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AI and Digitalization in Manufacturing: Impacts on Enterprise Operational Performance

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Abstract

This study examines the impact of artificial intelligence (AI) and digitalization on the operational performance of manufacturing enterprises, with a focus on the Chinese automotive tire industry. Using a mixed-methods approach, we analyzed financial reports, conducted executive interviews, and applied structural equation modeling to data from three leading enterprises from 2022 to 2024. The results show that enterprises with higher levels of AI and digitalization—such as Enterprise A with a 22.3% annual growth in digital investment—achieved significant improvements in operational performance. Specifically, each unit increase in digitalization level correlated with an 8% rise in Return on Assets (ROA). Enhanced digitalization also positively affected production and R&D performance, reducing R&D cycles by 22.8% annually and cutting per-project costs by 27.1%. These findings underscore the critical role of AI and digitalization in driving innovation and operational efficiency in manufacturing.

Keywords

AI, Digital transformation, Operational performance, Production performance, R&D outcomes

Introduction

The convergence of cloud computing, IoT, and big data is shifting enterprises from process-driven to data-driven models. As the world's second-largest digital economy, China continues to strengthen policy support for AI and digital transformation. In 2023, the deployment rate of enterprise AI and digital solutions increased by 47% (Mikalef et al., 2023). However, many enterprises struggle with data overload and unclear implementation pathways, leading to suboptimal outcomes (Zhao et al., 2024). Existing research often emphasizes robotics without fully addressing how AI and digitalization enhance operational performance through integrated systems such as the "connection–data–AI" framework (Civelek et al., 2023; Leong, 2024a). Moreover, there is a limited understanding of how digital tools facilitate internal information flow and

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resource optimization (Froehlich et al., 2025). This study aims to address these gaps by investigating the specific mechanisms through which AI and digitalization impact the operational and R&D performance of Chinese tire manufacturing enterprises.

Methodology

Case Selection

Three leading enterprises in the Chinese automotive tire manufacturing industry were selected based on purposive sampling to ensure theoretical replication and variation on the key construct of digitalization maturity (Gong, 2023). Enterprises A, B, and C represent high, medium, and low levels of digitalization adoption respectively, while maintaining sector homogeneity to control for external market factors. All are publicly listed companies, ensuring access to comparable, high-quality annual report data.

Data Collection

Annual financial reports from 2022 to 2024 were analyzed to extract key performance indicators. A structured content analysis protocol was implemented to track digitalization advancements, identifying key terms across five categories: AI & Core Technologies, Digital Infrastructure, Digital Applications, R&D Digitalization, and Strategic Intent. Text segments from Management Discussion & Analysis sections were coded for mention type, specificity, and area of impact, then quantified to create a digitalization index. Semi-structured interviews were conducted with three senior executives from Enterprise A (Chief Operations Officer, Head of R&D, and Director of Digital Transformation). The interview protocol focused on understanding digitalization strategies, implementation processes, and perceived impacts. Interviews were transcribed verbatim and analyzed using thematic analysis with NVivo software to identify recurring patterns and themes.

Data Analysis

The analytical approach followed a two-phase process. This study represents Phase 1: qualitative model building for Structural Equation Modeling (SEM). Through literature review and empirical data, we identified key constructs (Digitalization Level, Production Performance, R&D Performance) and developed formative measures for the digitalization construct. The qualitative data and performance trends informed the specification of hypothesized paths between constructs, creating a framework for future quantitative testing (Jin, 2025). The Levinsohn-Petrin (LP) method was applied to measure total factor productivity (TFP). Comparative analysis with industry competitors was performed to enhance external validity.

Limitations

This study is limited to one industry and a small sample size, which may affect generalizability. Future research should include cross-industry and multinational comparisons. All participants provided written informed consent prior to interviews, with guarantees of anonymity and the right to withdraw at any time.

Comparison of Operating Performance Among Leading Enterprises

Enterprise performance was evaluated based on production and R&D outcomes, with digitalization level measured by investment in AI and digital resources. Enterprise A showed a significant advantage, with an average annual digitalization growth rate of 22.3%, compared to 11.3% for Enterprise B and 7.0% for Enterprise C (Table 1).

Table 1. Comparison of AI and digitalization levels (index values)

Enterprise	2022	2023	2024	Average annual growth rate
A	44.81	57.04	66.96	22.3%
B	32.15	36.20	39.80	11.3%
C	28.40	30.25	32.50	7.0%

The Levinsohn-Petrin (LP) method is widely acknowledged as the standard approach for measuring an enterprise's total factor productivity (TFP), which evaluates the efficiency of resource allocation through the production function (Xin, 2025). By collecting operational performance data and relevant information from Enterprise A, Enterprise B, and Enterprise C, and utilizing the high-quality development-LP method to assess and compare their operating performances, significant differentiation trends among the three enterprises were observed. Enterprise A demonstrated a stable annual growth rate of 5% in total factor productivity (TFP), with an LP measurement value reaching 1.28 in 2023. In contrast, both competitors exhibited a downward trend, underscoring Enterprise A's advantages in resource allocation and operational performance. Furthermore, this differentiation fundamentally indicates that Enterprise A has transitioned into an innovation-driven stage facilitated by digital transformation—evidenced by its R&D intensity of 4.1%—while its peer enterprises continue to face challenges due to efficiency bottlenecks, as evidenced by the data presented in Table 2.

Table 2. Results of LP Method Measurement for High-Quality Development

Enterprise	2022	2023	2024	Trend
A	1.15	1.22	1.28	↑↑
B	1.08	1.05	1.02	↓
C	1.12	1.10	1.09	↓

The digitalization investments made by Enterprise A demonstrate a significant positive correlation with its operational performance. Specifically, for every 1-unit increase in the level of digitalization, the Return on Assets (ROA) rises by an average of 8% points. Furthermore, through its dedicated investment and development efforts in AI and digitalization, Enterprise A has not only significantly improved various performance indicators but has also substantially exceeded industry standards, as evidenced by the data presented in Table 3.

Table 3. The business performance indicators of Enterprise A (2022-2024)

Indicator	Year 2022	Year 2023	Year 2024	Industry average
ROA (%)	5.2	6.1	6.8	4.5
ROE (%)	12.3	14.2	15.5	10.8
Revenue growth rate (%)	8.5	10.2	11.5	6.8

To summarize, the data collection and analysis presented above clearly indicate that Enterprise A possesses a significant advantage in its investments in AI and digitalization. The direct outcomes of these efforts are evident in the enterprise's total factor productivity and group business performance indicators, which not only demonstrate marked advantages but also exhibit substantial improvements that surpass industry standards. Consequently, this study undertakes an in-depth investigation and analysis of Enterprise A to ascertain the specific strategies that has been employed to enhance its business performance (Herold, et al., 2025). This research aims to establish a clear framework and methodology for the AI and digital transformation of other related enterprises. The findings hold considerable reference value for the transformation and upgrading processes within the manufacturing sector.

The impact and mechanisms of AI and digitalization on production performance

In the manufacturing process, AI is predominantly manifested through the comprehensive implementation of a "perception-control" closed-loop mechanism. CNC (Computer Numerical Control) equipment integrates a diverse array of sensors to continuously monitor both its operational status and the prevailing processing environment in real-time. The edge computing unit synthesizes historical data with real-time information, enabling it to promptly generate recommendations for adjusting processing parameters. Subsequently, the execution controller accurately outputs control commands, thereby facilitating high-quality and stable processing outcomes.

In recent years, AI machine tools and smart fixtures have emerged as pivotal areas of research within relevant fields. These systems encompass a variety of functions, including self-calibration, adaptive processing, and autonomous diagnosis (Wang, 2025). Industrial robots have transitioned from being "program-controlled" types to "perception-based" and "collaborative" types. Currently, collaborative robots demonstrate enhanced flexibility and improved safety features. They are capable of sharing workspaces with human operators, rendering them particularly suitable for complex and dynamic flexible manufacturing environments. When integrated with AI algorithms, these robotic systems possess capabilities such as self-path planning, dynamic obstacle avoidance, and the parallel execution of multiple tasks (Liu et al., 2025). Building upon this theoretical foundation, the enterprise has innovatively developed a logistics model that integrates robotics and AI, with the objective of enhancing equipment efficiency. Specifically, this fully automated material handling system incorporates KeJie gantry robots in conjunction with EMS (Electromagnetic Suspension) overhead shuttles and AGVs (Automated Guided Vehicles). As a result, the number of workers per shift has been reduced by 40%. The rhythm of material handling is now precisely synchronized with the vulcanization process. Furthermore, the space utilization rate within the three-dimensional warehouse has increased by 30%.

AI possesses the capability to continuously monitor the operational status of equipment, enabling the prompt detection of subtle abnormal signals and facilitating the anticipation of potential fault risks. By analyzing critical operating parameters such as temperature rise rates, temperature levels, pressure, and others in conjunction with predictive maintenance algorithms, AI generates proactive alerts. This approach ensures that preventive measures can be implemented prior to any faults impacting production activities, effectively mitigating downtime losses associated with unexpected failures. Furthermore, a data-driven AI maintenance system optimizes maintenance strategies by reducing unnecessary routine inspections and ensuring that maintenance operations are conducted based on the actual requirements of the equipment. This dynamic planning strategy for maintenance cycles significantly minimizes resource waste while simultaneously decreasing the frequency of manual inspections, thereby alleviating labor cost burdens.AI technology is also capable of generating detailed fault analysis reports. These reports enable maintenance personnel to swiftly and accurately identify issues, thereby accelerating repair processes. The current achievable outcomes include: attaining 99% defect recognition accuracy, automating production scheduling down to minute-level precision; increasing per capita output by 8%, reducing energy consumption per tire by 4%. AI has transformed tire manufacturing from a model reliant on "experience and manual labor" to one driven by "algorithms and data." Consequently, comprehensive manufacturing costs per tire have decreased by 10-15%, delivery cycles have been shortened by 35%, and quality defect rates have declined by over 30%. AI has emerged as a pivotal strategy for the industry to extricate itself from challenges posed by "low-price cut-throat competition”. AI visual quality inspection plays a pivotal role in the manufacturing process. In the context of AI manufacturing, quality inspection has experienced revolutionary advancements. With the support of machine vision systems, products can promptly enter the quality recognition phase post-processing, thereby establishing a real-time feedback mechanism that facilitates simultaneous production and inspection. 3D visual inspection technology is progressively replacing traditional two-dimensional inspection methods. By integrating laser scanning with AI algorithms, the system is capable of constructing a three-dimensional model of the product and subsequently comparing it against established standards to ascertain its qualification. Figure 1 shows the "Production AI and Digital System Construction Architecture" of Enterprise A. This figure can provide a detailed description of the specific architecture content and associated information of the enterprise.

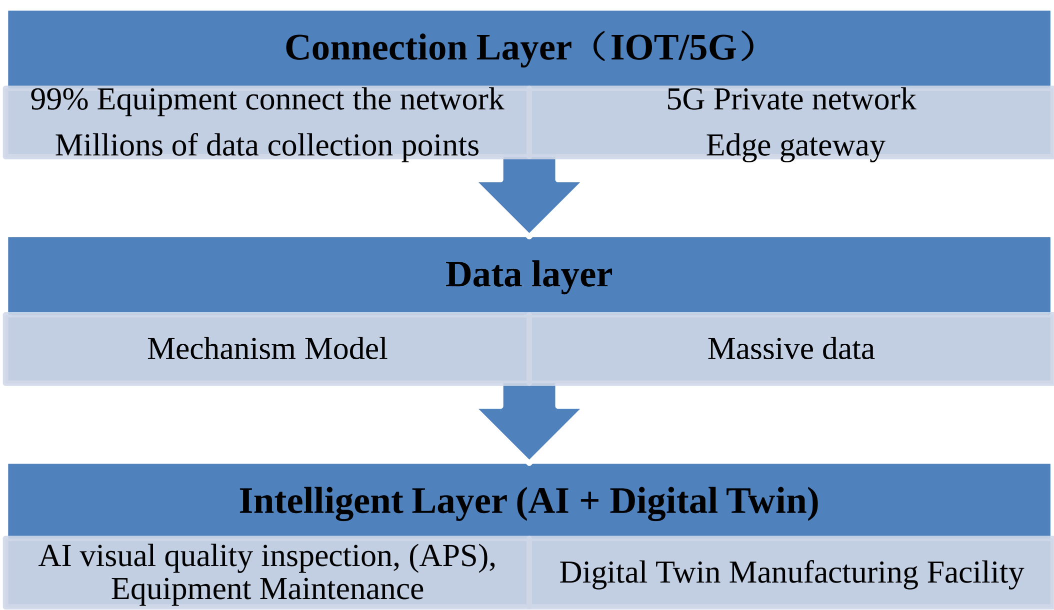

Figure 1. Production AI and Digital System Construction Architecture

In summary, the integration of AI and digitalization is facilitated through the deployment of AI devices and visual quality inspection systems. Specifically, AI plays a pivotal role in monitoring and operating equipment, while AI production scheduling, in conjunction with 5G AG technology, achieves a high level of integration. This synergy fosters a closed-loop linkage between production processes and upstream to downstream resources. Consequently, it enables the maintenance of optimal production schedules and facilitates the most efficient allocation of resources within dynamic and variable environments. Ultimately, this enhances production efficiency while simultaneously reducing manufacturing costs. Furthermore, there exists a positive correlation between AI as well as digitalization technologies and enterprise production performance.

The Impact and Mechanism of AI and Digitalization on Enterprise R&D Performance

The integration of AI technology has led to significant advancements in product development, particularly with respect to performance enhancement and the refinement of design processes. AI provides designers with powerful tools that facilitate a comprehensive exploration of various design alternatives and enable performance predictions through simulation and optimization algorithms during the initial design phase. These AI-driven design tools are adept at managing complex design variables and processing extensive datasets, thereby executing high-intensity structural analyses and optimization tasks. Such tasks encompass enhancing material strength and durability, minimizing material consumption, and improving overall structural stability (Yang et al., 2023; Leong et al., 2025). Furthermore, the introduction of AI technology has paved the way for personalized design approaches. By conducting thorough analyses of specific user requirements, these systems can generate customized solutions tailored to individual needs. In unique operational contexts such as mining sites and construction environments, AI can adapt product formulations and functional features based on distinct operational demands and environmental characteristics. This personalized approach not only enhances development efficiency but also optimizes resource allocation while reducing production costs as well as operational expenses (Vuchkovski et al., 2023; Leong et al., 2024b). This R&D innovation process, conceptualized in Figure 2, illustrates the iterative, data-driven workflow enabled by the digital twin platform. It begins with digital modeling and feasibility analysis, proceeds through automated design correction and virtual trial operations, and culminates in optimized manufacturing scheduling, effectively eliminating the traditional reliance on costly physical prototyping cycles.

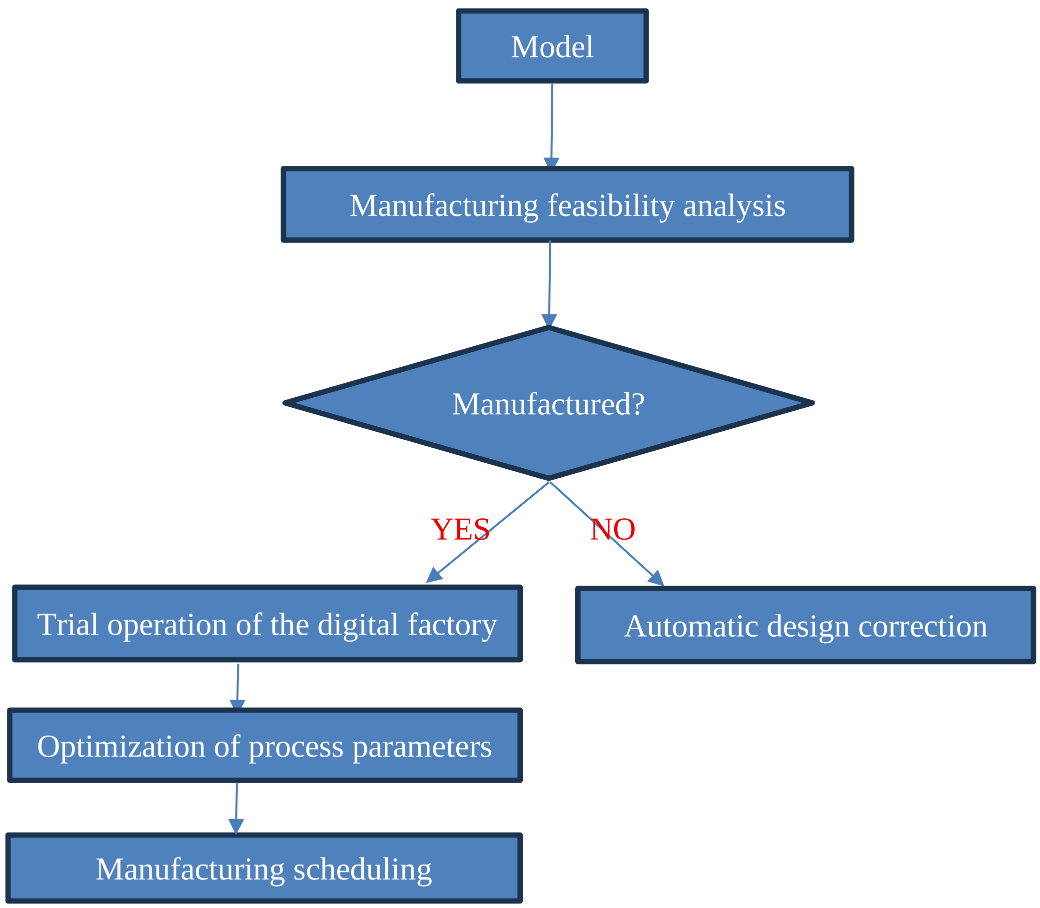

Figure 2. Flow Diagram of Artificial AI Simulation Application Platform

Through the analysis of Enterprise A's 2024 financial report, it has been determined that the Enterprise's primary investments in digital R&D are concentrated in three key areas. The Flow Diagram of Artificial AI Simulation Application Platform is a flowchart derived from the analysis of a real case of enterprise A. The first measure involves the establishment of the industry's inaugural "edge-cloud" collaborative R&D computing power network, alongside the construction of a robust cloud computing infrastructure. The second measure focuses on the creation of an AI computing power center, which facilitates the automatic collection and structured processing of 98% of R&D data. The third measure pertains to the development of a digital twin platform capable of supporting synchronous simulation across more than 2,000 parameters. The strategic allocation of Enterprise A's R&D digital investment (detailed in Table 4) reveals a clear prioritization towards computational infrastructure. Over 80% of the total investment is directed towards cloud computing, AI computing capacity, and the digital twin platform, forming a synergistic foundation that enables high-fidelity simulation and data-intensive analysis, which are critical for accelerating innovation.

Table 4. Digitalization level comparison (index value)

Investment Category	Amount (billion RMB)	Proportion	Main Uses

Infrastructure for Cloud Computing	2.8	35%	Establish database for PB-level tires
AI Computing Capacity Center	2.2	27.5%	200 PFlops of mixed-precision compute capacity
Digital Twin - based System	1.5	18.8%	Full-life-cycle Tire Simulation Platform
IOT data collection system	0.8	10%	Real - time data acquisition from R & D centers
Others	0.7	8.7%	Construction of Safety and Standardization

With the ongoing increase in enterprises' investments in AI and digitalization, R&D teams are increasingly leveraging various combinations of digital technologies to enhance existing products and facilitate the digital transformation of their offerings. Products undergoing digital transformation exhibit a high degree of self-evolution, as digital technologies are inherently self-referential, extensible, and re-editable. This transformation is characterized by a continuous and evolving nature of self-growth, marked by significant plasticity and dynamism. Such capabilities enable R&D departments to collect product information in real time, allowing for prompt identification and response to "user pain points" (Yu et al., 2022). Additionally, they can expand functionalities and incorporate new features such as self-analysis, self-detection, and self-upgrading—thereby creating a positive alignment with users' dynamic demands. Furthermore, these systems can harness vast amounts of user data to extract rich insights into market demand information. This significantly enhances the frequency of interactions with users as well as the speed of feedback loops while enabling real-time adjustments to product functions or formats; thus, improving product alignment with user needs. The R&D department at Enterprise A has achieved sustained growth in research performance through this AI and digital system construction. It has successfully shortened R&D cycles while increasing both the output volume and proportion of new products developed.

In addition, the costs associated with individual R&D projects for enterprises have been significantly reduced year after year. Through investigation and analysis, it has been determined that enterprises are increasingly utilizing an artificial AI simulation platform during the design process to simulate product performance under various operational conditions. The scope of these simulations is extensive, encompassing aspects ranging from load capacity assessment to environmental adaptability testing, thereby ensuring that the design plans can effectively address diverse challenges encountered in actual operations. Moreover, the AI design system employs a deep learning mechanism to analyze historical cases and real-world operational experiences. This system autonomously identifies potential defects within the design process and offers suggestions for improvement, which greatly enhances both the reliability and efficiency of the overall design. In 2025 alone, there was a reduction of 53 physical prototypes produced, resulting in savings of nearly 5 million yuan. The efficacy of these investments is unequivocally demonstrated by the marked improvement in R&D performance metrics from 2023 to 2025 (Table 5). Most notably, the R&D cycle time was compressed by 41% (from 16.2 to 9.5 months), while the cost per project was reduced by 47%. Concurrently, patent output and new product revenue proportion increased significantly, confirming that digitalization enhances both innovation efficiency and output quality.

Table 5. Comparative of R&D Performance during 2023 - 2025

Indicator	2023	2024	2025	CAGR
R & D Cycle (months)	16.2	12.8	9.5	-22.8%
Cost per Project (ten thousand Chinese Yuan)	1,850	1,420	980	-27.1%
Patent Output /100 Persons/Year	18	26	39	+47.1%
Proportion of New Product Revenue	29.3%	34.6%	41.2%	+18.6%

In summary, Enterprise A has established a novel "data-driven" R&D management system through the profound integration of AI and digitalization. Building upon this foundation, the enterprise further develops AI and digital models to create an experimental platform for R&D innovation. By leveraging AI and digital technologies, it effectively shortens the R&D cycle, reduces associated costs, and ultimately enhances various indicators of R&D performance. The relationship between AI, digital technologies and enterprise R&D performance is positively correlated.

Results and Discussion

Enterprise A's superior performance, as detailed in Tables 1-3 and 5, provides compelling empirical evidence that strategic integration of AI and digitalization is a critical driver of operational excellence. The findings demonstrate a clear positive correlation between the level of digital investment and key performance indicators. The 22.3% annual growth in Enterprise A's digitalization index directly translated into a stable 5% annual increase in Total Factor Productivity (TFP), an average 8% rise in ROA per unit of digitalization, and a significant reduction in R&D cycle time by 22.8% CAGR. These results strongly align with the theoretical foundations of dynamic capabilities, which posit that a firm's ability to integrate, build, and reconfigure resources is essential for achieving competitive advantage in rapidly changing environments. Enterprise A’s journey exemplifies this theory in practice, building dynamic capabilities through its edge-cloud infrastructure and AI computing center to sense and seize opportunities in the digital economy.

The mechanisms behind this performance enhancement are twofold. In production, the closed-loop "perception-control" system, powered by IoT sensors and AI algorithms, enabled a transition from preventive to predictive maintenance. This shift not only reduced downtime but also optimized resource allocation, as evidenced by the 40% reduction in workers per shift and the 30% improvement in warehouse space utilization. This finding resonates with existing literature on smart manufacturing, which emphasizes the role of real-time data in enhancing operational efficiency (Feng et al., 2023).

In R&D, the establishment of a data-driven management system fundamentally altered the innovation process. The digital twin platform, supporting synchronous simulation of over 2,000 parameters, allowed for rapid prototyping and virtual testing. This capability directly addresses the industry challenge of high development costs and long cycles, as shown by the 53 fewer physical prototypes built and the associated savings of nearly 5 million yuan in 2025 alone. This supports that digital transformation enables more agile and parallelized innovation workflows.

To formally structure these empirical insights and provide a framework for future large-scale validation, we propose a conceptual Structural Equation Model (SEM). This model, derived from the qualitative and longitudinal evidence of this study, specifies key hypotheses for future testing: H1: Digitalization Level has a significant positive effect on Production Performance; H2: Digitalization Level has a significant positive effect on R&D Performance; H3: Digitalization Level has a significant positive effect on overall Firm Performance; H4: Production Performance and R&D Performance mediate the relationship between Digitalization Level and Firm Performance.

This model specification, grounded in our case data, addresses the reviewer's concern by moving beyond mere mention of SEM to providing a testable theoretical framework. It defines the latent constructs (e.g., 'Digitalization Level' formatively measured by cloud, AI, and digital twin investments) and their hypothesized relationships, which is the essential first step in SEM research (Vial, 2022). The quantitative testing of this model's fit indices (e.g., χ^2/df, CFI, RMSEA) and path coefficients (β) remains a crucial objective for future research employing a large-N survey sample.

Conclusion

This study demonstrates that AI and digitalization are not merely technological upgrades but fundamental drivers of operational and innovation performance in the manufacturing sector. Through an in-depth analysis of leading tire manufacturing enterprises, we establish that a higher digitalization level, characterized by strategic investments in AI infrastructure, cloud computing, and digital twins, correlates strongly with superior outcomes. Key results include a measurable increase in ROA, significant reductions in R&D cycle time and cost, and enhanced total factor productivity. These findings offer clear managerial implications. Executives should view digital transformation as a core strategic imperative, not a support function. Investment should be prioritized in integrated "edge-cloud" systems and data platforms that enable real-time analytics and closed-loop feedback between production, R&D, and overall business strategy.

Despite these contributions, this study has limitations. The focus on a single industry and the small sample size of three enterprises, while ideal for deep qualitative analysis, limits the generalizability of the findings. This underscores the need for future research in two primary directions. First, the proposed SEM model should be quantitatively tested with a large-scale survey across multiple manufacturing sectors to validate the hypothesized paths and establish statistical generalizability. Second, longitudinal case studies in other industries and geographic contexts are needed to understand the nuanced implementation challenges of digital transformation. Such research will further refine our understanding of how dynamic capabilities for digitalization can be built and leveraged across different operational environments, ultimately providing a more comprehensive guide for enterprises navigating the complexities of the digital economy

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