

A Multi-Case Qualitative Study on the Strategic Socio-Industrial Integration of AI: Insights from China

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Abstract

This qualitative study explores the technological trajectory and socio-industrial integration of artificial intelligence (AI) in China, addressing the question: How has AI evolved from conceptual research to widespread industrial application? Using a multi-case design, we purposefully selected four sectors—generative AI, computer vision and audition, intelligent connected vehicles and intelligent robotics for analysis. Cross-case analysis is also conducted in the fields of business, news and research. Data drawn from academic literature, industry reports, and policy documents were examined through thematic analysis. Typical and representative cases in the sectors were selected to analyze.

The findings chart AI's progression toward greater multimodal capability and its concurrent penetration into diverse economic sectors. The study's primary contribution is its systematic, cross-case synthesis of China's application-driven AI development model, revealing both its transformative potential and persistent challenges. The paper concludes that future progress will hinge on pursuing both advanced general intelligence and deeper, more equitable socio-economic integration.

Keywords : Artificial Intelligence; Socio-Industrial Integration; Strategic Development; Multi-Case Study

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Introduction

Artificial intelligence, as a strategic technology leading the new round of scientific and technological revolution and industrial transformation, is profoundly reshaping development models and competitive landscapes across socio-economic domains globally. From its conceptual inception at the 1956 Dartmouth Conference to the present, AI has evolved from a laboratory theoretical concept into a core force driving industrial transformation. (McCarthy et al., 2006). The development of modern AI is primarily driven by the synergistic interaction of three fundamental elements: algorithms, computing power, and data (Vaswani et al., 2017). Data provides the foundation for model training; algorithms, from traditional machine learning to deep learning, determine AI's perceptual and cognitive capabilities; and computing power, particularly through specialized hardware such as GPUs and TPUs, enables the practical deployment of complex models. (Cai, 2024).

China constitutes a theoretically important context for AI research for several compelling reasons. As the world's second-largest economy and a leading contributor to AI research publications and patent filings, China represents a critical site of AI innovation and application. (Yan and Ren, 2025). More significantly, China's AI development unfolds within a unique institutional framework characterized by proactive industrial policies, substantial state-directed investment, and a vast, digitally native consumer market that generates unparalleled data resources. The country's approach to AI governance, which emphasizes both technological advancement and social stability, offers a distinctive model that contrasts with Western paradigms. (Qian et al., 2025). Furthermore, China's simultaneous pursuit of AI leadership across multiple domains—from generative AI and intelligent vehicles to robotics and smart manufacturing—provides a rich empirical basis for examining how general-purpose technologies evolve and diffuse across diverse sectors. (Zhao, 2025). Understanding China's AI trajectory thus not only illuminates a nationally specific pathway but also contributes to broader theoretical debates about technology-society evolution and the institutional foundations of technological leadership.

Despite the extensive body of research on AI's technological advancements and industrial applications, significant gaps remain in the existing literature, particularly concerning China's AI development trajectory. Current studies on China's AI landscape

suffer from three primary limitations. First, much of the existing research adopts a fragmented approach, focusing on isolated technological domains or specific application sectors without providing an integrated understanding of how these diverse elements coalesce into a coherent national innovation system (Zhang, 2019). Second, while numerous policy analyses and industry reports document China's AI achievements, they largely remain descriptive and lack theoretical depth, failing to extract the underlying developmental logics (Li et al., 2026). Third, the existing literature offers limited comparative insights into how China's distinctive institutional environment, data ecosystem, and industrial policies shape AI evolution. (Zhang, 2025).

Addressing the aforementioned research gaps, this study advances current debates by posing the following sharply defined research problem: How has artificial intelligence in China evolved from theoretical foundations through technological development to multi-domain industrial integration, and what common patterns, underlying logics, and future challenges characterize this evolutionary process? This study systematically investigates this question through a multi-case qualitative analysis of four representative domains. By integrating conceptual analysis, technological tracing, and industrial examination within a unified analytical framework, this study makes three distinctive contributions. First, it develops an integrative framework that reveals the interconnected dynamics across different AI domains—an approach that moves beyond fragmented single-sector analyses. Second, through cross-case comparison, it identifies common developmental patterns and systemic challenges that theoretical generalizations from isolated cases cannot capture. Third, it provides empirically grounded projections of AI's future trajectory, thereby offering a more robust foundation for anticipating and navigating AI's evolving landscape.

Research Objectives

- 1) To trace the conceptual and technological evolution of AI.
- 2) To analyze the new applications and industrial integration of AI in key domains within the context of China's development.
- 3) To synthesize cross-case findings to identify overarching patterns, persistent challenges, and future trajectories for AI development.

Literature Review

1. Algorithms and School of Thoughts

Machine learning algorithms, deep learning algorithms, reinforcement learning algorithms, generative adversarial networks, and numerous other algorithms have driven applicability across diverse scenarios and industry adaptation. Processors such as CPUs, GPUs, and TPUs have met the demand for efficient computing power and the increasing requirements of computational technology. Data, meanwhile, can be used for training models, supporting decision-making insights. (Zhang, 2026), and fostering innovation and discovery in various fields like agriculture and business (Shang, 2024).

During its theoretical evolution, the field of artificial intelligence has primarily formed three major schools of thought, each exploring the nature and realization of intelligence through different approaches: Symbolism: Originating from logic and philosophy, this school posits that intelligence stems from the manipulation and reasoning of abstract symbols. Its representative achievements include expert systems and knowledge graphs, excelling in interpretability and logical judgment.

Connectionism: Inspired by biological neural networks, this school advocates that intelligence emerges from the interconnection and learning of numerous neurons. Deep learning is the contemporary embodiment of this approach, having achieved breakthroughs in perceptual tasks such as computer vision and speech recognition. Behaviorism: This school emphasizes that intelligent behavior arises from the interaction between an agent and its environment, evolving through "perception-action" feedback loops. It has significant influence in fields such as robotic control and autonomous driving. These three major schools are not mutually exclusive; rather, they exhibit a trend of intersection and integration in current research and practice.

2. AI Technology Branches

Today, research and application in artificial intelligence are characterized by a high degree of specialization. Its technical system primarily revolves around four core branches: computer vision, computer audition, natural language processing, and intelligent robotics. These four areas constitute the foundation for AI's current role in empowering industries and enabling environmental perception and interaction. Their developmental trajectories and research outcomes clearly outline the technical contours of modern artificial intelligence.

Computer vision aims to endow machines with the ability to "see" and understand the visual world. The field has evolved from early techniques such as edge detection (Canny, 1986) and feature descriptors (Lowe, 1999) to deep learning methods dominated by convolutional neural networks (CNN). The groundbreaking success of AlexNet, proposed by Krizhevsky et al. (2012) in the ImageNet competition, fundamentally transformed the research paradigms for image classification, object detection, and image segmentation.

Natural Language Processing focuses on the interaction between human language and computers. Its development has progressed from rule-based methods to statistical machine learning, and now to deep learning dominated by pre-trained language models. Early research relied on Hidden Markov Models and Conditional Random Fields for tasks such as part-of-speech tagging and named entity recognition. A turning point came with pre-trained models based on the Transformer architecture, such as the GPT series proposed by Radford et al. (2018). These models, through self-supervised pre-training on massive corpora, have acquired powerful language representation and contextual understanding capabilities, achieving unprecedented performance in tasks like text summarization, machine translation and question-answering systems (Huang et al., 2025). Currently, large language models represented by ChatGPT are driving NLP from "understanding language" towards a new stage of "generating and creating language."

Computer Audition (or Machine Audition) enables machines to perceive, understand, and generate audio signals. Its progress in the field of speech recognition has been particularly remarkable, evolving from architectures based on Gaussian Mixture Models and Hidden Markov Models (GMM-HMM) to the current mainstream of feedforward neural networks and end-to-end models based on the Transformer architecture, such as DeepSpeech2 (Amodei et al., 2016), which have significantly improved recognition accuracy and robustness. In speech synthesis, waveform generation models like WaveNet (van den Oord et al., 2016) have achieved near-human-quality speech output.

Intelligent robotics, serving as the physical embodiment of AI, integrates multiple perceptual technologies mentioned above and emphasizes autonomous decision-making and action capabilities in the physical world. Its core research areas include simultaneous localization and mapping (Durrant-Whyte & Bailey, 2006), motion planning,

and multi-sensor information fusion. From industrial robots performing repetitive tasks in structured environments to specialized and service robots operating in complex, unstructured settings, the advancement of this field heavily relies on the successful application of algorithms such as reinforcement learning (Silver et al., 2016) and imitation learning in robotic control.

In summary, these four major technical branches do not develop in isolation but rather reinforce each other under the trend of "multimodal fusion." This study further investigates the innovative applications and viable development pathways of artificial intelligence.

Research Methodology

This study adopts a qualitative, multiple-case study approach to systematically investigate the technological evolution, industrial applications, and future trajectories of artificial intelligence. This method is appropriate as it allows for an in-depth, contextualized exploration of a complex contemporary phenomenon—AI development—within its real-world setting. The methodology is structured into four key phases: case selection, data collection, data analysis, and validity assurance.

1. Case Selection and Sampling Logic

To ensure the depth and breadth of the analysis, a purposive sampling strategy was employed to select four representative case domains. These cases were chosen based on two primary criteria: (1) Technological Significance, meaning the domain represents a core branch or cutting-edge frontier of AI; and (2) Industrial Impact, meaning the domain demonstrates substantial integration and transformative effects across various socio-economic sectors in China. The selected cases are:

Generative Artificial Intelligence: Focuses on NLP, text-to-image, and text-to-video technologies.

Computer Vision and Audition: Examines applications in perception and their integration into multimodal systems.

Intelligent Connected Vehicles and Autonomous Decision-Making: Explores the convergence of IoT and AI in transportation.

Intelligent Robots and Manufacturing: Investigates the role of AI in industrial automation and physical interaction.

The analysis period primarily covers developments from the early 2000s to 2024, capturing the rise of deep learning and the recent surge in generative AI.

2. Data Collection

This study relies on the collection and analysis of qualitative, documentary data. To build a robust and triangulated dataset, data was sourced from three main categories:

Academic Literature: Peer-reviewed journal articles and conference proceedings were retrieved from databases such as Google Scholar, IEEE Xplore, and the China National Knowledge Infrastructure (CNKI). Search terms included combinations of "artificial intelligence," "generative AI," "intelligent connected vehicles," "computer vision," "industrial robots," and "China."

Industry and Policy Reports: Grey literature, including reports from leading market research firms, white papers from technology companies, and official government documents were collected to provide industrial and policy context.

Case-Specific Documents: For specific sub-case examples, local news articles and public-facing reports were incorporated to provide illustrative depth.

The total corpus comprises approximately 100-150 documents. The collection process was iterative, with initial documents guiding the search for additional, more specific sources.

3. Data Analysis Procedure

The data analysis followed a two-stage thematic analysis approach.

Within-Case Analysis: For each of the four main cases, a detailed descriptive narrative was first constructed. This involved a close reading of all documents within that case to identify the key technological milestones, application scenarios, and reported challenges. The goal was to create a holistic understanding of AI's evolution within each specific domain.

Cross-Case Thematic Analysis: Following the individual case analyses, a cross-case synthesis was performed to identify recurring patterns, overarching themes, and key differences. This involved:

Coding: Key findings and observations from each case were coded. For example, mentions of "human-robot collaboration," "autonomous decision-making," and "data as fuel" were coded across cases.

Theme Development: These initial codes were then grouped into broader, higher-order themes. For instance, codes like "autonomous driving," "robot control," and "drone swarming" were synthesized into the theme of "Autonomous Decision-Making and Physical Interaction."

Iterative Refinement: Themes were constantly checked against the original data to ensure they accurately reflected the source material.

4. Research Validity and Limitations

To enhance the rigor and trustworthiness of the findings, data triangulation was employed: By using multiple data sources from academic, industry and policy area, the study mitigates the bias inherent in any single source type and provides a more comprehensive view of AI development.

This study acknowledges certain limitations. As a qualitative study based on documentary evidence, it does not offer quantitative measurements of AI's impact. Furthermore, the rapid pace of AI development means that the findings represent a snapshot in time, and some specific technological details or market figures may quickly become outdated. Future research could complement this work with quantitative analyses or in-depth interviews with AI practitioners.

Case Analysis and In-depth Exploration

1. Generative AI

1.1 NLP and Text Generation

Generative AI evolves through text, image, and video modalities. Text generation originated with ELIZA in the 1960s and progressed through retrieval-based systems (BaseBall, LUNAR), knowledge graphs (Google Knowledge Graph), and neural models (RNN, LSTM). Natural language processing encompasses tasks like translation, summarization, and dialogue, powered by architectures such as RNN, LSTM, and GRU. The industry chain comprises an upstream foundational layer (data, computing power), a midstream model layer (general vs. domain-specific), and a downstream application layer. In 2023, the global generative AI market reached approximately USD 67 billion, with China's market around RMB 17 billion.

1.2 A New Paradigm of Content Creation

Text-to-image and text-to-video technologies transform AI into a visual content engine, enhancing sectors like government with real-time analytics and dissemination (Pan, 2024). In 2023, global AIGC financing totaled USD 23.2 billion, with over 1,500 active companies. Text-to-image tools streamline creative production, while video generation models like Google's VideoPoet and Gemini illustrate multimodal advances. Chinese players divide into foundational model developers and product-focused firms (e.g., Right Brain Technology), targeting general or niche applications.

1.3 An Insight in Generative AI Convergence and Specialization

Through analysis, a key trend is the convergence of modalities—text, image, and video—into unified multimodal frameworks, as seen with Google's Gemini and VideoPoet. This integration allows models to leverage cross-modal data for richer, more coherent outputs, moving beyond isolated generation tasks. Simultaneously, a divergence is occurring at the application layer: while general-purpose large models aim for broad utility, specialized models are increasingly tailored to vertical domains such as healthcare, finance, or creative design. This duality reflects a maturing ecosystem where foundational infrastructure supports both horizontal scalability and vertical precision.

Another prominent characteristic is the strategic bifurcation of market players between infrastructure builders and application-focused innovators. Upstream, investment in computing power and data resources is consolidating around tech giants, while midstream model development sees competition between open-source ecosystems and proprietary platforms. Downstream, the rapid growth in AIGC financing—USD 23.2 billion globally in 2023—signals high-stakes experimentation, yet also pressures for monetization. As a result, companies are prioritizing either foundational R&D for long-term dominance or rapid deployment in niche markets, shaping a dynamic landscape where technological capability meets targeted problem-solving.

2. Computer Vision and Audition

2.1 Vision and Audition Applications

Computer vision seeks to endow machines with human-like visual capabilities, primarily through tasks such as image classification, segmentation, and facial recognition. Since the advent of convolutional neural networks in 1998, the field has evolved rapidly, expanding into applications like autonomous driving semantic segmentation, 3D reconstruction for VR/AR, and video content understanding. Audition, as the second most

critical sensory channel, finds its key applications in speech recognition, synthesis, and separation (Yang, 2019). These technologies are now ubiquitous in daily life through voice assistants and smart speakers, while also holding significant industrial value in areas like acoustic fault diagnosis for heavy machinery.

2.2 Multimodal Perceptual Interaction: Intelligent Technology

The integration of artificial intelligence with perceptual capabilities has most notably materialized in the development of intelligent robots. Unlike their traditional predecessors, these robots leverage human-like vision, multi-sensor information fusion, and autonomous decision-making for applications ranging from healthcare and industrial automation to military reconnaissance. Concurrently, the metaverse represents a fully immersive virtual realm, blending AR/VR with blockchain and 5G. Another significant trend is the rise of the low-altitude economy, propelled by drone technology, which is rapidly expanding into commercial aviation and logistics, supported by proactive regulatory frameworks and infrastructure development. (Tian, 2024).

2.3 Analytical Summary of Trends in Perceptual Intelligence

Based on the analysis, a dominant trend emerging from the evolution of both vision and audition technologies is the shift from unimodal recognition to multimodal perceptual fusion. Initially focused on isolated tasks like image classification or speech-to-text, the field now increasingly integrates diverse data streams—visual, auditory, and spatial—to enable more robust and context-aware intelligence. This convergence is exemplified by intelligent robots that combine vision for navigation with audition for command input, or by the metaverse, which demands the synchronized processing of visual and auditory inputs to create a convincing sense of presence. This trajectory suggests that the future of AI lies not in perfecting single senses in isolation, but in architecting systems capable of a holistic, human-like interpretation of the world through correlated sensory channels.

Furthermore, a clear trajectory is the application-driven specialization and industrial deployment of these technologies. Foundational models, once confined to academic research, are now being rigorously tailored and deployed in high-stakes, domain-specific environments. This is evident in the use of computer vision for precision tasks in autonomous driving and medical imaging, and the application of audio analysis for predictive maintenance in industrial settings. The rapid growth of the low-altitude

economy and the strategic investment in embodied intelligence (like humanoid robots) indicate a broader industrial strategy to embed perceptual AI into the physical fabric of society, transitioning from digital assistants to autonomous agents that can perceive, act upon, and interact with the real world.

3. Intelligent Connected Vehicles and Autonomous Decision-Making Systems

3.1 Unmanned Vehicles and Vehicle-Road Collaboration

Driven by the convergence of industrial and technological revolutions, the Internet of Things (IoT) has matured through advances in sensing, connectivity, and information processing. When applied to transportation, this has enabled Vehicle-to-Everything (V2X) and Intelligent Connected Vehicles (ICVs). ICVs integrate IoT perception with artificial intelligence for algorithmic analysis and intelligent decision-making, allowing vehicles to collect environmental data and communicate via networks. Their core functionality depends on onboard sensors for environmental perception and the control of steering, propulsion, and braking. AI now demonstrates strong adaptability to complex scenarios, including variable lighting and terrain, significantly enhancing autonomous capability.

3.2 Multi-purpose Development of Unmanned Vehicles

Autonomous driving applications can be categorized into five types. Regional traffic intelligent vehicles feature redesigned structures, improved navigation accuracy, and wireless communication for functions like smart road green wave passage. Intelligent connected trucks require standardized testing criteria and share applications with regional traffic vehicles in ports and mines. Intelligent cars, developed by companies such as Google, GAC, and Huawei, focus on comprehensive performance testing but remain in research phases. Additional types include intelligent buses with redesigned bodies and fixed smart routes, as well as movable modular vehicles distinguished by multi-element control and integration into full-network systems. The intelligent vehicle market is projected to exceed 600 billion yuan by the end of the “14th Five-Year Plan” period, though challenges like cement road recognition persist. (Wang, 2023).

3.3 Analysis insights in Vehicle Trends

Through analysis of the cases, the development of intelligent connected vehicles reveals a clear trajectory toward systemic integration and specialization. On one hand, the convergence of IoT perception and AI-driven decision-making is enabling vehicles to operate in increasingly complex environments, as seen in the adaptability to terrain and

lighting variations. This trend points to a future where vehicles are not merely autonomous but deeply embedded in intelligent transportation ecosystems, leveraging vehicle-road collaboration and real-time data exchange to optimize traffic flow and safety. The emergence of specialized vehicle types—such as modular vehicles for disadvantaged groups and fixed-route intelligent buses—indicates a shift from generalized automation to purpose-built solutions tailored to specific operational contexts and user needs.

On the other hand, the uneven progress across vehicle categories highlights critical challenges and priorities. While regional traffic vehicles and connected trucks have advanced through standardized testing and infrastructure integration, intelligent cars remain in developmental stages, underscoring the gap between controlled experimentation and real-world deployment. The projected market growth underscores economic momentum, yet persistent technical hurdles—such as cement road recognition—reveal the limits of current AI adaptability. These factors suggest that future breakthroughs will depend not only on algorithmic improvements but also on robust infrastructure, regulatory alignment, and cross-sector collaboration to bridge the divide between innovation and practical implementation.

4. Intelligent Robots and Manufacturing

4.1 Industrial Robots and Drones

Industrial robots are pivotal to global manufacturing revitalization, with leaders like Japan and the US launching strategic initiatives. While China has established robotics hubs, a significant gap persists, as giants KUKA and ABB command nearly half the global market, dwarfing domestic players like Siasun. China's development is bottlenecked by three core "chokepoint" technologies: precision reducers, industrial software, and control algorithms. Despite lagging in manufacturing processes and cost efficiency, China has achieved relative strength in autonomous positioning and multi-robot collaboration. The future trajectory points toward enhanced human-robot interaction and integrated control systems.

Drones, remotely controlled aircraft, are predominantly used in military applications for reconnaissance and electronic countermeasures, with civilian roles in agriculture and meteorology. Their key advantages—eliminating pilot risk, small size, low cost, and flexible deployment—are counterbalanced by low survivability and poor wind

resistance. Future evolution will focus on extended endurance, collaborative swarming, and vertical takeoff and landing capabilities. (Yi, 2024).

4.2 Physical Interaction: Intelligent Manufacturing and Industry

Global shifts in labor division, coupled with China's rising costs and dwindling demographic dividend, are compelling its manufacturing sector to move up the value chain. Process technology, as the primary determinant of quality, is the critical focus. China's smart manufacturing model is structured as a multi-layer hierarchy (from enterprise to equipment), interconnected via a big data platform. However, current progress is hindered by insufficient investment, a lopsided emphasis on informatization over automation, and a shortage of skilled technicians. In response, China is adopting Germany's precision-engineering approach to elevate its manufacturing standards while bolstering support for its high-end sector.

4.3 Analytical Summary and Trends Analysis

From the realistic analysis, the evolution of intelligent robotics and manufacturing reveals a clear trend toward the convergence of digital and physical systems. In industrial robots, the shift from simple automation to advanced human-robot interaction and integrated control systems signifies a move beyond isolated mechanical tasks toward collaborative, software-defined processes. This is mirrored in smart manufacturing's hierarchical architecture, where the big data platform acts as the central nervous system, integrating the enterprise with the physical equipment layer. The core characteristic is the transition from hardware-defined capacity to software-defined capability, where control algorithms and industrial software become the primary arbiters of competitive advantage.

A second critical characteristic is the formation of a dual-track competitive landscape. On one track, global incumbents like KUKA and ABB maintain dominance through entrenched advantages in core components and software, creating persistent "chokepoints" for latecomers. On the other, nations like China are leveraging their strengths in application scenarios—such as multi-robot collaboration and drone swarming—to carve out niches. This creates a dynamic where competition is no longer just about the machine itself, but about the ecosystem: the ability to integrate precision mechanics (the German model) with vast data and agile software development. The

future belongs to players who can master both the physical constraints of process technology and the limitless potential of digital integration.

Cross-Case Analysis and Theoretical Findings

1. AIGC Impact on Research

Generative AI, particularly ChatGPT, has significantly advanced natural language processing, machine learning, and reinforcement learning. Through large-scale pre-training and extended context handling, models have achieved notable progress in dialogue fluency, multi-turn interaction, and semantic comprehension. This has driven a trend toward larger models and more diverse training data encompassing broader knowledge domains.

Additionally, AIGC has stimulated progress in symbolic logic integration. Researchers are increasingly combining symbolic reasoning with deep learning to enhance logical coherence and commonsense understanding in dialogue systems. The use of dialogue managers and rule-based mechanisms has improved context tracking and response generation, enabling more sophisticated handling of logical relationships (Xu, 2023).

2. AIGC and Cross-Industry Integration

2.1 AI and Chinese News Industry

At the Jiaxing City Media Convergence Center, AIGC has been deployed to develop virtual anchors for public service programs, exemplifying "AI + media" integration (Hu, 2024). These AI anchors feature realistic appearances and strong language and emotional expression, demonstrating that generative AI is approaching practical application standards. However, challenges remain in areas such as nuanced phrasing and emotional delivery, where human performance remains superior.

Beyond virtual anchors, AIGC has been applied to short-form video production and poster generation, yielding outputs nearly indistinguishable from manually created content. These applications highlight the technology's versatility and growing role in media production workflows.

2.2 AI and Business

In the current era where "AI + X" is gaining momentum, accounting intelligence and FinTech are increasingly replacing traditional accounting and financial economics practitioners (Peng, 2024). From an application perspective, bank branches have already

adopted unmanned "integrated service machines" in their lobbies to replace manual transaction processing. Academically, the field of accounting has engaged in research related to AI. Addressing the uncertainty of intangible assets (Penman, 2014), the academic community has reached somewhat divergent conclusions using artificial intelligence: AI may not be a panacea. When institutional or soft information, including intangible assets, plays a significant role, human accountants outperform machine measurement. Conversely, machines hold an advantage when information is relatively transparent and voluminous. This indicates that AI also faces significant challenges in processing information related to intangible assets and accounting judgment (Cao, 2024).

3. Cross-case Theoretical Findings

The cross-case analysis reveals that AIGC's impact varies significantly across domains, shaped by the nature of tasks and the types of knowledge involved. In research settings, AIGC enhances symbolic reasoning and large-scale data processing, leading to theoretical advances in integrating neural networks with rule-based systems. This suggests a convergence of connectionist and symbolic AI paradigms, with implications for developing more interpretable and logically consistent models. The Jiaxing media case further illustrates that AIGC can achieve human-like output in structured tasks such as news delivery and content generation, yet struggles with subtle emotional and contextual nuances, indicating that theoretical models of AI performance must account for task granularity and affective complexity.

In the business domain, the comparative advantage of AIGC versus human expertise hinges on information transparency and the degree of institutional embeddedness. The accounting case demonstrates that while AI excels in processing standardized, high-volume data, it falls short in contexts requiring tacit knowledge and professional judgment. These finding challenges purely technical interpretations of AI capability and underscores the need for socio-technical theories that incorporate organizational and institutional factors. Collectively, these cases suggest that theoretical frameworks for AIGC must move beyond general claims of superiority toward domain-specific models that consider task characteristics, knowledge types, and human-AI complementarity.

Discussions

This study's cross-case analysis of China's AI development across generative AI, intelligent vehicles, and robotics reveals a trajectory that both confirms and extends existing theories of innovation and technological catch-up. The findings resonate with the concept of national innovation systems, illustrating how China's state-guided capitalism orchestrates a tripartite synergy among vast data resources, strategic computational infrastructure, and applied algorithmic research to facilitate rapid industrial integration. However, the case of generative AI, particularly in content creation, also complicates a purely state-centric view. The proliferation of foundation models and AIGC applications is equally driven by fierce market competition and entrepreneurial dynamism, suggesting a hybrid model where state ambition and private-sector innovation are deeply intertwined.

Furthermore, the observed tensions—such as the struggle of AI hosts to replicate human emotional nuance or the debate over AI's efficacy in accounting for intangible assets—provide empirical grounding for debates within the political economy of technology. These findings challenge technologically deterministic narratives by highlighting the social embeddedness of AI. The technology's successful integration is not merely a technical challenge but a social one, contingent on its ability to navigate institutional logics and complement, rather than simply replace, human labor. By situating China's developmental path within these broader international discourses on innovation systems and the socio-technical nature of AI, this study moves beyond a descriptive account. It demonstrates that China's experience offers a critical case for understanding how a major global actor is navigating the complex interplay between technological ambition, industrial policy, and the enduring frictions of integrating intelligent machines into human-centered social and economic structures.

New Knowledge from Research

This study's primary contribution is the formulation of the "Dual-Pathway Synergy" framework, which conceptualizes China's distinct trajectory in AI development. The framework posits that China's progress is not merely a linear technological advance but a synchronized evolution along two interdependent pathways: 1) Technological Sovereignty, characterized by a state-guided push to master foundational "chokepoint"

technologies to achieve self-sufficiency; and 2) Socio-Industrial Embedding, defined by the rapid, top-down integration of AI across diverse sectors—from media and finance to manufacturing and urban infrastructure—through an "AI+" model. Unlike Western models often driven purely by market forces or corporate R&D, the Chinese pathway is uniquely propelled by the synergy of strategic state policy, massive infrastructural investment, and a vast, unified market that enables rapid scaling and real-world application of AI technologies.

Furthermore, the cross-case analysis reveals a novel governance dynamic inherent in this model: "Regulatory Agility through Application." The study finds that China's approach involves deploying AI in controlled, real-world environments—such as intelligent vehicles in Shenzhen's low-altitude economy or virtual hosts in state media—to empirically test and refine governance frameworks. This creates a feedback loop where practical application directly informs and accelerates the development of agile, inclusive regulations, such as the Shenzhen Low-Altitude Economy Promotion Regulation. This insight reframes the narrative of AI governance from a purely restrictive or precautionary model to a more dynamic, iterative process of co-evolution between technological deployment and policy formation, offering a distinctive contribution to the global understanding of AI's socio-technical integration.

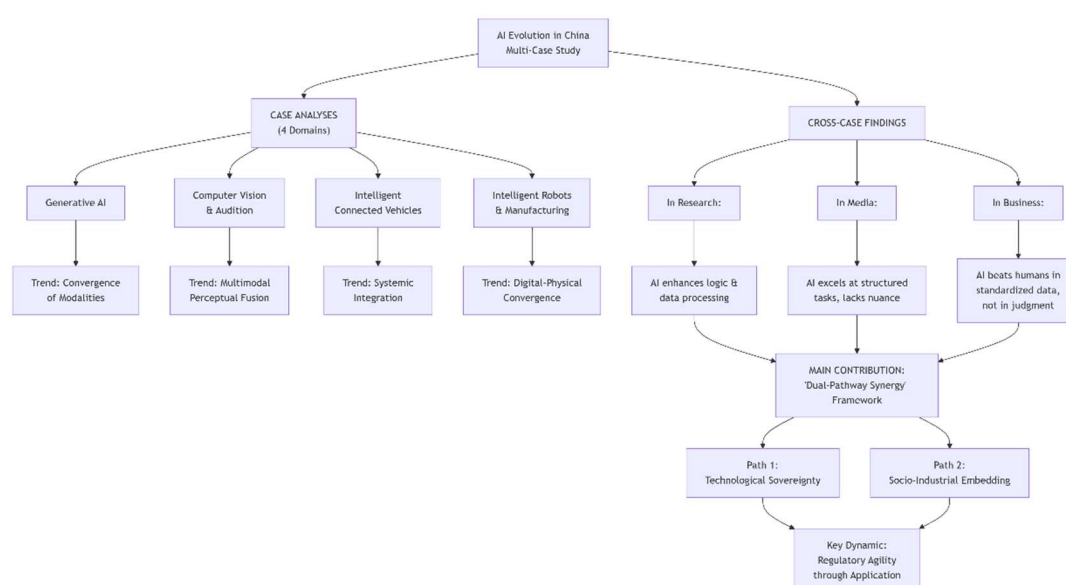


Figure 1 Research Finding Framework

Conclusion and Advice

This study systematically reviews and explores artificial intelligence, particularly its multidimensional evolution in key domains such as generative content creation, multimodal perception, intelligent connected vehicles, and smart manufacturing. By adopting a qualitative research approach based on multiple case studies, this paper not only delineates the technological trajectory of AI from theoretical conception to broad industrial integration but also extracts its inherent development logic and identifies core future challenges.

Looking ahead, the development of artificial intelligence will unfold along two dimensions: "greater capability" and "broader integration." On one hand, technology will pursue "stronger" intelligence, exploring paths toward artificial general intelligence and embodied intelligence with physical interaction capabilities. On the other hand, applications will achieve "wider" integration, permeating every corner of the socio-economic landscape through the "AI+" model. Seizing the opportunities of this era hinges on: maintaining steadfast confidence and increasing long-term investment in basic research and core technologies; fostering innovation and promoting the deep integration of AI with the real economy, particularly manufacturing; and preparing proactively by establishing inclusive, prudent, and agile governance frameworks. Embracing this trend requires not only continuous technological innovation but also synergistic advances in institutions, ethics, and talent development. Only in this way can we harness this wave of intelligence and move toward a future characterized by human-machine collaboration and pervasive wisdom.

Reference

- Amodei, D., Anantha, S., Manubhai, R., Bai, J., Battenberg, E., Case, C., Casper, J., Catanzaro, B., Cheng, Q., Chen, G., Chen, J., Chen, J., Chen, Z., Chrzanowski, M., Coates, A., Diamox, G., Ding, K., Du, N., Elsen, E., Zhu, Z. (2016). Deep Speech 2: End-to-End Speech Recognition in English and Mandarin. *Proceedings of the 33rd International Conference on Machine Learning*, 48, 173–182.
- Cai, W. (2024). Optimization Engine to Enable Edge Deployment of Deep Learning Models. *The ITEA Journal of Test and Evaluation*, 45(2).

- Canny, J. (1986). A Computational Approach to Edge Detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-8(6), 679–698.
- Cao, S. Jiang, W. Wang, J. Yang, B. (2024). From Man vs. Machine to Man + Machine: The art and AI of stock analyses, *Journal of Financial Economics*, 160, 103910,
- Durrant-Whyte, H., & Bailey, T. (2006). Simultaneous Localization and Mapping (SLAM): Part I. *IEEE Robotics & Automation Magazine*, 13(2), 99–110.
- Hu, J. B. (2024). Creating a virtual host for livelihood programs to enable sustainable innovation in business processes: Jiaying News Media Center vigorously promotes the integration and transformation of "AI + media". *Media Review*, (10), 16–18.
- Huang, Y. C., Zheng, Y. J., & Huang, G. D. (2025). Exploring the integration of artificial intelligence and natural language processing. *Wisdom China*, (04), 74–75.
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet Classification with Deep Convolutional Neural Networks. *Advances in Neural Information Processing Systems*, 25.
- Li, H., Su, L. N., Zhou, H. X., Li, S. S., Wang, M. T., Xie, B. Y., & Liu, G. Y. (2026). Research and countermeasure suggestions on the use of artificial intelligence policies in Chinese scientific journals: An NVivo analysis based on 40 core scientific journal policy texts. *Science-Technology & Publication*, 1–11.
- Lowe, D. G. (1999). Object Recognition from Local Scale-Invariant Features. *Proceedings of the Seventh IEEE International Conference on Computer Vision* (Vol. 2, pp. 1150–1157).
- McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. *AI Magazine*, 27(4), 12.
- Oord, A. van den, Dieleman, S., Zen, H., Simonyan, K., Vinyals, O., Graves, A., Kalchbrenner, N., Senior, A., & Kavukcuoglu, K. (2016). WaveNet: A Generative Model for Raw Audio. *ArXiv preprint arXiv:1609.03499*.
- Pan, J. F. (2024). Artificial intelligence is triggering an intelligence revolution. *Financial Think Tank*, 9(3), 79–96+142.
- Peng, F. (2024). Analysis of problems and countermeasures in the intelligent management of commercial bank accounting. *China Market*, (27), 139–142.
- Penman, S. H. (2014). *Accounting for Value*. Columbia University Press.

- Qian, G. M., Yang, Z., & Shi, L. (2025). Reshaping the AI large model industry policy system: U.S. experience and China's path. *Technology Economics*, 44(01), 14-27.
- Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving Language Understanding by Generative Pre-Training. OpenAI.
- Shang, X. (2024). The three major engines of artificial intelligence development: Algorithm, computing power, and data. *Commercial Culture*, (17), 34-35.
- Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., van den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., ... Hassabis, D. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, 529(7587), 484-489.
- Tian, Z. N. (2024). Research on the development strategy of the entire low-altitude economy industry chain in the Guangzhou-Shenzhen region. *China Journal of Commerce*, 33(16), 108-113.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Proceedings of the 31st International Conference on Neural Information Processing Systems, NIPS'17*, 6000-6010.
- Wang, X. N., Li, J. H., & Zhai, Y. (2023). Analysis of the development environment of China's intelligent vehicle industry. *Automotive Industry Research*, (4), 8-10.
- Xu, C. S. (2023). The current situation and future development direction of ChatGPT and generative artificial intelligence. *Bulletin of National Natural Science Foundation of China*, 37(5), 743-750.
- Yan, X., & Ren, B. (2025). Global competition drives differentiated development of China's AI chips. *Enterprise Management*, (07), 11-15.
- Yang, X. (2019). A review of research on power equipment condition monitoring based on computational auditory scene analysis technology. *Guangdong Electric Power*, 32(9), 24-32.
- Yi, Z. (2024). Application of UAV aerial survey technology in the South Open-pit Coal Mine of Xinjiang Tian Chi Energy. *Opencast Mining Technology*, 39(5), 22-25.
- Zhang, X. (2025). Policy-led AI empowerment: Co-creating a new intelligent manufacturing ecosystem. *Modern Manufacturing*, (09), 3.

- Zhang, Y. (2026). Administrative liability pathways for harm caused by algorithmic decision-making in automated administration. *Administrative Law Review*, 1-13.
- Zhao, C. C. (2025). A study on the relevance and regional differences of China's artificial intelligence policies. *World Scientific Research and Development*, 47(02), 247-259.