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Artificial Intelligence and Innovation Management: A Research Review

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Abstract: In the era of digitalization, informatization, and intelligent transformation, artificial intelligence (AI) technology is developing rapidly, exerting a profound impact on various fields of the social economy. As a key factor for enterprises and organizations to maintain competitiveness in a competitive environment, the importance of innovation management has been increasingly emphasized. As the core driving force behind the new round of scientific and technological revolution and industrial transformation, AI not only improves production efficiency and optimizes resource allocation but also creates new industrial forms and business models, injecting new momentum into economic development. This paper reviews existing research in the field of AI and innovation management, examining relevant studies from three perspectives: the transformation of innovation management models driven by AI, the reform of organizational structures driven by AI, and the ethical challenges posed by AI applications in innovation management.

Keywords: Artificial Intelligence; Innovation Management; Organizational Structure.

1. Introduction

Amid the prevailing wave of digital, informational and intelligent upgrading, artificial intelligence technologies are evolving at an unprecedented pace and comprehensively reshaping socioeconomic operation mechanisms. Concurrently, innovation management, as an indispensable instrument for enterprises and organizations to maintain operational vitality and competitive edges in turbulent market landscapes, has garnered mounting academic and practical attention. Technological progress constitutes the fundamental driving force of economic expansion and social advancement. As a strategic core technology spearheading the new wave of technological revolution and industrial transformation, artificial intelligence has become a top-priority development domain for economies worldwide. Beyond boosting production efficiency and streamlining resource allocation, AI generates novel industrial forms and business models, delivering powerful momentum for sustained economic development.AI bears immense transformative value and untapped potential for innovation management: it can substantially lift the efficiency and output quality of the full innovation lifecycle, ushering in a new epoch of intelligent innovation governance [1-3]. Nevertheless, scholars also highlight substantial practical barriers to effective AI integration within innovation management, with marked disparities across organizations in digital strategy formulation, internal structural design and technical implementation pathways. Against this contextual backdrop, exploring how enterprises can embed AI technologies into innovation management workflows to streamline R&D cycles and generate high-value innovative outputs has emerged as a converging research focal point for academia and industrial practitioners alike.

Conventional innovation management frameworks suffer inherent limitations when confronted with fast-shifting market demands and increasingly sophisticated innovation requirements. The proliferation of artificial intelligence has unlocked transformative opportunities for innovation governance: AI has transitioned from abstract theoretical constructs to large-scale industrial applications, penetrating nearly all vertical industries. Equipped with robust capabilities for mass data collection, real-time analysis, predictive modeling and quantitative decision support, AI rapidly processes multi-source heterogeneous datasets, identifies latent innovation opportunities, and furnishes managers with data-backed empirical evidence, thereby drastically enhancing the efficiency and precision of innovation management practices.

2. AI-Driven Transformation of Innovation Management Paradigms

Within the technological revolution of the 21st century, artificial intelligence stands as an irresistible transformative force reshaping industrial landscapes with unparalleled speed and depth. Ren et al. (2023) demonstrate that comprehensive optimization of project planning and deployment underpins the formation of a holistic panoramic decision-making system fueled by big data analytics [4]. Enterprises are actively integrating AI modules into innovation management systems to realize holistic managerial model upgrading. Functioning as an ultra-high-precision predictive tool, AI streamlines resource allocation, slashes opportunity search costs and reconstructs traditional innovation logics throughout the R&D pipeline; it drastically improves the efficiency and success rate of scientific discovery, delivering disruptive reform to technological innovation governance [5-8].

2.1. Data-Driven Decision-Making

Traditional corporate management predominantly relies on managers' accumulated experience and intuitive judgment for decision-making. While this mode retains certain flexibility and adaptability, its structural drawbacks become increasingly prominent amid complex, volatile market environments and exponential data proliferation. The introduction of artificial intelligence introduces a revolutionary decision-making paradigm for enterprises:

data-driven governance [9-11]. Amid the big data era, managerial decision-making research is undergoing a methodological paradigm shift. As Chen et al. (2020) elaborate, decision-making logics are shifting from process-centric governance to data-centric operation, featuring diversified and interactive analytical frameworks [12]. This transition endows contemporary decision-making systems with panoramic, big-data-enabled attributes, triggering profound changes across core decision-making dimensions including information environments, decision subject identities, theoretical assumptions and operational methodologies. Yu (2022) posits that the "data-prediction-decision" analytical chain constitutes the dominant framework for scientific decision-making within modern management science [13]. Artificial intelligence further accelerates data processing throughput, enhances the predictive accuracy of complex decision scenarios, and realizes intelligent optimization of decision outcomes, with its core competitive advantage lying in enabling seamless, high-efficiency conversion from raw data to predictive insights and actionable decisions. Vocke et al. (2019) observe that iterative advances in AI technologies incentivize enterprises to adopt and integrate cutting-edge innovative tools, creating pathways to boost productivity and operational performance, and call for deeper exploration of AI's untapped industrial application potential [14]. Though AI within big-data ecosystems does not subvert the fundamental logic of forecasting and decision-making, it remedies critical defects of traditional predictive frameworks: it processes massive data volumes, extracts valuable information from low-density unstructured datasets, accommodates multi-modal data formats, conducts real-time streaming data analysis, and fits nonlinear relational patterns. These advantages accelerate predictive and decision-making workflows while elevating analytical accuracy, ultimately upgrading the overall efficiency and quality of organizational decision-making.

2.2. Intelligent Full-Lifecycle Innovation Processes

AI deployment delivers revolutionary upgrades across every stage of the innovation value chain, covering product research and development, industrial design and performance testing. At the process restructuring dimension, AI shifts innovation activities from manual operation to intelligent operation via novel human-machine interaction frameworks and augmented cognitive capacities. It automates and intellectualizes R&D, design, testing and other core links, thereby drastically boosting innovation efficiency and output quality [15-16]. In terms of innovation outputs, AI expands the connotation and scope of innovation: beyond facilitating product, process and business model innovation, it also gives rise to social innovation as an emerging innovative category [17]. During new product development, Transformer-based large language models extract latent consumer insights and emotional cues from massive text corpora to streamline brainstorming and troubleshooting. Such tools diversify the divergent thinking of innovation teams, while slashing development and maintenance costs and strengthening product stability and user satisfaction [16]. Deep integration of AI into product design, simulated testing and performance optimization also significantly lifts product innovativeness and market adaptability [18]. Collectively, multi-perspective empirical evidence corroborates AI's intelligent reengineering of end-to-end innovation workflows, whose impacts permeate the full innovation lifecycle spanning idea generation to commercialization.

2.3. Precision Marketing and Personalized Service Systems

The innovation and advancement of emerging technologies including mobile internet, cloud computing, artificial intelligence, the Internet of Things (IoT) and blockchain are driving the transition from traditional human-centric Marketing 3.0 to Marketing 4.0 in the digital era. AI also brings transformative changes to marketing and customer service domains. Conventional mass marketing uniformly delivers identical promotional content and service packages to all user groups; despite its low operational complexity, this model fails to satisfy heterogeneous personalized consumer demands. Artificial intelligence operationalizes precision marketing and customized service targets. Compared with conventional marketing analytics frameworks, integrated artificial intelligence and big data systems are capable of processing large-scale, heterogeneous multimodal datasets. This capability unlocks untapped avenues for scholars to excavate novel consumer insights and expands firms' scope for developing differentiated marketing strategies [19]. Supported by such comprehensive data infrastructure, marketers leverage programmatic algorithmic tools to automatically deploy customized marketing solutions for individual consumers, materializing the full potential of hyper-personalized one-to-one marketing [20]. More critically, granular unstructured individual-level data generated by big data platforms captures not only tangible quantitative metrics including audience demographics, interaction timestamps and distribution channels, but also intangible perceptual indicators such as consumer sentiment, mental dispositions and physiological feedback signals. This dual-layer data coverage transcends superficial behavioral analysis and enables in-depth exploration of consumers' psychological mechanisms and experiential perceptions, supplying multi-dimensional evidence for holistic customer value evaluation [21]. By synthesizing the above hard and soft indicators, enterprises implement information extraction, knowledge fusion and logical reasoning to construct knowledge graphs mapping heterogeneous attribute correlations between consumers and products, generating granular user profiles that deliver systematic, actionable data foundations for precision marketing decision-making [22]. Taken together, AI-powered precision marketing has formed a cohesive, end-to-end value chain covering data collection, strategic formulation, consumer insight mining and user profile deployment.

2.4. Cross-boundary integration and Innovation

Beyond reshaping internal corporate management frameworks and upgrading standalone innovation workflows, artificial intelligence facilitates cross-domain boundary integration and multi-stakeholder collaborative innovation. Traditional industries feature rigid institutional barriers and clear sectoral divisions, hindering cross-field knowledge sharing and technological integration. AI dismantles these industrial boundaries and enables cross-sector integrated innovation collaboration. Supported by AI platforms and analytical tools, enterprises can conduct in-depth joint research and resource sharing with external firms, research institutions and industrial alliances. Song & Zhang (2023) find that late-stage AI enterprises leverage targeted knowledge search to identify cross-industry technical resources, internalize external technologies via cross-sector mergers and acquisitions, and build technology-centric industrial ecosystems to concentrate innovation resources for targeted technical commercialization [23]. Similarly, Wang & Sun (2024) observe that non-linguistic service enterprises accelerate cross-industry integration by harnessing AI technical strengths to develop innovative language service products [24]. Through embedded case analysis, Jin & Cao (2023) demonstrate that the new industrial revolution characterized by big data, IoT and artificial intelligence exhibits high innovation intensity, strong technical penetration and broad industrial coverage [25]. It accelerates breakthroughs in digital manufacturing, internet industries, bioelectronics and advanced new materials, while speeding up technological convergence and cross-sectoral innovation activities. Mariani & Dwivedi (2024) cite generative AI application cases spanning media, broadcasting, film production, chemical engineering, pharmaceuticals and healthcare, illustrating the extensive cross-industry coverage and deep transformative capacity of generative technologies in driving innovation [26]. Sjödin et al. (2021) similarly affirm that AI reconstructs core innovation workflows, facilitates interdisciplinary and cross-domain collaboration, optimizes innovation pipelines via intelligent algorithms, reduces overall R&D expenditures and elevates the commercialization success rate of innovative projects [27].

Furthermore, AI facilitates interactive co-creation between enterprises and end users. By constructing open innovation ecosystems and user community platforms, firms invite consumers to participate in product design, prototype testing and market promotion stages; simultaneously, users convey personalized demand information and creative proposals to enterprises via these platforms to realize bidirectional collaborative innovation. Xiao et al. (2020) argue that compared with offline enterprise-user interaction models without big-data support, data-driven product R&D innovation achieves qualitative improvements in feedback frequency and response speed: information cycles shift from weekly/monthly lagged feedback to millisecond-level real-time interaction, laying the technical foundation for instant collaborative innovation between firms and consumers [28].

3. Artificial Intelligence and Organizational Structural Restructuring

Hierarchical bureaucratic organizations suffer prominent drawbacks including elongated decision-making chains, information distortion and delayed market responses amid the AI technological revolution. Under conventional bureaucratic hierarchies, corporate expansion inevitably leads to multi-layered administrative structures, which hinder employee initiative and impede rapid market responsiveness. In contrast, the AI era drives a steady shift toward flat organizational architectures. This structural transformation empowers frontline staff and customers with greater decision-making voice, dismantling the centralized power regime dominated by corporate executives and ushering in increasingly decentralized authority distribution within firms [29]. In the AI era, internal organizational architectures gradually evolve toward flat structures, granting greater voice to frontline staff and end consumers. The traditional top-down power structure dominated by enterprise leadership is disrupted, and organizational power allocation shifts toward decentralized distribution. Powered by robust data processing and intelligent decision-support functions, artificial intelligence provides solid technical backing for organizational restructuring, with flat organizational frameworks emerging as a landmark trend of AI-enabled institutional transformation. By streamlining administrative tiers and facilitating cross-departmental communication, this flattened institutional framework accelerates intra-firm data sharing and interdisciplinary collaboration, enabling agile decision-making and unimpeded information flows across the organization [30]. Such institutional transformation strengthens corporate market sensitivity and environmental adaptability, while stimulating internal organizational innovation vitality. AI's value within flat organizations extends far beyond workflow simplification and efficiency improvement: it delivers quantitative, evidence-based foundations for corporate decision-making through intelligent data analysis, predictive modeling and multi-objective optimization, enhancing the foresight and accuracy of strategic judgments.

More fundamentally, AI deployment drives systemic shifts in organizational culture. Within flat institutional frameworks, open, collaborative and innovation-oriented cultural norms become mainstream. AI platforms provide employees with channels to acquire emerging technical skills and expand interdisciplinary knowledge boundaries, fostering cross-departmental and cross-disciplinary communication and joint research, and advancing the construction of enterprise-wide integrated innovation ecosystems. This cultural transformation delivers sustained momentum and vitality for long-term corporate sustainable development. As Mao (2020) notes, innovative spirit, specialized innovation teams and innovation-friendly organizational atmospheres constitute the core components, foundational carriers and external manifestations of corporate innovation culture, collectively forming the institutional bedrock of enterprise innovation capacity [31].

4. Ethical Risks of Artificial Intelligence Application in Innovation Management

Alongside rapid technological iteration, artificial intelligence has become a core driving force for social progress and industrial upgrading. Within innovation management, AI delivers unprecedented developmental opportunities for enterprises through powerful data processing capacity, efficient decision support systems and customized user service experiences. Nevertheless, widespread AI deployment also generates a series of complex, far-reaching ethical challenges and latent risks. These issues not only constrain sustainable technological development but also exert direct impacts on social equity, distributive justice and fundamental human welfare.

4.1. Algorithmic Bias and Institutional Discrimination

Algorithmic bias is defined as systematic, recurrent computational faults that generate discriminatory outcomes against specific individuals, demographic groups or types of information throughout the entire lifecycle of algorithmic operations [32]. Such systemic biases do not emerge arbitrarily. Rooted in real-world datasets that rarely maintain neutrality, algorithms inherently absorb and amplify pre-existing prejudices embedded in raw training data, including stereotypes concerning gender, ethnicity and socioeconomic standing [33]. As algorithms transition from laboratory prototypes to large-scale social deployment, inherent bias risks are continuously triggered. Misapplication and improper rollout of algorithmic technologies further trigger cascading hazards such as algorithmic black-box opacity and algorithmic alienation. Empirical evidence confirms pervasive gender bias across mainstream algorithmic frameworks, including word embedding models, collaborative filtering recommenders, ranking screening algorithms and biometric recognition systems. Human gender stereotypes infiltrate model architectures via data labeling, training dataset construction and model tuning pipelines, calling for targeted governance strategies rooted in the underlying drivers of bias [34]. Two divergent governance approaches have been proposed in extant scholarship. One strand advocates source-side intervention: researchers argue that maintaining objective, high-quality input datasets and mandating ethical audits alongside multi-scenario validation prior to system launch can preempt moral prejudice and inequitable outcomes [35]. The alternative perspective emphasizes that algorithmic biases have pervasively permeated social production and interpersonal relations, manifesting complex, diverse and concealed attributes. Against the backdrop of intricate algorithmic ecosystems, ex ante preventive measures alone prove inadequate, necessitating human-machine collaborative social governance frameworks [36].

Despite their distinct focal points, both strategies converge on a core consensus: algorithmic bias governance must cover the full technological lifecycle spanning data ingestion, model training, industrial deployment and continuous public oversight. Partial optimization of any isolated stage cannot independently resolve systemic algorithmic inequities.

4.2. Algorithmic Transparency and Model Explainability

The inherent complexity and high automation of advanced AI systems render their internal decision-making logics incomprehensible to human operators. This “black-box” operational mode elevates uncertainty in technological application and erodes public trust in artificial intelligence systems.AI applications obscure traceable decision-making processes within technical black boxes, casting severe doubts over the authenticity, reliability and transparency of core judgments in innovation management, which outpaces human cognitive capacity for full verification [37]. Such opacity undermines the rational foundation of corporate strategic decisions, triggers misjudgments and erodes public trust in AI systems. When AI generates flawed outputs, untraceable internal reasoning impedes root-cause diagnosis and corrective adjustments.

Scholars widely regard enhanced algorithm transparency and explainability as the key to restoring public confidence. Buhmann & Fieseler (2021) propose multi-stakeholder deliberative frameworks to secure public informed consent and advance responsible AI innovation [38]. Their 2023 research further develops a responsibility framework guiding practitioners to engage experts and laypersons for balanced assessment of opaque AI models [39]. Algorithmic explainability means translating complex reasoning into intelligible logic chains accessible to users with diverse expertise, enabling comprehension of automated outcomes [40]. Systematic transparency mechanisms are therefore essential to expose operational logic to end users [41]. Nevertheless, technical measures alone cannot eliminate risks; algorithmic explainability must be institutionalized via legal regulations to clarify liability and safeguard human dignity and fundamental rights [42].

4.3. Data Privacy and Information Security Vulnerabilities

Data collection constitutes the fundamental pillar of AI-enabled innovation management, yet this practice is plagued by frequent privacy violations that draw widespread public concern. To maximize commercial gains, many firms harvest sensitive personal data including identity credentials, geographic coordinates and browsing histories without obtaining users’ explicit informed consent [43]. Tech providers deploy pervasive monitoring algorithms to track and analyze user behaviors continuously. Combined with smart home hardware and recommendation systems, such technologies render personal information nearly fully exposed, breaching legal rules, eroding user trust and hindering the sustainable growth of the AI industry in the long run [44].

Deficient data governance frameworks further exacerbate privacy leakage. Though global governments and international bodies have rolled out regulatory instruments such as the EU’s General Data Protection Regulation, substantial implementation gaps persist. Drawing on feedback from 262 stakeholders regarding the EU AI Act draft, Năstasă (2023) demonstrates that policy-making must reconcile technological advancement with social trust, ethical standards and legal compliance [45]. Technical constraints, delayed law enforcement and inadequate corporate compliance awareness together create systemic vulnerabilities in data protection. To address this structural dilemma, clear institutional rules should be established to define legitimate data collection scopes and operational protocols, impose statutory confidentiality obligations, clarify legal liabilities for unauthorized data exploitation and mismanagement, and build standardized supervision and evaluation systems [46].

5. Conclusion

Amid the global wave of digital, informational and intelligent transformation, rapid artificial intelligence development comprehensively reshapes socioeconomic operational modes, with particularly profound disruptive impacts on innovation management as a core industrial governance domain. Through systematic collation of interdisciplinary literature integrating artificial intelligence and innovation management, this review confirms that AI unlocks unprecedented innovative development opportunities for enterprises and comprehensively accelerates the upgrading of traditional innovation management paradigms.

As AI permeates every stage of organizational decision-making, latent risks such as algorithmic bias and unfair automated judgment emerge as prominent research concerns. Future scholarship will deepen investigations into constructing standardized ethical guidelines and multi-layer supervision mechanisms to align AI-driven decision-making with core principles of fairness, impartiality and human dignity, rendering ethical dilemmas of AI deployment a sustained research hotspot.

Data serves as the fundamental fuel for artificial intelligence advancement, yet cross-institutional data sharing for innovation governance must be balanced with robust privacy safeguards for individual users and corporate entities. Current privacy protection frameworks face severe challenges in cross-border data circulation and multi-party federated data analysis scenarios, highlighting the critical research value of privacy governance mechanisms for AI-enabled innovation.

Moreover, continuous iterative upgrades of artificial intelligence expand its application boundaries within innovation management while generating novel unaddressed contradictions. On one hand, rapid technological breakthroughs create a lag between emerging AI practices and existing legal statutes and ethical norms; on the other hand, the inherent complexity and uncertainty of intelligent systems elevate the difficulty of standardized industrial governance. Accordingly, exploring adaptive policy and regulatory optimization frameworks matching dynamic AI technological evolution, alongside cultivating ethical awareness and legal literacy among managerial and technical practitioners, constitutes another pivotal direction for subsequent research.

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