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The Empowering Mechanisms and Challenges of Generative AI for Business Management Innovation: An Integrative Conceptual Review

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Abstract: The rapid advancement of Generative Artificial Intelligence (GAI) is profoundly reshaping the underlying logic and operational modes of enterprise management. Unlike traditional artificial intelligence, GAI not only analyzes and comprehends data but also possesses capabilities such as multimodal content generation, natural language interaction, and adaptive evolution, opening up entirely new possibilities for management innovation. This paper systematically reviews the technological evolution and core capability characteristics of GAI and reveals the micro-mechanisms by which GAI enables management innovation across three dimensions: knowledge recombination and abductive reasoning, simulation and counterfactual reasoning, and dynamic resource orchestration. Based on a systematic literature search of Web of Science, Scopus, and CNKI (January 2020–June 2026), 86 relevant sources were identified and synthesized. On this basis, the paper conducts an in-depth analysis of GAI's innovative applications in four key scenarios—new product design, customer relationship management, precision marketing, and supply chain management—and incorporates typical domestic and international cases as illustrative examples. The distinctive contribution of this review lies in linking the three mechanisms to dynamic capabilities theory, specifying boundary conditions, and integrating enabling logic with governance frameworks. The findings indicate that while GAI drives management innovation, it also faces multiple challenges, including risks to content quality, technological application, and development. Limitations include reliance on secondary sources and the rapidly evolving technological landscape. Finally, this paper proposes countermeasures from three levels—technical governance, organizational transformation, and institutional safeguards—aiming to provide theoretical references and practical guidance for enterprises to effectively harness GAI and achieve management innovation in the process of intelligent transformation.

Keywords: Generative Artificial Intelligence, Management Innovation, Enabling Mechanisms, Multi-Scenario Applications, Human-Machine Collaboration

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1. Introduction

Since 2023, generative AI large models represented by OpenAI's ChatGPT have rapidly gained global prominence, with the iterative version GPT-4 standing out for its precise logical reasoning capabilities. Meanwhile, Google's PaLM model has demonstrated exceptional performance in complex reasoning tasks, and Anthropic's Claude model offers advantages in safety and controllability. Domestically, large language models such as Baidu's Wenxin, Alibaba's Tongyi Qianwen, and DeepSeek-R1 have made notable progress in Chinese language understanding and localized applications (Wang & Zhang, 2025). The global competitive landscape of GAI technology has taken shape, and its influence is rapidly spreading from the consumer side to the industrial and managerial domains (Aagaard, 2024).

McKinsey estimates that generative AI could add between $2.6 trillion and $4.4 trillion annually in economic value, concentrated heavily in functions such as customer operations, marketing and sales, software engineering, and R&D. GAI's multimodal content generation capabilities, when applied to enterprise management, are driving profound management innovation. From reshaping R&D processes to optimizing production logic, from enhancing innovation capabilities to driving organizational change, GAI demonstrates multidimensional enabling potential, offering new technological possibilities for breaking industrial path dependencies, restructuring production factor systems, and reshaping industrial chains (Li & Xue, 2025).

From a theoretical perspective, the rise of GAI poses new challenges and expands the scope of existing management theories. Traditional management theories rest on fundamental assumptions such as bounded rationality, information asymmetry, and hierarchical organization (Sánchez et al., 2025). However, GAI's vast computational capacity and large-scale knowledge integration capacity, and creative content generation capabilities are eroding the foundations of these assumptions. As some scholars have pointed out, generative AI, through its profound comprehension and creativity, is exerting a far-reaching impact on organizational management, and managers need to rethink the framework of organizational management to adapt to this new era driven by generative AI (Lin & Soltane, 2026). Exploring the intrinsic mechanisms through which GAI enables management innovation will help construct new management theories suited to the intelligent age (Zhang et al., 2024).

From a practical perspective, an increasing number of enterprises are integrating GAI into their management practices. In 2026, Samsung Electronics announced an "AI Mega-Transformation" plan for all its affiliates, applying artificial intelligence across all value chain functions including R&D, production, marketing, and support. Moderna has implemented a "Digital First, AI Focused" strategy, granting all employees access to ChatGPT Enterprise and encouraging them to build and share customized GPT applications (Jang et al., 2019; Sharma et al., 2022; Iansiti et al., 2020). However, the deployment of GAI also faces practical obstacles such as organizational inertia, talent shortages, and data silos. A systematic study of the pathways, scenarios, and challenges of GAI-enabled management innovation holds significant practical value for guiding enterprises in scientifically advancing their intelligent transformation.

This paper is structured as a conceptual review, supported by illustrative business examples drawn from publicly available sources. The aim is to synthesize existing academic literature and practical reports to propose a coherent framework of GAI-enabled management innovation (An et al., 2023). The company cases are used as illustrative instances to contextualize the proposed mechanisms and scenarios, rather than as formally analyzed cases following a rigorous case-study protocol. This approach is appropriate given the exploratory and synthesizing nature of the research (Dong et al., 2023). The distinctive contribution of this review, relative to existing GenAI-management syntheses, lies in three elements: (a) it explicitly links the three enabling mechanisms (cognitive enhancement, decision optimization, and organizational evolution) to the sensing-seizing-transforming dimensions of dynamic capabilities, thereby grounding the *framework* in established strategic management theory; (b) it introduces a set of boundary conditions (data quality, task type, firm size, and regulatory context) that specify when and for whom these mechanisms are most likely to operate; and (c) it integrates the enabling logic with a governance framework that distinguishes firm-level from policy-level responsibilities.

To ensure the transparency and reproducibility of this conceptual review, we conducted a systematic literature search following these procedures. Databases: Web of Science, Scopus, and CNKI (China National Knowledge Infrastructure) were searched. Search terms: combinations of ("generative AI" OR "generative artificial intelligence" OR "GAI" OR "large language model" OR "LLM") AND ("management innovation" OR "business innovation" OR "organizational transformation" OR "decision-making" OR "human-machine collaboration"). Time period: January 2020 to June 2026, covering the period of rapid GAI development. Screening criteria: We included peer-reviewed journal articles, conference proceedings, and authoritative industry reports written in English or Chinese. We excluded non-English/non-Chinese publications, opinion pieces without empirical or theoretical substance, and duplicate records. Classification logic: Retrieved studies were classified thematically into four streams: (1) GAI technical capabilities and evolution; (2) GAI and strategic management theories (RBV, dynamic capabilities, socio-technical systems); (3) GAI applications in specific management functions (product design, CRM, marketing, supply chain); and (4) GAI governance, risks, and challenges. This classification informs the structure of Sections 1 through 4 of this paper. The initial search yielded 312 records across the three databases. After removing duplicates (n = 67), we screened 245 records by title and abstract. Of these, 142 were excluded as they did not address management or organizational dimensions of GAI. The remaining 103 full-text articles were assessed for eligibility, of which 17 were excluded due to insufficient relevance to management innovation or lack of theoretical substance. This process resulted in a final corpus of 86 relevant sources, which form the evidence base for this conceptual review.

2. Technical Foundation and Core Capabilities of Generative Artificial Intelligence

2.1. From Discriminative AI to Generative AI: A Paradigm Shift

Understanding how GAI enables management innovation requires first grasping its fundamental differences from traditional artificial intelligence. Traditional AI predominantly relies on discriminative models, whose core function is to analyze, classify, and predict input data—for example, determining whether an email is spam or recognizing objects in an image. Discriminative AI excels at extracting patterns from known data and making judgments, but its capability is confined to "understanding" rather than "creating".

GAI, in contrast, represents a paradigm shift from "understanding" to "creating". It not only analyzes and comprehends data but also possesses the capacity to generate novel content, with substantial improvements in both creativity and ease of use (Sedkaoui & Benaichouba, 2026). OpenAI's large language model GPT, used to build the conversational AI system ChatGPT, can efficiently

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comprehend natural language input and produce meaningful responses; DALL-E-2 can generate high-quality images from textual descriptions. This leap from "discrimination" to "generation" elevates GAI from a mere "analytical tool" to a "creative partner," laying the technical groundwork for its role in enabling management innovation.

From a technological evolution perspective, GAI models have progressed from task-specific to general-purpose intelligence. Early generative models were primarily trained for domain-specific tasks such as machine translation and text summarization. With breakthroughs in unsupervised pre-training, large language models can now learn general language representations and knowledge structures from massive datasets, subsequently adapting to diverse downstream tasks through fine-tuning or prompt engineering. This versatility enables GAI to span multiple management scenarios—from product design to customer service, from marketing content generation to supply chain optimization—demonstrating broad application potential.

2.2. Core Capability Characteristics of GAI

Synthesizing existing research and technical practices, the core capabilities of GAI that enable management innovation can be summarized as follows:

First, multimodal content generation capability. GAI can generate content in multiple forms—text, images, audio, video, and even code. This multimodal generative capacity makes it broadly applicable across enterprise management, from writing market analysis reports and generating product design sketches, to producing marketing materials and writing automation scripts.

Second, natural language understanding and interaction capability. Large language models represented by ChatGPT can comprehend natural language instructions in a near-human manner and engage in meaningful dialogue and responses. This capability substantially lowers the threshold for human-computer interaction, enabling non-technical managers to conveniently leverage AI capabilities, thereby promoting the "democratization" of AI technology.

Third, knowledge integration and reasoning capability. GAI models absorb vast amounts of structured and unstructured knowledge during training, enabling cross-domain knowledge recombination and associative reasoning. Through knowledge recombination and abductive reasoning, GAI enhances the identification of weak signals and the generation of hypotheses (Qiao, 2026). This cross-domain knowledge integration capability is of great value for information synthesis and solution generation in management decision-making.

Fourth, adaptive and evolutionary capability. GAI models can, under appropriate conditions, improve their performance through ongoing learning and feedback optimization, though such improvements depend on data quality, model architecture, and governance practices. This adaptive evolution allows GAI to dynamically adjust to changing enterprise environments and needs, avoiding the pitfall of "outdated upon deployment" that plagues traditional information systems (Florina et al., 2025).

Fifth, simulation and counterfactual reasoning capability. GAI can compress trial-and-error cycles and strengthen inter-temporal validation through simulation and counterfactual reasoning. This capability is particularly critical for scenario analysis and risk assessment in strategic decision-making, enabling enterprises to test the potential consequences of different decision alternatives in a virtual environment.

3. Theoretical Mechanisms of Gai Enabling Management Innovation

3.1. Theoretical Foundations

The theoretical mechanisms through which GAI enables management innovation are best understood not as isolated lenses but as a nested and complementary set of perspectives. At the resource level, the resource-based view (RBV) frames GAI as a strategic technological asset that can be rare, valuable, and difficult to imitate, thereby serving as a potential source of sustained competitive advantage. However, RBV alone is static; it explains what an organization has but not how it deploys and reconfigures resources in response to change (Zhang et al., 2025). This gap is addressed by the dynamic capabilities perspective (Teece, 2007), which emphasizes sensing, seizing, and transforming capacities—precisely the organizational processes that GAI can enhance. At the system level, the socio-technical systems perspective complements these views by reminding us that GAI adoption is never purely technological; it entails co-evolving adjustments in organizational structure, management processes, workforce competencies, and cultural values (Wamba et al., 2025). Together, these three perspectives form an integrated framework: RBV identifies the resource potential of GAI, dynamic capabilities explain the processes through which this potential is activated, and socio-technical systems theory highlights the contextual and structural enablers and constraints that shape outcomes.

It should be noted, however, that these perspectives are not mutually aligned on all dimensions. The RBV and dynamic capabilities views tend to emphasize internal firm-level factors, whereas socio-technical systems theory foregrounds broader contextual and institutional forces. This creates productive tension: the former may overstate managerial agency, while the latter may underspecify how firms actively shape their environments. The framework proposed in this paper does not attempt to resolve these tensions entirely, but rather uses them as complementary lenses that highlight different facets of GAI-enabled management innovation.

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3.2. Micro-Mechanisms of GAI Enabling

Building upon the integrated theoretical foundation above, we now propose that the micro-mechanisms of GAI-enabled management innovation operate at three interconnected levels—cognitive enhancement, decision optimization, and organizational evolution—which correspond respectively to the sensing, seizing, and transforming dimensions of dynamic capabilities, while being simultaneously shaped by socio-technical system conditions.

It should be emphasized that these enabling mechanisms are not automatic outcomes of GAI deployment. Their realization depends critically on factors such as data quality, task suitability, organizational readiness, and governance practices. The following discussion presents the potential pathways, which may be facilitated or hindered by contextual contingencies. Based on the above theoretical foundations, this paper further categorizes the micro-mechanisms of GAI-enabled management innovation into three levels:

3.2.1. Cognitive Enhancement Mechanism: Knowledge Recombination and Abductive Reasoning

Traditional management decisions are constrained by decision-makers' bounded rationality and information processing capacity, making them prone to cognitive narrowing—that is, over-reliance on existing experience and known information while neglecting novel, weak, but potentially critical signals. Through pre-training on massive datasets, GAI acquires cross-domain knowledge graphs and reasoning patterns, enabling it to identify potential correlations and trends from seemingly unrelated information fragments. This knowledge recombination and abductive reasoning capability effectively lowers the cognitive threshold for managers to generate novel hypotheses (Shi & Wang, 2024). In strategic foresight scenarios, GAI can scan global technological dynamics, policy changes, consumer behaviors, and competitive landscapes, extracting "weak signals" that human analysts might overlook, thereby expanding the organization's cognitive boundaries.

3.2.2. Decision Optimization Mechanism: Simulation and Counterfactual Reasoning

The essence of management decision-making is resource allocation under uncertainty. Traditional decision processes often rely on managers' experiential judgments and limited pilot experiments, with high trial-and-error costs and lengthy cycles (Sjödin, 2023; Liu, 2026). GAI's simulation capability enables enterprises to construct decision scenario models in digital space, using counterfactual reasoning—that is, "what would happen if we adopt Plan A instead of Plan B"—to evaluate the potential consequences of different decision paths. This capability, which substantially reduces the marginal cost of experimentation (though not entirely eliminating it), can compress the strategic validation cycle, allowing enterprises to obtain decision-relevant information that may support more informed judgments, provided that the underlying data and model assumptions are adequately validated. From a strategic management perspective, GAI enables enterprises to replace traditional one-time strategic bets with agile, iterative, high-frequency decision-making.

3.2.3. Organizational Evolution Mechanism: Dynamic Resource Orchestration and Capability Reconfiguration

The deepest impact of GAI on management innovation lies at the organizational level. GAI not only changes "how to decide," but also transforms "who decides" and "what is decided". Through dynamic resource orchestration, GAI enhances organizational strategic flexibility and resource allocation efficiency in complex environments. Specifically, GAI enables three levels of organizational transformation: at the process level, shifting from linear processes to intelligent, adaptive processes; at the structural level, shifting from hierarchical to networked, platform-based organizations; and at the capability level, shifting from reliance on individual experience to human-machine collaborative collective intelligence. This organizational evolution is not a simple "technology overlay" but a paradigm-level restructuring of management.

3.3. Human-Machine Collaboration: A New Management Model Enabled by GAI

A core feature of GAI-enabled management innovation is the emergence of a new human-machine collaborative management model. As some scholars have noted, generative AI is fundamentally transforming the model of human-machine collaborative innovation, reshaping the stages of idea generation, development, and evaluation. However, to achieve optimal human-machine collaborative innovation, enterprises need a deep understanding of the respective strengths and limitations of GAI and humans, finding a balance that ensures human dominance in critical aspects.

At the cognitive level, enterprises should establish a "machine broad-scanning – human value-focusing" collaborative mechanism to mitigate algorithmic bias. GAI excels in breadth—rapidly identifying patterns and generating options from massive information; humans excel in depth—possessing irreplaceable advantages in value judgment, ethical considerations, and contextual understanding. The effective combination of the two can achieve a "1 + 1 > 2" synergy. At the decision-making level, GAI provides "decision support" rather than "decision substitution," with final judgment and accountability remaining with human managers.

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3.4. Boundary Conditions and Contingency Factors

The enabling mechanisms proposed above are not universally applicable. Their realization depends on several boundary conditions that should be explicitly acknowledged.

Data quality and availability: GAI's knowledge recombination and simulation capabilities are only as reliable as the training data and enterprise-specific inputs; poor-quality or biased data will propagate and amplify errors.

Task type: GAI is more effective for well-structured tasks with clear evaluation criteria (e.g., content generation, pattern recognition) than for highly unstructured, value-laden strategic judgments that require deep contextual sensitivity.

Firm size and resource base: Large firms with dedicated AI infrastructure and talent are better positioned to realize GAI's enabling potential than resource-constrained SMEs, which may face prohibitive entry costs.

Regulatory and institutional context: Stringent data protection regimes (e.g., GDPR in Europe, China's PIPL) may constrain GAI application scope and increase compliance costs, particularly in cross-border operations.

These boundary conditions suggest that the conceptual relationships advanced in this paper should be interpreted as context-contingent theoretical predictions rather than universal laws.

4. Analysis Of Gai Applications in Multi-Scenario Management

4.1. New Product Design: From Experience-Driven to Generation-Driven

New product design is a domain that relies heavily on creative thinking and is one of the most transformative application scenarios for GAI. Traditional new product design processes typically involve market research, concept generation, solution screening, detailed design, prototyping, and testing—lengthy cycles with high costs and heavy dependence on designers' personal experience and creative inspiration. The intervention of GAI is fundamentally changing this model.

The core value of GAI in new product design is reflected in several aspects. First, GAI can generate novel product design concepts based on analyses of market trends, consumer preferences, and historical sales data. This "data-driven creative generation" greatly expands the space for design exploration, enabling enterprises to screen and optimize among a broader range of design solutions. Second, GAI accelerates design iteration. In traditional design, moving from concept to prototype requires multiple rounds of manual revision; GAI can generate dozens of design variants within seconds for evaluation and selection by the design team. Third, GAI enables personalized design. By analyzing individual consumer preference data, GAI can generate customized product design solutions, promoting the shift from "mass production" to "mass customization".

In terms of case examples, for example, NVIDIA has integrated generative AI into its chip design workflow since 2024. The company's engineers use GAI to generate multiple circuit layout alternatives based on performance constraints, reducing initial design iteration time by approximately 30% in reported internal evaluations. This application exemplifies the cognitive enhancement mechanism: GAI expands the design space by proposing novel configurations that human designers might not initially consider, while human experts retain final selection and validation authority. Some studies have proposed the "Recombination-Repositioning-Improvement" (RTI) innovation paradigm for GenAI, demonstrating how organizations can leverage GAI to reshape product and service innovation strategies. In the manufacturing sector, GAI enables manufacturers to rapidly traverse a wide range of design ideas and select the models that best meet requirements. It is foreseeable that as GAI capabilities continue to evolve, new product design will transition from an "experience-driven trial-and-error process" to an intelligent "data-driven generation-screening-optimization" workflow.

4.2. Customer Relationship Management: From Standardized Service to Intelligent Interaction

Customer relationship management (CRM) is the systematic process by which enterprises establish, maintain, and develop relationships with customers. The introduction of GAI is transforming CRM from a standardized, passively responsive service model to an intelligent, proactively predictive interaction model.

GAI's innovative applications in CRM manifest at three levels. First, intelligent customer service and interactive experience. GAI-powered conversational AI can interact with customers naturally and fluently, understanding complex query intents and providing precise responses. Unlike traditional rule-based or keyword-matching chatbots, GAI-powered customer service can handle open-ended, unstructured customer questions and even perceive customer emotional states to adjust response strategies. Second, customer insights and demand prediction. GAI can integrate multi-channel customer data—transaction records, browsing behaviors, social interactions, feedback comments—to generate deep customer profiles and demand forecasts. This depth of insight enables enterprises to proactively offer solutions before customers explicitly express their needs. Third, personalized customer journey design. GAI can generate customized customer journey maps based on each customer's preferences and behavioral patterns, delivering differentiated interaction experiences at various touchpoints.

Taking IKEA as an example, the company is leveraging generative AI and agent technologies to reshape customer experiences, shifting customer interactions from transactional relationships to immersive, solution-oriented engagements. In the retail sector, GAI is being used to integrate fragmented customer data, product information, and store operations into real-time operational capabilities. These practices demonstrate that GAI is upgrading CRM from a "tool for managing customer relationships" to a "platform for creating customer value".

4.3. Precision Marketing: From Group Profiling to Individual-Level Real-Time Response

Precision marketing is one of the most mature and widespread application areas of GAI. The combination of GAI's multimodal content generation capabilities and data analytics capabilities is driving the evolution of marketing from "group profiling" to "individual-level real-time response".

GAI's innovative applications in precision marketing are reflected in several dimensions. In content generation, GAI can automatically produce high-quality marketing copy, advertising creatives, social media posts, emails, and other marketing materials. This automated content generation substantially reduces the cost and time of marketing content production, enabling enterprises to achieve scale and diversity in marketing content at lower marginal costs. In audience targeting, GAI can identify high-value potential customer groups based on deep customer analysis and predict the effectiveness of different marketing channels and messaging strategies. In real-time optimization, GAI can dynamically adjust marketing strategies and content based on real-time feedback data (click-through rates, conversion rates, engagement rates, etc.), realizing a closed-loop "sense-respond-optimize" process.

Some studies have experimentally validated the effectiveness of GAI-based marketing digital twins, showing that they can effectively understand and apply enterprise proprietary knowledge to provide professional and relevant marketing recommendations. In the financial sector, Bank SinoPac has launched intelligent financial services integrated with GAI, where customers express needs through voice, text, or images, and GAI identifies the intent and generates transaction forms. This embedding of GAI into specific business scenarios represents a shift in precision marketing from "push marketing" to "embedded service marketing".

4.4. Supply Chain Management: From Linear Optimization to Adaptive Networks

Supply chain management is an emerging frontier for GAI applications. Traditional supply chain management relies on historical data and deterministic models for demand forecasting, inventory planning, and logistics optimization, often proving inadequate in the face of black swan events and high uncertainty. The introduction of GAI is transforming supply chain management from linear, static optimization to adaptive, dynamic networked coordination.

GAI's innovative applications in supply chain management span multiple levels. In demand forecasting, GAI can integrate multi-source heterogeneous data—including sales data, market trends, weather information, and social media sentiment—to generate more accurate forecasts. In inventory optimization, GAI can simulate the performance of different inventory strategies under various scenarios and recommend optimal inventory levels and replenishment plans. In supplier risk management, GAI can continuously monitor suppliers' financial conditions, geopolitical risks, natural disasters, and other factors to provide early warnings of potential supply chain disruptions. In logistics route planning, GAI can generate dynamic delivery plans that consider real-time traffic and weather conditions.

Some studies have tested the latest GAI reasoning models in autonomously managing supply chains, finding that they can coordinate demand forecasting, inventory planning, and replenishment decisions across departments with minimal human supervision. GAI is emerging as a new decision-making layer that can generate scenarios, synthetic data, and actionable textual insights, rather than merely point predictions. This capability leap from "forecasting" to "scenario generation" moves supply chain management from passive response to proactive anticipation, and from post-hoc analysis to pre-emptive simulation.

5. Challenges And Risks of Gai-Enabled Management Innovation

5.1. Content Quality Risks: Accuracy, Reliability, and Bias Issues

The accuracy and reliability of GAI-generated content are primary challenges for enterprises in management applications. GAI models are statistical models trained on massive datasets; their "understanding" is essentially the recognition and reproduction of linguistic patterns rather than genuine semantic comprehension and logical reasoning. This technical characteristic can cause GAI to produce "hallucinations"—content that appears plausible but is factually incorrect. In management decision-making scenarios, if managers rely on erroneous GAI-generated information, it may lead to serious strategic missteps.

Moreover, GAI models may inherit and amplify biases present in training data. If the training data contains systematic biases regarding gender, race, geography, etc., GAI-generated content may carry these biases. In human resource management scenarios, using biased GAI tools for resume screening or performance evaluation could trigger fairness disputes and legal risks. Therefore, enterprises must establish rigorous content review and quality control mechanisms when integrating GAI into management processes.

5.2. Technological Application Risks: Data Security, Compliance, and Organizational Fit

Technological application risks represent another major challenge for GAI-enabled management innovation. The first is data security and privacy protection. GAI applications often require inputting substantial enterprise data—including customer information, financial data, and trade secrets—for model fine-tuning or prompt engineering. If such data is improperly used or leaked, it could cause severe business losses and legal consequences. Especially in cross-border operations, different jurisdictions impose varying regulatory requirements on data outflows, requiring enterprises to balance GAI application with compliance.

Second, legal compliance risks. Issues such as copyright ownership and liability attribution for GAI-generated content remain legally ambiguous. If GAI-generated content infringes on third-party intellectual property rights, or if GAI decision recommendations cause harm, who bears responsibility? These questions lack clear answers under existing legal frameworks, creating legal uncertainties for enterprises' GAI applications.

Third, organizational fit risks. Effective GAI application requires corresponding adjustments and investments in technical infrastructure, talent capabilities, and management processes. However, many enterprises rush to deploy GAI before resolving issues such as outdated network architectures, fragmented systems, and data silos, making AI difficult to truly realize its value. Gartner's forecast report identifies "six core bottlenecks" in enterprise-grade AI deployment, including trust issues, legacy system conversion, permission management, and sensitive information protection.

Beyond these immediate risks, several emerging concerns warrant attention. Model drift—the gradual degradation of GAI performance as real-world conditions diverge from training data—can undermine the reliability of long-term deployments. Automation bias, where human operators over-rely on GAI recommendations even when contradictory evidence exists, poses particular risks in high-stakes decisions. At the organizational level, deskilling effects may emerge if routine analytical tasks are fully automated without corresponding investments in higher-order human capabilities. Workforce redesign must therefore accompany technological deployment, with attention to skill displacement and reskilling needs. Cybersecurity vulnerabilities specific to GAI systems, including prompt injection and data poisoning attacks, require dedicated protection measures. The environmental cost of training and running large-scale GAI models (energy consumption, water usage for cooling) is increasingly material and should be factored into adoption decisions. Finally, vendor dependence and power concentration—where a small number of firms control foundational models—create strategic vulnerabilities and raise antitrust concerns.

5.3. Developmental Constraints: Talent Shortages, Cost Inputs, and Path Dependency

From a broader perspective, GAI-enabled management innovation also faces several developmental constraints.

Talent shortages are the foremost constraint. Effective GAI application requires not only technical AI experts but also interdisciplinary talents who understand both business and AI—those who can "translate" AI capabilities into concrete management solutions. However, such talents are extremely scarce in the market, and enterprises often face the dilemma of "wanting to use but having no one to use". McKinsey's research indicates that organizational inertia and talent shortages together amplify the difficulty of enterprise AI transformation.

Cost inputs are another significant constraint. The training and deployment of large-scale GAI models demand enormous computational resources and data reserves, posing a high entry barrier for small and medium-sized enterprises. Even with lightweight approaches such as API calls, long-term usage costs are considerable. Finding a balance between cost and benefit is a strategic question that enterprises must address in GAI adoption.

Path dependency is equally important. Many enterprises have made substantial investments in traditional management information systems, forming entrenched workflows and management habits. Transitioning to a GAI-driven management model entails not only technological replacement but also systematic changes in mindsets, organizational culture, and capability systems. Such transformation requires time, patience, and resolute leadership.

6. Management Countermeasures and Recommendations

6.1. Technical Governance: Building a Responsible AI Application Framework

Enterprises should establish a governance framework covering the entire lifecycle of GAI applications. At the data level, implement strict data security management systems to ensure that sensitive data input to GAI is adequately protected. At the model level, establish multi-level review mechanisms for GAI-generated content, with critical decisions subject to manual verification. At

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the application level, clearly position GAI as “assistive” rather than “substitutive,” ensuring that humans retain final decision-making authority in key aspects. At the compliance level, closely monitor the evolution of relevant laws and regulations to ensure that GAI applications operate within compliant boundaries.

Some scholars propose that enterprises should build a “machine broad-scanning-human value-focusing” human-machine collaborative mechanism to mitigate algorithmic bias. Specifically, three lines of defense can be established: “technical protection – management supervision-audit traceability”. At the technical level, reduce GAI error probabilities through prompt engineering and adversarial testing; at the management level, ensure output quality through manual sampling and expert evaluation; at the audit level, achieve traceability and accountability through full-link logging.

To operationalize this framework, firms should designate a cross-functional AI governance committee comprising members from IT, legal, HR, and business units. This committee is responsible for approving high-risk applications. Decisions that involve significant financial outlays, legal liability, or ethical trade-offs must retain human final approval—GAI outputs in these cases serve as advisory inputs only. Performance should be measured not only by efficiency gains but also by failure metrics such as error rates, bias audits, and user satisfaction surveys. A quarterly “AI incident log” should be maintained to track near-misses and actual failures, enabling continuous learning and governance refinement.

6.2. Organizational Transformation: Reshaping Processes, Structures, and Culture

Effective GAI application requires systematic organizational transformation. At the process level, enterprises should redesign management processes around GAI capabilities, rather than simply overlaying GAI tools onto existing processes. This means identifying which steps can be enhanced or automated by GAI, and which still require human judgment and intervention, and reconfiguring workflows accordingly.

At the structural level, enterprises may need to establish dedicated AI governance bodies or centers of excellence to coordinate GAI strategic planning, technology selection, application promotion, and effect evaluation. At the same time, departmental silos should be broken down to promote deep integration between business and technical teams—business teams need to strengthen their understanding and application of GAI, while technical teams need to deeply comprehend business needs and pain points.

At the cultural level, enterprises need to cultivate an “AI-ready” organizational culture—neither over-believing in AI’s omnipotence nor blindly resisting its involvement. This requires leadership to lead by example, initially trying and using GAI tools in daily management, while enhancing the data literacy and AI application capabilities of all employees through training and incentive mechanisms.

6.3. Institutional Safeguards: Policies, Standards, and Ecosystem Development

From a broader industrial and policy perspective, the sustainable development of GAI-enabled management innovation requires sound institutional safeguards. Governments and industry organizations should accelerate the formulation of relevant standards and guidelines for GAI applications, particularly providing clear norms in key areas such as data security, algorithmic fairness, and content liability. At the same time, industry-university-research collaboration should be encouraged to promote empirical research and best-practice sharing in GAI management applications.

For small and medium-sized enterprises, due to limited resources, they can hardly bear the R&D and deployment costs of GAI independently. Governments and industry organizations can lower the entry barrier for SMEs to adopt GAI by building public AI service platforms and providing subsidies and tax incentives. Additionally, attention should be paid to cultivating interdisciplinary talents, strengthening the cross-integration of AI and management disciplines in higher education and vocational training systems. SMEs face distinct adoption challenges beyond financial constraints. The build-versus-buy decision is particularly acute: while public GAI platforms offer low entry costs, they raise data privacy concerns; conversely, custom deployments require technical expertise and infrastructure that most SMEs lack. API-based integration can bridge this gap but incurs ongoing usage costs that may become burdensome at scale. Legacy system compatibility is often overlooked—many SMEs operate on outdated IT architectures that cannot easily interface with GAI services. Vendor lock-in, where switching costs between GAI providers become prohibitive, is a growing concern. Furthermore, the cost of human review and audit does not diminish with automation; indeed, it may increase as the volume of GAI-generated outputs expands, requiring proportionally more human oversight. Public platforms and subsidies, while helpful, cannot address these structural barriers alone.

Societal implications of GAI-enabled management innovation should be disaggregated by responsibility level. At the firm level, organizations are accountable for fair treatment of employees (surveillance, performance evaluation), transparent communication about AI use, and investment in reskilling programs to mitigate displacement effects. At the policy level, governments and regulators bear responsibility for establishing accessibility standards (preventing digital divides), mandating algorithmic impact assessments, defining liability frameworks for AI-related harms, and incentivizing sustainable AI practices (e.g., through energy-ef-

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ficiency standards or carbon accounting for AI compute). The digital divide—where larger firms capture disproportionate AI benefits while SMEs lag—requires policy interventions beyond market mechanisms, such as publicly funded AI literacy programs and shared infrastructure for underserved sectors.

7. Conclusion and Outlook

7.1. Research Conclusions

This paper systematically investigates the enabling mechanisms and challenges of generative artificial intelligence for enterprise management innovation, drawing the following main conclusions:

First, GAI enables management innovation at three levels—cognitive enhancement, decision optimization, and organizational evolution. Through knowledge recombination and abductive reasoning, GAI expands organizations' cognitive boundaries; through simulation and counterfactual reasoning, GAI improves the quality and efficiency of strategic decisions; through dynamic resource orchestration, GAI enhances organizations' strategic flexibility and adaptive capacity.

Second, GAI demonstrates significant innovative value in four key scenarios: new product design, customer relationship management, precision marketing, and supply chain management. Its core mode of action can be summarized as: providing "breadth" in the creative generation phase, "speed" in the solution screening phase, and "precision" in the continuous optimization phase.

Third, GAI-enabled management innovation faces multiple challenges, including content quality risks, technological application risks, and developmental constraints. These challenges are not insurmountable, but require systematic countermeasures across technical governance, organizational transformation, and institutional safeguards.

Fourth, the essence of GAI-enabled management innovation is the emergence of a new human-machine collaborative management model. The optimal role of GAI is to "augment" rather than "replace" human managers. Successful GAI applications require a dynamic balance between fully leveraging machine efficiency advantages and preserving human judgment advantages.

7.2. Research Limitations and Future Directions

This study has certain limitations. First, GAI technology is still rapidly evolving, and the enabling mechanisms and application scenarios analyzed in this paper may change as technology iterates. Second, the analysis in this paper is primarily based on secondary sources, lacking primary enterprise survey data, which may not fully capture the complexity and contextual dependence of GAI applications. Third, the analysis of GAI challenges focuses mainly on technical and managerial aspects, with insufficient discussion of ethical, social, and policy dimensions.

Future research can be deepened in the following directions: First, conduct empirical studies on GAI-enabled management innovation, quantitatively assessing the effects of GAI on different types of enterprises and management functions through surveys or enterprise case tracking. Second, explore differentiated application models and success factors of GAI across industries and enterprise sizes. Third, conduct in-depth research on human-machine collaborative management models, especially the new roles and capability requirements for human managers in the GAI era. Fourth, focus on the theory and practice of GAI governance, constructing a new paradigm of enterprise governance suitable for the intelligent age.

Generative artificial intelligence is reshaping the underlying logic and operational modes of enterprise management. For business managers, the important question is not "Will GAI replace managers?" but "How can we collaborate with GAI to become better managers?" In this sense, the ultimate goal of GAI-enabled management innovation is not "machines replacing humans," but "human-machine co-progress"—letting technology expand the boundaries of human capabilities, and letting human wisdom guide technology toward beneficial directions.

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