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When Investment Meets Competition: The Logic and Responses of Product Market Structure Evolution in the AI Era

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Abstract: ***Artificial intelligence (AI) investment is fundamentally reshaping the landscape of product market competition, yet its systematic impact and underlying mechanisms remain inadequately theorized. Based on the practices of China's A-share listed companies, this paper develops a comprehensive theoretical framework from both supply-side capability reconstruction and demand-side structural transformation perspectives to analyze how AI investment influences product market competition. The study yields three key findings. First, AI investment fundamentally transforms firms' competitive strategy sets and capability boundaries through three channels: reducing marginal costs, enhancing demand forecasting accuracy, and expanding product functional spaces. Second, the intrinsic characteristics of AI—including increasing returns to scale in data, algorithmic black boxes, and cross-scenario knowledge transfer capabilities—drive the competitive boundaries of product markets to shift from the traditional two-dimensional "product-geography" definition toward a multidimensional "scenario-time-ecosystem" structure. Third, the relationship between AI investment and competition intensity follows an inverted U-shaped pattern, with the inflection point determined by the relative dynamics between the intensity of data-driven positive feedback and user multi-homing costs. Further analysis reveals that supply-side R&D transformation barriers and demand-side financing constraints constitute dual dilemmas that may accelerate market concentration toward leading platforms. The theoretical contribution of this paper lies in incorporating the competitive effects of AI investment into an inverted U-shaped dynamic framework while explicitly distinguishing supply-side capability mechanisms from demand-side structural mechanisms. These conclusions provide theoretical foundations and decision-making references for product market competition governance, digital antitrust policy formulation, and corporate AI investment strategies in the AI era.***

Keywords: Artificial Intelligence Investment; Product Market Competition; Inverted U-Shaped Effect; Data Positive Feedback; Competitive Boundary.

1. INTRODUCTION

Artificial intelligence technology is evolving from a supplementary tool into a core component of corporate competitive strategy, profoundly transforming the production methods, business models, and competitive landscape of individual firms. Unlike previous investments in information technology, AI investment not only optimizes existing business processes but also fundamentally alters how firms understand market demand, the logic behind product creation, and the ways they interact with consumers. From generative AI empowering product design to recommendation algorithms reshaping consumer decision-making paths, and from intelligent supply chain management to the widespread deployment of dynamic pricing systems, artificial intelligence is expanding product-market competition from the traditional three-dimensional space of "cost–price–quality" into a complex arena of strategic competition that encompasses new dimensions such as the speed of intelligent response, the depth of personalized adaptation, and the breadth of ecosystem synergy.

Chinese enterprises' investment in artificial intelligence is undergoing a critical shift from "proof of concept" to "large-scale implementation." China's AI industry is experiencing rapid expansion; according to estimates by the China Academy of Information and Communications Technology (CAICT), the scale of the domestic core AI industry will exceed 1.2 trillion yuan by 2025. AI technology is accelerating its penetration into sectors such as manufacturing, retail, finance, and digital content, while industry investment in AI continues to grow at a high rate. Globally, AI is also in a phase of rapid expansion. According to statistics from the data analytics firm Dealroom, global venture capital investment in the AI sector exceeded $110 billion in 2024—a 62% surge from the previous year and a new record high—as capital continues to converge on the AI sector. In this process, a core question that combines both theoretical value and practical urgency has become increasingly prominent: Do large-scale AI investments by enterprises ultimately strengthen or weaken competition in product markets? What are the mechanisms behind these effects?

From a theoretical perspective, the impact of AI investment on competition in product markets is highly complex. On the one hand, by reducing marginal costs, improving the accuracy of demand forecasting, and expanding the scope of product functionality, AI significantly enhances companies' ability to compete in the market, which theoretically contributes to increased competition. Companies' investment decisions regarding AI are constrained by multiple factors, including internal resources, market conditions, and technological maturity [1]; meanwhile, the application of AI technology can enhance companies' ability to identify consumer needs, accelerate the iteration of new products and services, and thereby reshape the competitive landscape [2]. On the other hand, AI investment exhibits significant economies of scale and scope—the more data, the greater the computing power, and the more optimized the algorithms, the easier it is for early movers to establish a "winner-takes-all" scenario through their first-mover advantage. Some large technology companies have leveraged their technical advantages and data resources in the field of artificial intelligence to establish new competitive advantages [3], which may lead to increased market concentration and a solidification of the competitive landscape.

Recent research has further revealed the underlying logic of this trend. The OECD (2025) report points out that the competitive effects of AI in downstream markets are highly context-dependent; structural advantages formed by incumbent firms through data, computing power, and integration capabilities may enable them to capture disproportionate market returns [4]. In an environment of algorithmic competition, firms are prone to falling into a "prisoner's dilemma"-like investment game, where continuously increasing AI investment often serves only to maintain their relative market position [5].

Although the aforementioned studies provide important insights into the relationship between AI investment and market performance, theoretical and empirical research directly examining the impact of AI investment on product market competition—rather than financial market performance or firm-level performance—remains scarce. Existing research has three gaps that urgently need to be addressed: First, most studies focus the effects of AI investment on corporate performance, lacking a systematic description of the transmission mechanisms for "relational" variables such as product market competition; second, there is a lack of theoretical explanation for the nonlinear characteristics of how AI investment affects competition—particularly the possibility of phased turning points; third, there is insufficient discussion of the process by which the endogenous nature of AI technology reshapes the boundaries of product market competition.

Based on this, this paper examines the theoretical logic and practical challenges of AI investment's impact on product market competition. It explores this impact from both supply-side and demand-side perspectives and, by combining theoretical analysis with comparative case studies, proposes targeted policy recommendations. The aim is to provide theoretical support for building a virtuous cycle among "technology, finance, and industry" and for advancing the refinement of modern market competition mechanisms.

2. LITERATURE REVIEW

2.1 Related Research on Artificial Intelligence Investment

Artificial intelligence investment (AI Investment) refers to capital expenditures and expensed investments made by enterprises in areas such as AI technology R&D, computing infrastructure, algorithm model development, deployment of intelligent application systems, and recruitment of relevant talent. Distinct from broadly defined digital transformation investments, the core characteristic of AI investment lies in its direct focus on the development and application of technologies such as machine learning, deep learning, and natural language processing, and is characterized by high uncertainty, long return cycles, and strong data dependency. Product market competition refers to the process by which different firms compete for consumers within the same product market across dimensions such as price, quality, functionality, service, and innovation; its intensity can be measured through indicators such as market concentration, firm entry and exit rates, and marginal prices. This paper focuses on how AI investment alters the nature, intensity, and structure of this competitive process.

AI investment has become a core driver of global industrial competition and economic growth, with existing research primarily concentrated on the strategic attributes and economic consequences of AI. At the macro level, most scholars focus on the impact of AI on economic growth, productivity gains, industry transformation, and employment restructuring. The widespread application of AI technology can significantly improve production efficiency and inject new momentum into economic growth. As companies integrate AI-driven automation technologies into their business operations, global productivity is expected to see a significant boost. At the industrial level, large enterprises have begun leveraging AI to transform business processes such as production, sales, marketing, and analytics, thereby driving industrial upgrading and the restructuring of value chains. At the same time, the application of AI can also offset, to some extent, the job losses resulting from automation by creating new jobs and occupational types.

At the micro level, research focuses more on investment decisions at the enterprise level, technology adoption, and the impact on competition in product markets.AI technology can enhance enterprises' data analysis capabilities, capture dynamic consumer demand, and drive business model innovation and marketing capability upgrades. Internally, AI can collect and process massive amounts of data to support data-driven, scientific decision-making, optimize business processes, and drive organizational innovation and transformation [6], helping enterprises achieve innovative reorganization of existing technologies and thereby improve operational efficiency [7]. Externally, AI can reshape marketing models and restructure collaborative relationships with industry partners [8] [9], contributing to value chain upgrading.

Regarding the impact of AI investment on corporate decision-making, existing research has established several key consensus points. First, corporate investment decisions regarding artificial intelligence are not isolated technological choices but are subject to the combined constraints of multiple factors, including internal resource endowments, the external market environment, and technological maturity. Second, AI technology is profoundly reshaping corporate business models and the sources of competitive advantage; its impact has transcended the level of operational efficiency and extended to a fundamental restructuring of the logic of value creation and competitive positioning. Third, at the inter-firm level, the introduction of AI technology is altering competitive dynamics and the balance of power within industries, driving profound adjustments to the competitive landscape.

2.2 Factors Influencing Competition in Product Markets

The intensity and evolution of product market competition are influenced by multiple factors, stemming from both the market's intrinsic characteristics and driven by the external environment and institutional design. From a corporate strategy perspective, differentiation strategies can alter the competitive landscape through AI-driven functional innovation, brand building, and other approaches. The price war that has erupted in the new energy vehicle industry stems, to a certain extent, from converging technological pathways and insufficient product differentiation. According to the "competition avoidance effect," in markets where competition is not yet fully established, competitive pressure incentivizes firms to increase innovation investment to break free from competitive constraints [10]; however, when an industry is highly concentrated, firms' incentives to innovate are often weakened.

In terms of technological barriers, capital barriers resulting from technological accumulation, algorithmic advantages, and initial investments constrain the competitive capabilities of new entrants, thereby shaping the industry's competitive landscape. From an external perspective, consumers' sensitivity to product price, quality, and user experience guides the evolution of market competition; the internet and social media have broadened consumers' access to information, thereby curbing market behaviors characterized by low quality and low prices. Online review platforms leverage word-of-mouth to amplify differences between brands, compelling companies to continuously enhance their product competitiveness. At the same time, local protectionism and unreasonable subsidy policies can easily trigger a surge of investment, leading to overcrowding in certain sectors and misallocation of resources, which further intensifies competition within the industry.

2.3 AI Investment and Product Market Competition

As a disruptive technology, artificial intelligence is profoundly reshaping the competitive landscape of product markets. AI technology can lower the barriers to technology adoption, improve the efficiency of resource allocation, and weaken traditional market entry barriers; however, the accumulation of data and computing power resources creates entirely new barriers, helping leading companies consolidate their market positions. This has given rise to a market structure dominated by leading technology oligopolies, alongside a large number of long-tail innovators.AI is gradually becoming a key tool for enterprises to engage in differentiated competition, altering the intensity of market competition through data-driven personalized services and product innovation, while effectively optimizing supply chain efficiency [11].

However, overreliance on cost-based competition can stifle corporate innovation; if capital markets overinvest in AI infrastructure, it may crowd out R&D resources at the application level, further fueling homogenized competition. Government subsidies and tax incentives can accelerate the diffusion of AI technology, but they also tend to trigger a surge of speculative investment. From the perspective of industrial chain evolution, AI is driving a shift in industrial organization from traditional linear division of labor to an ecosystem-based collaboration model, intensifying cross-industry competition and giving rise to new forms of competitive cooperation.The absence of an AI ethical governance framework can easily distort the order of market competition; at the same time, the competition over technical standards among nations also increases the potential risk of global market fragmentation.

From a dynamic evolutionary perspective, AI's impact on product market competition is multidimensional: on the one hand, technology diffusion lowers barriers to market entry and stimulates innovation; on the other hand, capital misallocation and inappropriate policy intervention may also exacerbate market distortions. From an evolutionary standpoint, AI tends to drive up market concentration in the short term, but as technology spillovers occur and open-source ecosystems mature, it is expected to promote more robust competition in the long term. Some research in the financial sector suggests that technological convergence leads to strategy homogenization and the dissipation of excess returns; this line of reasoning also offers valuable analogies for understanding AI competition in the real economy.

2.4 Literature Review

In summary, a wealth of research on AI investment has been conducted by scholars both domestically and internationally, providing important and robust literature support for this study. However, most studies focus the effects of AI investment on corporate performance or financial market performance, lacking a systematic description of the transmission mechanisms for the "relational" variable of product market competition; they also lack theoretical explanations and empirical tests regarding the nonlinear characteristics of how AI investment affects competition; regarding the relationship between AI investor behavior and the competitive landscape, existing evidence largely originates from developed markets, and its applicability to China's Shanghai and Shenzhen A-share markets remains to be verified. Therefore, this paper adopts a dual perspective—examining both the supply side and the demand side—and is grounded in the dual pathways of technological penetration and the reshaping of competitive boundaries resulting from AI investment. By deconstructing the theoretical logic, practical obstacles, and institutional innovation pathways through which AI investment empowers competition in product markets, this paper aims to provide theoretical support and policy insights for establishing effective market competition mechanisms in the AI era.

3. THEORETICAL MECHANISMS THROUGH WHICH AI INVESTMENT INFLUENCES PRODUCT MARKET COMPETITION

3.1 Three Channels Through Which AI Investment Reshapes Corporate Competitive Capabilities

The impact of AI investment on product market competition is transmitted through three parallel channels of capability reshaping.

First, the decline in marginal costs and the restructuring of pricing strategies. AI systems significantly reduce both the average and marginal costs of products by optimizing production scheduling, lowering defect rates, shortening inventory turnover cycles, and automating repetitive cognitive labor. Changes in the cost structure directly expand firms' pricing flexibility—during periods of weak demand, firms can maintain capacity utilization at lower prices without incurring losses; during periods of strong demand, they can secure greater profit margins to reinvest in R&D. In standardized product markets, this cost advantage directly translates into price competition pressure, driving down the industry-wide price level.

Second, improved demand forecasting accuracy and deeper market segmentation. Traditional demand forecasting relies on simple extrapolation from historical sales data or limited market research, whereas AI systems can integrate multi-source, heterogeneous data—including social media sentiment, weather changes, macroeconomic shocks, and competitor dynamics—to generate high-frequency, granular demand forecasts. This enables companies to precisely identify consumer groups with different willingness to pay and preferences, implementing more refined market segmentation and differentiated pricing. The competitive implication is that the competitive dimension in product markets has shifted from "battling for market share at a uniform price" to "precise matching across multiple price dimensions," significantly increasing the intensity of competition at the micro level.

Third, the expansion of product functionality and the acceleration of differentiation. AI-enabled R&D and design tools (such as generative design and virtual simulation testing) have drastically reduced the time it takes for new products to progress from concept to prototype. More importantly, AI enables "software-defined functionality"—the core functions of many products can be continuously iterated through OTA (over-the-air) updates, eliminating the need to wait for hardware replacement cycles. This means that product differentiation is no longer a one-time R&D outcome but rather a continuous, user-perceivable, dynamic evolutionary process. The timeframe for competition has been drastically compressed, and companies must possess the ability to continuously deliver differentiated updates to maintain their competitive position.

3.2 Multidimensional Expansion of Product-Market Competition Boundaries in the AI Era

Traditional industrial organization theory defines the boundaries of product-market competition in terms of two dimensions: "product substitutability" and "geographic scope." This analysis is based on the premise that product functions are relatively stable and industry boundaries are clearly defined. Investment in artificial intelligence is systematically deconstructing this premise, driving the expansion of competitive boundaries from two dimensions to multiple dimensions.

Scenario Dimension: AI-driven intelligent recommendations and personalized services have shifted the primary focus of competition from a product's physical attributes to the extent to which it is embedded in consumer scenarios. Competition among smart speakers no longer centers on sound quality specifications but rather on whether their voice interaction capabilities and connected ecosystems can integrate into users' daily lives. When "scenario adaptability" becomes the core competitive dimension, the boundaries of traditional product categories blur—cross-category substitutes may prove more competitive than products within the same category.

Temporal Dimension: AI systems continuously learn user behavior and optimize response strategies in real time, shifting competition in the temporal dimension from a "cyclical game" to a "continuous game." Companies must not only provide the optimal product at a specific point in time but also maintain a quality advantage in intelligent interaction throughout the entire user lifecycle. This expansion of the temporal dimension raises competitive barriers—new entrants cannot quickly acquire the relational assets formed by "learning accumulation" through short-term price discounts.

Ecosystem Dimension: The competitive impact of AI investment extends beyond the level of individual products to encompass a "technological ecosystem" comprising data interfaces, algorithmic models, cloud infrastructure, and developer communities. Within this ecosystem structure, competition between products is partially transformed into competition between systems—the competitiveness of an individual product no longer depends solely on its own functionality and quality, but also on the technical standard compatibility of the ecosystem in which it is embedded, developer activity, and the capacity for cross-product collaborative innovation. Consequently, the competitive boundaries of the product market expand from the level of individual products to that of the entire technological ecosystem.

3.3 The Inverted-U Effect of AI Investment on Competition Intensity

Based on the aforementioned mechanisms, this paper proposes a core theoretical proposition: the impact of AI investment on the intensity of competition in product markets follows an inverted U-shaped curve—as the level of AI investment in the industry rises, the intensity of competition first increases and then decreases.

In the early stages of AI investment (the technology diffusion phase), access to AI tools is relatively equitable (as cloud service providers offer standardized AI capabilities), enabling small and medium-sized enterprises (SMEs) to acquire predictive and optimization capabilities—previously exclusive to large enterprises—at a lower cost. During this phase, the primary effects of AI investment are to lower market entry barriers, increase avenues for differentiation, and enhance price transparency, thereby effectively stimulating competitive vitality. New entrants can use AI to precisely target niche markets overlooked by incumbent firms, while traditionally weaker firms can narrow the gap with market leaders through intelligent service experiences. The application of AI technology enables companies to identify consumer needs more accurately and rapidly launch new products and services, thereby intensifying market competition.

However, once AI investment crosses a certain tipping point, the positive feedback loop of "data—algorithms—users" begins to dominate the competitive landscape. Specifically: AI systems continuously generate and collect data during use; more data trains better algorithms; better algorithms provide a superior user experience; a superior user experience attracts more users; and more users, in turn, generate even more data. This cycle causes the first-mover advantage to accumulate exponentially over time.

At the same time, the fixed costs associated with AI infrastructure create a steadily widening funding gap for small and medium-sized enterprises (SMEs) in areas such as computing power procurement, talent recruitment, and data governance. The combination of these two factors leads to a structural contraction in market competition, shifting from a "diverse and vibrant" landscape to one dominated by "a few major platforms with many players surviving on the periphery." At this stage, although the apparent variety of products may increase, the number of truly competitive alternatives decreases, and market dominance tends to become more concentrated.

The location of the inflection point in this inverted U-shaped relationship is influenced by multiple factors, including industry-specific data characteristics, the degree of technological standardization, regulatory policies, and user switching costs. In industries where data is highly substitutable and user switching costs are low, the inflection point may occur later; in industries where data is highly exclusive and network effects are significant, the inflection point may occur earlier. It should be noted that the three channels continue to play a role throughout the entire investment cycle, and their promotional effects do not disappear; however, in the later stages of investment, the growth rate of the structural inhibitory effects of data lock-in and ecosystem barriers outpaces the growth rate of the promotional effects of the three channels, causing the net effect to turn negative.

4. PRACTICAL CHALLENGES OF HOW AI INVESTMENT AFFECTS PRODUCT MARKET COMPETITION

4.1 From a Supply-Side Perspective: Insufficient Corporate R&D Investment and Low Efficiency in Commercializing Research Outcomes

From a supply-side perspective, insufficient corporate R&D investment and low efficiency in commercializing research outcomes are the primary obstacles constraining the competitive effects of AI investment. China's traditional innovation system exhibits a "three-way sequential synergy" path dependence, forming a sequential chain in which universities focus on basic research, research institutes focus on applied research, and enterprises focus on industrialization. This model is prone to the "innovation valley of death" problem: Universities and research institutes produce a large number of papers and patents, but the rate of commercialization of these outcomes is low, hindering breakthroughs in the industrial implementation of key core technologies. Under this division of labor, a misalignment of roles among innovation actors often occurs: universities and research institutes extend their reach into applied technology development, while enterprises struggle to fully leverage their role as primary innovation drivers, further reducing the efficiency of R&D commercialization.

This issue is even more pronounced in the context of AI investment. Overall, corporate investment in AI R&D remains relatively low; the average R&D intensity among Chinese manufacturing enterprises is only 1.5%, far below the 3% level seen in developed countries. On the one hand, AI R&D is characterized by high investment, long cycles, and high failure rates, and ordinary enterprises often harbor reservations about investment projects with long payback periods; on the other hand, the complexity of AI technology requires enterprises to establish deep cooperation with universities and research institutions, but the disconnect between industry, academia, and research under the "three-way collaborative" model makes it difficult for enterprises to effectively absorb external AI R&D outcomes. According to research, the commercialization rate of scientific and technological achievements from China's universities and research institutes remains low. Researchers face numerous challenges regarding the commercialization of their work, such as "unwillingness to commercialize" and "fear of commercializing." There is a widespread tendency in these institutions to "prioritize publications over commercialization," and researchers lack strong incentives to conduct research aligned with industrial development and corporate needs.

4.2 Demand-Side Perspective: Financing Constraints and Shortage of Research Funding

From the demand side, enterprises face significant financing constraints in AI investment. There is a structural mismatch between the traditional financing system and the risk characteristics of technological innovation: core technology R&D is characterized by high investment, long cycles, and high failure rates, while financial institutions generally exhibit a "risk-averse" tendency. Bank lending relies excessively on fixed-asset collateral, but more than 70% of a technology company's assets are intangible, leading to systemic financing exclusion for AI R&D projects.

This financing dilemma creates a threefold transmission bottleneck: First, enterprises' overreliance on internal financing limits the intensity of AI R&D investment. For A-share listed companies, self-funded capital accounts for as much as 81.4% of R&D expenditures, while venture capital provides insufficient support for early-stage AI technology projects. Second, the indirect financing market exhibits "ownership discrimination" and "scale bias." Due to insufficient fixed-asset collateral and their small scale, financial institutions have low confidence in small and medium-sized technology enterprises. As a result, these firms face higher average interest rates on bank loans than state-owned enterprises, and loan terms are generally shorter than AI R&D cycles, which conflicts with the needs of technology R&D. Third, the direct financing market lacks tolerance for technological innovation failures. Companies listed on the STAR Market allocate an average of 12% of their revenue to R&D, yet the failure rate for such projects is high. Meanwhile, venture capital firms generally require an exit within 3 to 5 years, which is severely out of sync with the R&D cycle for core AI technologies.

Excessive investment in AI infrastructure by capital markets may crowd out R&D resources at the application layer, triggering homogenized competition. Meanwhile, government subsidies and tax incentives accelerate the diffusion of AI technology but may also induce a "tidal wave effect" [12]. Furthermore, disparities in AI development across regions, the urban-rural digital divide, and insufficient service coverage for small, medium, and micro enterprises remain prominent issues, making it difficult for some enterprises to obtain the financial support needed for AI investment.

4.3 From the Perspective of Competitive Structure: Algorithm Convergence, Data Barriers, and Blurred Competitive Boundaries

Structural competition issues triggered by AI investment also warrant close attention.

Data barriers have become new obstacles to market entry. The high sensitivity of AI system performance to data scale has led to the formation of "data moats"—the larger and more diverse the proprietary data accumulated by early-market entrants, the more difficult it is for new entrants to bridge the data volume gap in the short term, even if they possess equivalent technical capabilities and financial strength. Some large platform companies, through extensive product portfolios and investment and mergers and acquisitions, have achieved the aggregation and cross-utilization of data across various scenarios, forming a "data ecosystem advantage" that competitors in a single business domain find difficult to match [13].

The market risks posed by algorithmic convergence cannot be overlooked. When a large number of companies within an industry use AI models and training datasets with similar structures, their pricing strategies, product recommendation logic, and customer response patterns are prone to behavioral convergence, creating a herd effect at the algorithmic level. In a state of algorithmic equilibrium, even if companies continue to increase their technological investments, the overall excess returns that can be achieved will tend to converge; this logic serves as an analogical reference for understanding AI-driven product competition in the real economy [14].

The blurring of competitive boundaries poses challenges for traditional regulatory tools. The rapid expansion of AI-driven smart ecosystems enables companies to cross industry lines and enter multiple market segments, making it difficult to directly and simply apply the traditional two-dimensional framework for defining relevant markets based on product and geography. Algorithm-driven pricing behavior is dynamic, opaque, and non-transparent; regulatory agencies face obstacles in obtaining complete, real-time transaction data, which increases the difficulty of identifying and determining price discrimination and predatory pricing. The "black box" nature of AI algorithms makes it difficult to trace the causal relationship between the algorithms and competitive harm; the current Antitrust Law still faces practical challenges in applying its rules to new types of conduct, such as algorithmic collusion, data abuse, and ecosystem exclusion.

5. OPTIMIZATION PATHWAYS AND POLICY RECOMMENDATIONS FOR AI INVESTMENT TO EMPOWER COMPETITION IN PRODUCT MARKETS

5.1 Optimization Pathways

5.1.1 Promote Deep Integration of AI Investment with Industry-Academia-Research Collaboration to Strengthen Enterprises' Role as Primary Innovators

To address the inefficiency in the commercialization of R&D outcomes resulting from the "three-way serial collaboration" model on the supply side, institutional innovation is needed to further strengthen the leading role of enterprises in AI technology breakthroughs and promote the deep integration of AI investment with the industry-academia-research system() [15]. A parallel collaboration mechanism driven by industrial demand should be established, in which enterprises identify industrial technology needs, universities conduct research on foundational and key technologies, and research institutions provide technical support—thereby replacing the traditional sequential "serial" innovation chain. At the national level, R&D intensity could be incorporated into the performance evaluation system for state-owned enterprises, while tax incentives—such as additional deductions for R&D expenses—should be implemented to fully stimulate the endogenous innovation drive of AI technology companies.

5.1.2 Establish a Tiered and Categorized AI Investment Guidance Mechanism to Alleviate Financing Constraints

To address the financing constraints faced by the demand side, a tiered empowerment system combining government guidance with market-driven forces should be established. Large, leading enterprises should be encouraged to build industry-level open AI platforms and provide customizable AI capability modules to downstream small and medium-sized enterprises (SMEs), thereby forming an industrial chain collaboration model where leading enterprises build platforms and SMEs reuse technological capabilities. For small, medium, and micro enterprises, they should be guided to prioritize the implementation of lightweight AI applications, focusing on business scenarios with high standardization, short deployment cycles, and rapid return on investment—such as intelligent customer service, inventory forecasting, and pricing assistance—to avoid blindly investing in the construction of large-scale, all-encompassing AI infrastructure.

5.1.3 Improve the Mechanism for Data Element Circulation to Prevent Algorithm Convergence and Homogenization of Competition

To address the risks posed by data barriers and algorithmic convergence, efforts should be accelerated to build industry-level data-sharing platforms and trusted data spaces. While fully protecting trade secrets and personal privacy, these initiatives should promote the interconnectivity of non-competitive data [16]. Within the existing regulatory framework of the Personal Information Protection Law, implementation rules regarding data portability should be further refined to ensure consumers can easily transfer their personal data among different service providers, thereby mitigating the distortion of market competition caused by user lock-in effects. With regard to non-personal data, we can explore establishing industry-specific data-sharing mechanisms in key sectors. Provided that competition-sensitive information is strictly excluded, non-core, non-differentiated basic data resources should be made equally accessible to all industry participants.

Establish a system for algorithm filing and tiered, transparent regulation. For core algorithms that directly impact market price formation, the range of consumer choices, and market entry conditions—such as dynamic pricing algorithms, search ranking algorithms, and recommendation systems—require companies to file documentation detailing the core operational logic of the algorithms with regulatory authorities and to periodically submit impact assessment reports on algorithmic behavior. At the same time, guide AI service providers to offer differentiated algorithm architectures and optimization objectives to reduce the problem of algorithmic decision-making convergence caused by excessive reliance on the same open-source models within the industry. Develop a tiered standard for algorithm transparency, establishing differentiated transparency obligations based on the scope of a AI system's social impact and risk level, and applying different regulatory approaches such as internal audit filing, independent review by expert committees, and limited public disclosure.

5.2 Policy Recommendations

5.2.1 Continue to Increase Investment in AI to Drive Technological Innovation and Enhance Inclusivity

In light of the strategic opportunities presented by the rapid development of digital technologies, China should increase support in areas such as public R&D investment, open-sourcing of foundational algorithms, and the sharing of computing resources. This will lower the barriers for small and medium-sized enterprises (SMEs) to participate in AI innovation, ensuring that the benefits of AI investment reach a broader range of market entities. It is recommended to establish a special fund for inclusive AI innovation, focusing on providing support for AI application demonstration projects targeting SMEs, central and western regions, and sectors related to people's livelihoods. Promote the compliant opening and sharing of public data—such as meteorological, transportation, and statistical yearbook data—and, subject to anonymization, provide usable training data resources to various market entities, thereby alleviating at the source the issue of unequal starting points in market competition caused by the data divide. At the same time, public R&D investment in the AI sector should be increased, with a focus on tackling common technological challenges such as foundational algorithms, open-source frameworks, and AI security, thereby reducing the marginal cost of AI innovation across society. Drawing on the model of the National Integrated Circuit Industry Investment Fund—which combines government guidance with market-oriented operations—a long-term financial support mechanism for the AI sector should be established.

5.2.2 Improve Digital Competition Regulations and Strengthen Competition-Neutral Regulation

Based on the inverted U-curve hypothesis, the timing of policy intervention is critical: during the investment growth phase, monitoring during the process should take precedence to avoid excessive intervention that stifles innovation; as investment approaches an inflection point, preemptive reviews should be strengthened to prevent the data lock-in effect from accelerating market concentration; and during the investment decline phase, ex post corrective measures should be reinforced, with targeted enforcement against monopolistic conduct. To address the risks that investment in the AI sector may drive up market concentration and induce competitive polarization, a comprehensive competition regulatory framework should be established that integrates ex ante prevention, ex ante monitoring, and ex post corrective measures. During future revisions to the Antimonopoly Law, consideration should be given to adding a dedicated chapter on competition in digital markets to further clarify the criteria for identifying and the legal liabilities associated with new types of conduct, such as algorithmic collusion, data abuse, and ecosystem self-preferencing. For new business practices such as AI-driven dynamic pricing and personalized recommendations, specialized and detailed industry regulatory guidelines should be issued to clarify the boundary between reasonable commercial differentiation and unfair algorithmic discrimination.

Consider developing specialized guidelines for assessing the competitive impact of artificial intelligence, establishing a framework for evaluating the competitive effects of AI investments across different industries and for entities of varying sizes, refining the specific factors to be considered in competition reviews of M&A transactions in the AI sector, clarifying the criteria for determining whether algorithmic behavior constitutes anti-competitive coordination, and establishing a paradigm for analyzing competitive harm resulting from data concentration and data abuse. To address the issue of "stranglehold mergers"—where large tech companies acquire AI startups to eliminate potential competitive threats—review criteria could be optimized based on the existing merger control system. Dynamic competition assessments should be strengthened for transactions involving key AI innovation elements, and the introduction of an "innovation space test" should be explored to balance the evaluation of innovation potential with future competitive prospects. Efforts should also be made to establish a regulatory sandbox mechanism to test the market impact of various AI competition strategies within controlled parameters, thereby enabling early risk identification.

5.2.3 Promote International Rule Coordination and Establish a Discourse Framework for AI Competition Governance

Market competition issues arising from AI investment constitute a global governance challenge; relying solely on unilateral regulation is insufficient to adequately address the competitive behavior of transnational AI enterprises. China should leverage multilateral platforms such as the BRICS cooperation mechanism, the G20 Digital Economy Working Group, and WTO e-commerce negotiations to promote consensus at the principled level among all parties on issues such as transparency in AI investment, cross-border data flows, and algorithmic accountability. In bilateral and regional trade agreement negotiations, the principle of competitive neutrality could be extended to the field of artificial intelligence to safeguard the fair competitive rights of Chinese enterprises in overseas markets and contribute Chinese solutions to improving global AI governance.

At the same time, coordination on transnational technical standards should be strengthened to mitigate the risk of transnational market fragmentation. Building on the high-quality joint construction of the "Belt and Road," pilot initiatives for bilateral and multilateral cooperation in the field of AI competition governance should be launched to accumulate practical experience in rule-making and gradually establish a framework for AI competition governance that aligns with the realities of China's digital economic development while ensuring international compatibility. It is recommended that relevant government authorities regularly compile and release annual assessment reports on AI and market competition to enhance regulatory transparency and strengthen the guidance of market expectations.

6. CONCLUSION

This paper adopts a dual perspective—from both the supply and demand sides—to systematically analyze the mechanisms through which AI investment affects competition in product markets, as well as its dynamic evolution and practical challenges. The study indicates that AI investment does not simply promote or inhibit market competition in a unidirectional manner; rather, it reshapes the structure of firms' competitive capabilities through three transmission channels: reducing marginal costs, improving the accuracy of demand forecasting, and expanding the scope of product functionality. At the same time, AI technology possesses endogenous characteristics such as increasing returns to scale in data, unobservable algorithmic strategies, and cross-scenario knowledge transfer, which cause the boundaries of product market competition to transcend traditional product substitutability and geographic scope, extending further into dimensions such as scenarios, time, and ecosystems. Based on this, this paper proposes an inverted-U-shaped theoretical hypothesis regarding the impact of AI investment on the intensity of market competition: in the early stages of technology diffusion, AI-enabled effects dominate, and market competition tends to be vigorous; when AI investment crosses a critical threshold, the positive feedback loop of data-algorithm-user drives the concentration of market power toward leading firms, and the vitality of market competition tends to weaken.

On the supply side, insufficient corporate investment in AI R&D, coupled with low efficiency in commercializing research outcomes under the three-pronged collaborative innovation system, constrains the full realization of the competitive effects of AI investment [17]; on the demand side, there is a structural mismatch between the traditional financing system and the high-risk nature of AI innovation, resulting in significant financing constraints for science and technology innovation enterprises; and on the competitive structure side, data barriers, algorithmic convergence, and the blurring of competitive boundaries pose systemic challenges to traditional regulatory frameworks. This nonlinear characteristic indicates that encouraging AI investment and maintaining effective market competition are not inherently compatible; a coordinated balance between the two must be achieved through precise institutional design.

Based on the above theoretical analysis and empirical examination, this paper proposes optimization pathways such as promoting the deep integration of AI investment with industry-academia-research collaboration, establishing a tiered and categorized AI investment guidance mechanism, and improving the circulation mechanism for data as a production factor. It also offers specific policy recommendations across three dimensions—strengthening AI investment to drive technological innovation, improving digital competition regulations, and promoting the coordination of international rules—with the aim of providing systematic policy guidance for the governance of product market competition in the AI era.

Future research could build upon the theoretical framework of this paper to empirically test the inverted U-shaped hypothesis using panel data on AI investment and market competition indicators at the firm level. It could further examine the differentiated impacts of various types of AI technologies (predictive AI, decision-making AI, and generative AI) on the competitive landscape, thereby providing a more robust empirical basis for refined policy formulation.

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