely, the stage of product design and development, AI provides organizations with error-correction functions for product design. By analyzing existing products in the market and incorporating feedback from a limited set of internal users, AI helps to offset the limitations of designers' experience, thereby forming production-feasible product prototype networks. At the back end, the stage of product testing and commercialization, AI enables self-testing, preemptively identifying functional errors, conducting A/B test with AI-simulated user data, and forming product networks with highly interrelated functions. Regarding the influence of innovation processes on innovation subjects, integration across the front, middle, and back ends renders the fixed sequence of product development more flexible, increases the possible combinations of process stages, diversifies the modes of factor combination, and further drives qualitative changes in knowledge accumulation, ultimately enhancing the stability and

effectiveness of the human-AI collaboration mechanism in product innovation.

Third, the two-way influence between innovation strategy and innovation processes is also manifested in two main ways. Regarding the impact of innovation strategy on the innovation process, the strategic deployment of AI must not only align with internal organizational factors but also synchronize with the ecosystem of participants across the entire value chain. Enterprises need to develop a synchronized AI cognitive strategy with both upstream and downstream stakeholders, thereby achieving seamless integration across front-end, mid-end, and back-end operations. Regarding the influence of innovation processes on innovation strategy, the inspiration and error-correction mechanisms between humans and AI within an integrated innovation process can facilitate the realization of corporate strategies. At the same time, strategy should not be regarded as static; rather, enterprises need to adjust and refine their strategic direction in a timely manner to adapt to evolving market and technological environments, thereby maintaining a competitive edge in a highly contested marketplace.

Within the SSP framework, the involvement of AI directly reshapes the structure of innovation subjects and triggers a chain of reactions in both innovation strategy and innovation process. Consequently, the structural transformation of innovation subjects brought about by AI constitutes a core feature of the AI ecosystem for product innovation. To examine the specific impacts of this core feature on product innovation, this study elaborates on two aspects separately: the foundational changes through which the structural transformation of AI-enabled innovation subjects reshapes innovation strategy, and the influence of such transformation on changes in innovation processes.

3 The Structural Changes in AI Innovation Agents Reformulate the Foundation of Innovation Strategy Transformation

Unlike traditional human-centric strategic innovation, the application of AI technology in manufacturing product innovation exhibits a structural shift in innovation agents toward human-AI collaboration. In innovation strategy, humans often provide directional guidance for new product development through qualitative experience, while AI's intrinsic characteristics combine with human expertise to form a new innovation agent. Compared to other digital technologies, AI possesses three core innovative features: composite agency, self-generation, and qualitative transformation in knowledge accumulation. Firstly, the composite agency of AI refers to its dual characteristics as both a general-purpose technology and a social entity. As a general-purpose technology, AI contributes to value creation and process optimization within organizations. As a social entity, anthropomorphic attributes and ethical considerations traditionally applied to human agents are embedded in algorithmic models, influencing factors such as organizations' willingness to adopt AI, trust levels, and perceived technological efficacy. Secondly, the self-generation capability of AI denotes its ability to rapidly feedback and instantaneously adjust based on data, algorithms, and models. Finally, the qualitative transformation in knowledge accumulation describes how, within

AI ecosystems or smart manufacturing models, digital technologies must be highly aligned with business operations. The speed of knowledge accumulation undergoes a qualitative leap compared to previous forms of knowledge emergence. Accordingly, the structural transformation of AI-enabled innovation subjects establishes a new foundation for strategic change in two main respects.

3.1 New Transformation in Factor Combination and Knowledge Accumulation

AI automates decision-making and learning while also driving the new transformation in the way knowledge is accumulated. The organic integration of AI technology into organizational processes is essential for addressing challenges encountered in innovation development. In the course of innovation development, AI continuously collects real-time data from its interactions with users or from the enterprise's surrounding ecosystem. Embedded AI within products interprets these data, performs natural language modeling, and generates predictions to guide enterprises' decision-making. With the support of algorithms, AI can autonomously generate new, specific solutions for users without human intervention. In this cycle, as new data are continually collected, AI taps into its learning capabilities to refine the accuracy of its predictions in relation to user needs and behavioral tendencies (Keding & Meissner, 2021). In AI-driven systems, much of the innovation-related knowledge is gathered and accumulated automatically through algorithms, which then pass the data to AI. In the process of problem-solving, AI integrates data from diverse sources, and these processes of data handling and decision-making further facilitate open innovation and distributed innovation, thereby forming valuable ecosystems. It is worth noting that AI tends to increase knowledge accumulation by exploring new knowledge rather than exploiting existing knowledge (Rittle-Johnson & Siegler, 2022). Therefore, the structural characteristic whereby human and AI actors collaborate brings about the new transformation in factor combination and knowledge accumulation within innovation strategy, thus greatly accelerating knowledge accumulation. The algorithmic models generated after AI training on data can create reusable and insightful new knowledge based on existing data, thereby expanding the traditional approaches through which organizations and humans have accumulated knowledge via exploratory and exploitative learning.

3.2 Adaptive Alignment of Enterprises' Cognitive Strategies about AI

The collaborative innovation subjects of humans and AI establish adaptive alignment of enterprises' cognitive strategies for AI as a new foundation for transforming product innovation strategy. By aligning these AI strategies with competitive strategy, organizational culture, business model, and ecosystem, enterprises can realize the strategic application of AI in an integrated manner across all stages of product innovation. From the competitive strategy perspective, technology must dynamically integrate with business operations to gain a competitive advantage. Under the guidance of an organization's competitive strategy,

AI technology is embedded across the front, middle, and back ends of product innovation, which empowers these processes and delivers competitive benefits. From the organizational culture perspective, drawing on the resource-based view and dynamic capabilities theory, Lee et al. (2023) argue that AI should be integrated into an enterprise's business analytics tools to transcend traditional organizational boundaries, thereby fostering a data-driven culture. This culture can significantly impact product innovation strategy and organizational processes, enable integrated and dynamic coordination across the front, middle, and back ends, and allow enterprises to overcome many limitations inherent in traditional labor-intensive innovation processes. From the business model perspective, some organizations have already developed AI-based business models that create new value for stakeholders and fundamentally reshape the front, middle, and back ends of the entire value chain (Mariani et al., 2023). From the ecosystem perspective, the introduction of AI enables the processes of value creation, delivery, and capture to transcend existing boundaries, which provides a more favorable operational environment for new activities and processes in product innovation. This environment spans the front, middle, and back ends of product development.

It can be argued that among the four types of alignment mentioned above, the alignment between AI cognitive strategy and competitive strategy holds paramount importance. It provides enterprises with a competitive advantage and serves as the primary prerequisite for the realization of cognitive strategy, playing a decisive role in shaping the alignment of organizational culture, business models, and ecosystems. The alignment between AI cognitive strategy and organizational culture is a key factor at the level of internal operations. In the AI era, enterprises must foster an open, innovative, and inclusive organizational culture to adapt to rapidly changing market environments and technological advancements. Such a culture can stimulate employees' creativity and innovative spirit, thereby promoting the research, development, and application of AI technologies. The alignment between cognitive strategy about AI and business models is a key determinant of product launch and profitability. Enterprises can utilize AI to continually explore new business models. The alignment between cognitive strategy about AI and ecosystems is a holistic factor in realizing the strategic application of AI. In the AI era, enterprises need to establish robust ecosystems involving other enterprises, institutions, and government bodies. Through value co-creation, they can attract multi-actor participation in innovation, break through traditional value chains and innovation models, and create a favorable environment for implementing their competitive strategies. Such ecosystems can foster information sharing, collaborative innovation, and mutual development. These four types of alignment are also necessary conditions for achieving integration across the front, middle, and back ends. Each alignment manifests at all three stages. For example, enterprises' product development activities across the front, middle, and back ends are all carried out under the guidance of competitive strategy. The structural transformation of AI as an innovation subject, through the two pathways of factor combination and knowledge accumulation, exerts a significant impact on transforming the strategy layer of product innovation.

4 The Impact of Structural Changes in AI Innovation Agents on the Transformation of Innovation Process

From the perspective of the innovation process, the collaborative innovation subjects of humans and AI have introduced three new features distinct from traditional product innovation: full-process diffusion in the FFE, nonlinear iteration of demand-solution pairs, and generative self-testing in intelligent manufacturing. These three features essentially represent the three key impacts of structural transformations of AI as an innovation subject on reshaping the product innovation process.

4.1 Full-Process Diffusion of the FFE

The FFE of product innovation generally refers to activities carried out before detailed design and development, such as opportunity identification, opportunity assessment, idea generation, idea screening, and concept development. It is characterized by three features: unstructured data, dynamic management, and uncertain decision-making (Heck et al., 2020). In product innovation, effective implementation of the FFE can directly contribute to the success of new products, as up to 80% of product costs are determined at this stage. AI has altered the division of labor in the FFE and shifted the innovation process to focus more on uniquely human capabilities for creativity and problem-solving, thereby improving the quality of front-end activities. The most notable impact of AI's involvement in the FFE lies in full-process diffusion. For example, AI-driven cognitive strategies enable enterprises to update their beliefs in real time during product innovation and keep product boundaries in a constant state of flux (Borges et al., 2021). This, in turn, extends the FFE across the entire innovation process, as an enterprise's ability to create value from AI depends on integrating AI creatively into new or improved processes. Accordingly, AI applications should extend beyond a single business unit to cover the entire operational process, including idea generation, design and development, and testing and commercialization. For instance, by combining the Apriori algorithm with LDA and QFD techniques in machine learning and by applying text mining and analysis, enterprises can extract objective information on customer needs and market competition from online user reviews. They can then transform it into data and input it into models to drive product innovation (Huang et al., 2022). Similarly, in the FFE stage, where the number of employees involved in concept development is usually small, AI as a social actor can compensate for human shortcomings in idea generation. However, the full-process diffusion of the FFE can also increase the risk of interdepartmental conflict later in development due to heightened ambiguity. The "black-box" nature of AI can make its product concepts more difficult for humans to understand, thus raising concerns that expanding the FFE could mislead product innovation efforts. Such concerns may prompt resistance to AI adoption (Arias-Pérez & Vélez-Jaramillo, 2022). Therefore, governance mechanisms are needed to manage the full-process diffusion of the FFE enabled by AI.

It can be said that, in the FFE, the information used for decision-making is qualitative, informal, and imprecise. AI's analytical capabilities can effectively process such information

and offer deeper and more accurate insights that help decision-makers better understand markets and users. In the context of AI, the dual innovation subjects, namely, humans and AI, retain human experience, intuition, and understanding in product innovation, while highlighting AI's generative capacity for rapid feedback and real-time adjustment. During both local and remote searches for knowledge, humans are inspired by AI to generate product ideas that have never been conceived before. In this way, knowledge is reorganized into an idea network, in which the multiple possibilities of products are preserved throughout subsequent processes of prototype design and product testing, thus allowing employees to adjust product details on demand. The cross-business-unit nature of AI extends the possibilities of the FFE to every stage of the product innovation process, breaks down idea silos among departments involved in product innovation, and enables them to "speak the same language." In this process, AI plays a dual role as both a general-purpose technology and a social actor.

4.2 Nonlinear Iteration of Demand-Solution Pairs

A demand-solution pair is essentially a problem-solving process in which, without first formalizing the problem, employees search for and integrate information to construct scenarios of demands and solutions. A pair is considered feasible if the benefits derived from the solution are no less than the costs incurred in providing it within the pairing (von Hippel & von Krogh, 2016). Introducing AI technology changes the human-dominated modes of information aggregation and knowledge accumulation and generates more diverse demand-solution matching scenarios through opaque cognitive forms. For example, the generative capacity of AI models for rapid feedback and real-time adjustment offers abundant opportunities for extracting heterogeneous knowledge and enables new product development teams to apply a single model to multiple tasks. By expanding the space of demands and solutions that product innovation teams can work with, AI enables organizations to uncover more potential links between problems and solutions (Bouschery et al., 2023). Users, drawing on their demands, experience, and expertise, may proactively improve products, while product developers within enterprises can leverage AI to mine, on a global scale, information about demands and solutions for new products, assess the generalizability of these demands, and evaluate the commercial feasibility of the solutions, thereby facilitating a new division of labor in product innovation (von Hippel & Kaulartz, 2021). In this process, AI's capabilities in text summarization, sentiment analysis, and user insight perception play a key role in identifying significant connections within given texts and extracting relevant information and knowledge.

For example, in the context of intelligent business, data resources from multiple actors engage in loosely coupled interactions on AI platforms, with algorithms undergoing continuous iterative enhancement. This enables enterprises to break away from the traditional linear paradigm of "demand identification-problem solving." AI can manage nonlinear

and complex relationships, handle multiple tasks, increase fault tolerance in learning, and process both quantitative and qualitative information simultaneously. Consequently, the knowledge spillover effect from AI applications connects multiple product domains, whereby innovation in a single product category often heuristically stimulates innovation in multiple other categories (Borges et al., 2021). Therefore, the impact of AI on demand-solution pairs is reflected in their nonlinear iteration, which manifests in both the FFE and the detailed design and development stages of the product innovation process. The involvement of AI and humans as dual innovation subjects transforms the process from a traditional linear model into a nonlinear feedback-iteration model. In this model, the boundaries between demands and solutions become less distinct: a solution at one stage may evolve into a demand at the next stage, and a demand in one stage may serve as a solution in another. The idea networks formed by demands and the prototype networks formed by solutions engage in mutual error correction, thereby establishing the iterative foundation for the next cycle of adaptive product innovation. Big data on large-scale product categories will support AI in accurately identifying demands, while AI's predictive power will drive the intelligent identification of solutions. Through nonlinear iteration, a collaborative innovation network of multi-product demand-solution pairs emerges.

4.3 Generative Self-Testing in Intelligent Manufacturing

While the back end of the product innovation process includes product testing, production, and market launch, this study focuses on the testing and production modules to explain how structural changes in the dual innovation actor model of humans and AI affect the back end of product innovation. In testing and commercialization, humans and AI work together for testing and production by constructing a human-network-physical system that integrates physical entities, virtual models, and the physical-virtual interaction linkages between them. Such systems have been applied in various fields, including healthcare, manufacturing, and aviation (Okegbile et al., 2023). Consequently, AI-enabled intelligent manufacturing integrates testing and production, characterized by autonomous adaptation and self-optimization. It can test and improve physical products in virtual environments, operate independently with minimal human intervention or control, and project the final optimized results back into the physical world.

Human digital twins, at the level of innovation subjects, provide the foundation for intelligent manufacturing, with applications including but not limited to production data collection and analysis, RFID-based production monitoring, and digital-twin-based cyber-physical integration. For instance, a knowledge-driven digital-twin manufacturing unit for intelligent manufacturing can think, decide, execute, and improve autonomously, enabling intelligent process planning, intelligent production scheduling, and production process analysis and dynamic adjustment (Zhou et al., 2020). Similarly, Sbai and Elboukhari (2018) employ Creative Adversarial Networks (CANs) to encourage Generative Adversarial

Networks (GANs) to deviate from existing painting styles, thereby producing original product designs. CANs allow for the generation of diverse, unconventional products while prioritizing originality; more than 60% of the designs generated by the model have been judged to be created by human designers, indicating that generative self-testing constitutes one of the key features of AI's impact on product development in intelligent manufacturing.

Thus, at the back end of product innovation, deep interaction and integration between humans and AI help AI demonstrate its generative capacity in virtual space. By adjusting reward algorithms based on human input, AI can adaptively optimize products toward more innovative directions, thereby enhancing its creativity. In the product testing process, AI can enrich the conclusions drawn from A/B test conducted in the physical world by leveraging algorithms to carry out generative self-testing. In the intelligent production process, drawing on human digital twins, dynamic knowledge bases, and self-learning technologies, AI can optimize manufacturing workflows through intelligent perception, simulation, comprehension, prediction, optimization, and control strategies, thereby enabling better integration of product innovation with manufacturing processes.

In summary, the structural transformation of AI as an innovation subject reshapes the product innovation process in three key ways: full-process integration, nonlinear iteration, and generative self-testing, ultimately fostering dynamic coordination across the front, middle, and back ends of product innovation. First, the full-process diffusion of the FFE highlights AI's dynamic involvement at the early stages of product innovation and renders the process more fluid and real-time. The application of AI is no longer confined to a single business unit but extends across the entire innovation process. This diffusion breaks down traditional innovation barriers and creates opportunities for cross-departmental collaborative innovation. While AI offers significant advantages in data analysis and idea generation, careful management is required to maintain balance during front-end diffusion so as to avoid interdepartmental conflicts. Second, through heterogeneous knowledge extraction enabled by the dual innovation actor model of humans and AI, product innovation teams can draw inspiration to form a collaborative innovation network of multiple demand-solution pairs. This nonlinear iteration blurs the boundaries between needs and solutions and establishes the foundation for subsequent adaptive product innovation cycles. Finally, deep human-AI interaction and integration underpin the creation of human digital twins, which provide the basis for intelligent manufacturing. At the back end of product innovation, AI demonstrates its generativity by leveraging intelligent perception, simulation, comprehension, prediction, optimization, and control strategies to support autonomous manufacturing. This generative self-testing approach makes product testing and production more autonomous and adaptive, thereby accelerating the iteration from virtual space to physical reality. As a result, AI applications blur the boundaries between idea generation, detailed design and development, and testing and commercialization, creating a product innovation model characterized by fluidity, cyclicality, and feedback. This holistic process coordination and dynamism offer enterprises a more flexible and adaptive innovation environment that expands possibilities

for product iteration, with deep human-AI collaboration emerging as a key driver of product innovation.

5 Conclusions and Future Prospects

Drawing on the theory of big data cooperative assets and the perspective of adaptive innovation of enterprise-user interaction, this study proposes the SSP analytical framework of BI for big data-driven product innovation and arrives at three main conclusions.

Firstly, from an innovation management perspective, AI essentially functions as a digital ecosystem integrated into corporate strategy and innovation development, which enables value creation and product innovation across business units, processes, and time dimensions. Through the two-way engagement of humans and AI, a dual feedback-enhancement mechanism of factor combination and knowledge accumulation emerges, which structurally transforms innovation subjects and lays a new foundation for strategic and process transformation in product innovation.

Secondly, an enterprise's cognitive strategy for AI refers to its shared strategic understanding of AI's value and modes of realization, as well as its associated management practices. Such a strategy must be aligned with the organization's competitive strategy, organizational culture, business model, and ecosystem, thereby collectively shaping the integrated application of AI in innovation processes.

Thirdly, compared with product innovation management based on previous technological advancements and other general-purpose technologies, three distinctive features define big data-driven product innovation processes: the full-process diffusion of the FFE, the nonlinear iteration of demand-solution pairs, and the generative self-testing of intelligent manufacturing.

Based on the above three research dimensions, this study has two main contributions. First, it embeds the core ideas of endogenous growth theory and Schumpeter's theory of innovation into the theoretical foundation of big data cooperative assets to develop the SSP analytical framework. By highlighting AI's role in driving product innovation, it emphasizes that AI's impact arises from big data cooperative assets formed through enterprise-user interactions. Through the dual pathways of factor combination and knowledge accumulation, AI gives rise to a new type of innovation subject, fosters deep human-AI collaboration, and ultimately forms BI for big data-driven product innovation. In doing so, this study extends the understanding of innovation networks and supports the perspectives on knowledge diffusion and industrial interaction in endogenous growth theory. It argues that AI, as a composite innovation subject combining the attributes of a general-purpose technology and a social actor, is not merely a new technology input, but also transforms the ways enterprises combine factors of production and accumulate knowledge, thus promoting a cross-disciplinary integration of AI innovation management with big data cooperative assets, endogenous growth theory, and Schumpeter's theory of innovation. Second, through the SSP framework,

this study elaborates the realization mechanism of BI for big data-driven product innovation and analyzes AI's application at the levels of innovation subjects, innovation strategy, and innovation processes, as well as the logical relationships among them. It examines the two-way involvement of humans and AI, the strategic use of AI, and AI's reshaping of innovation processes. The findings show that the SSP framework effectively captures the characteristics and patterns of BI for big data-driven product innovation and offers a novel analytical lens for research on the relationship between AI and product innovation.

In future research, the key concepts and internal relationships within the SSP framework could be further operationalized and empirically validated. This includes developing measurable approaches to characterize the full-process diffusion of the FFE, the nonlinear iteration of demand-solution pairs, and generative self-testing in intelligent manufacturing, thereby developing an operational empirical model. Relevant representative literature and practical observations could be used to extract key variables and build a research model within the field of BI. In addition, further studies are needed to develop measurable variables and empirical data to examine the mechanisms through which the strategic use of AI facilitates front-middle-back-end integration and, in turn, affects product innovation performance. Moreover, this study does not explore the mechanisms of interaction among the creative network, prototype network, and product network formed after AI is integrated into BI for product innovation, nor the internal interrelationships among the elements within each network; these issues merit an in-depth inquiry in future research.

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