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A Systematic Review on Architecture, Applications, and Challenges of Large Model-Driven Intelligent Business Information Systems

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Abstract

Against the backdrop of rapid IT development, large, model-driven intelligent business information systems have become a research focus. Integrating large-scale deep learning models, they have significantly boosted business intelligence. However, with explosive data growth, traditional systems face severe challenges in processing efficiency and decision-making quality. Large models exhibit powerful NLP and image recognition capabilities, achieving technological leaps and expanding commercial possibilities. By efficiently adjusting algorithms in resource-constrained environments, they meet diverse business needs, enhancing both data processing efficiency and decision intelligence. Yet, challenges persist. Key issues including data privacy, security, model interpretability, and system compatibility remain urgent to solve. In today's era of increasing focus on commercial secrets and user privacy, ensuring safe, efficient, and rights-respecting data processing and intelligent decision-making with large models has become an important topic in academic research and industrial practice. To address such problems, the academic community has explored various solutions. By building a dynamic data governance system, designing a highly transparent model architecture, and promoting cross-subject collaboration, it has laid a solid theoretical foundation and provided practical guidance for the application of large models in business intelligence. From the perspective of existing research, the intelligent business information system empowered by large models is not merely a technical upgrade, but an in-depth reconstruction of the business operation model. Its transformative impact far exceeds the traditional management paradigm, promoting a fundamental shift in business decision-making logic from manual experience judgment to data-driven scientization.

Keywords

large model, intelligent business information system, business intelligence, data-driven decision-making, risk governance

1. Introduction

Against the backdrop of global digital and intelligent transformation and the “Artificial Intelligence +” initiative, large model technology is reshaping the industrial and value chains as a core driving force, promoting the upgrading of Business Information Systems (BIS) from traditional data processing to intelligent decision-making empowerment [1]. The in-depth integration of intelligent systems and business information has become the core path for enterprises' digital transformation. By integrating key elements such as computing power, algorithms, and data, it has been applied and empowered across various commercial scenarios, including finance, auditing, and engineering construction. In the field of intelligent auditing, it can complete automatic verification of full-volume data and intelligent identification of abnormal transactions, greatly improving the efficiency of auditing work and the accuracy of compliance detection [2]; in links such as risk control modeling and customer service optimization in the financial industry, it has realized the intelligent upgrading of business processes, solving problems such as low efficiency of traditional financial data processing and slow decision-making response [3]; in the field of engineering construction, it can support dynamic prediction of project progress, refined cost control and collaborative decision-making of the supply chain [4]. The application in multiple scenarios fully demonstrates the excellent value of technology empowering business operations [2-4].

However, implementing large models in business information systems still faces multiple challenges: insufficient adaptability between general models and vertical scenarios, imperfect data governance systems, bottlenecks in computing power scheduling, and a lack of full-life-cycle management, which have seriously restricted the full release of technical value [5, 6].

As the core carrier of enterprise data flow and decision support, business information systems have an urgent demand for intelligent upgrading. Traditional business intelligence systems rely on fixed rules and limited data, making it difficult to adapt to a dynamically changing business environment [7]. In contrast, large models offer a new paradigm for addressing this dilemma through their powerful semantic understanding, multi-modal fusion, and knowledge transfer capabilities [8]. From the perspective of the digital intelligence business, the vertical application of large models has achieved breakthroughs in fields such as finance, engineering construction, and auditing. For example, it has realized precise service reach in inclusive finance and improved the efficiency of compliance detection in intelligent auditing [2, 9]. However, issues such as value alignment, legal compliance, and risk control during technology implementation still need to be systematically addressed [2, 10].

As an important carrier integrating academic research and industrial practice, systematic review can provide clear guidance for technological iteration and application innovation in this field.

Existing studies mostly focus on a single technical dimension of large models or specific industry applications, lacking a comprehensive analysis of the integration architecture, core technologies, and practical challenges of “large model-business information system” [1, 5]. Based on this, this paper takes “large model-driven intelligent business information system” as the core, combs the research progress of five key technologies including computing power scheduling, algorithm optimization, data governance, architecture adaptation and application operation and maintenance through systematic review method [5], analyzes the implementation path and core challenges of large models in commercial scenarios, to provide theoretical reference for the optimal design and industrial application of intelligent business information systems, and clarify the key directions for subsequent research.

2. Theoretical Background

This chapter defines the core theoretical support of the large model-driven Intelligent Business Information System (BIS), which is elaborated around three interrelated pillars: the technical essence of large language models, the evolutionary logic of business information systems, and the theoretical foundation for their integration.

Large Language Models (LLMs) based on the Transformer architecture have become the core technical support for intelligent business information systems, leveraging their powerful few-shot learning, semantic understanding, and knowledge reasoning capabilities [6, 8]. Their Parameter-Efficient Fine-Tuning (PEFT) technologies (such as LoRA and Adapter) can efficiently adapt to commercial vertical scenarios under resource-constrained conditions, resolving the core trade-off between model lightweightness and performance [6]. At the same time, the emergence of large models in vertical fields has further strengthened the alignment between technical capabilities and business needs, integrating industry knowledge through professional pre-training and fine-tuning to provide more accurate decision support [1, 5]. However, the "hallucination" problem of generative AI brings inherent risks to business decisions. It is necessary to build a multi-party, collaborative risk-constraint mechanism based on evolutionary game theory and to establish a full-process decision verification system, combined with risk management theory, to avoid decision deviations across both technical and management dimensions and to ensure the commercial credibility of large-scale model output results [10]. This is also an important governance logic that distinguishes large model-empowered BIS from traditional intelligent systems.

The evolution of business information systems follows the logical context from traditional data processing to intelligent decision-making. Early business intelligence systems relied on fixed rules and static data analysis, making it difficult to adapt to dynamic market changes [7]. With the integration of artificial intelligence technology, modern business information systems have transformed into data-driven intelligent systems that integrate data governance, real-time analysis, and decision optimization [1].

Information system theory emphasizes the efficient flow and value transformation of data in the process of organizational operation. With its multi-modal data processing capabilities, large models have broken the single dependence of traditional BIS on structured data, enabling the integrated processing of structured transaction data and unstructured text and image data [5, 11], and significantly improving the dimensionality of data flow and the depth of value mining.

Decision Support System theory focuses on improving the scientificity of management decisions through technical means. With their knowledge, reasoning, and dynamic predictive capabilities, large models have upgraded the "data presentation" decision support in traditional BIS to "intelligent deduction" decision suggestions [1, 8], enabling a transformation from passive data support to active decision empowerment. The introduction of large models has further reconstructed the technical architecture of business information systems, forming a four-layer framework of "computing power layer - algorithm layer - data layer - application layer" to support end-to-end intelligent business processes [5].

The integration of large models and business information systems relies on multi-disciplinary theoretical support. Information fusion theory provides methodological support for integrating multimodal commercial data. With its unified semantic representation capability, large models have solved the problems of feature heterogeneity and semantic fragmentation existing in the multi-modal data fusion of traditional BIS, enabling a qualitative leap in the fusion efficiency and value transformation efficiency of multi-source data [8, 11].

Digital transformation theory clarifies the mechanism by which intelligent business information systems promote organizational efficiency improvement and value creation. Through the in-depth integration of technology and business, large models have reconstructed the business adaptation logic of BIS, enabling the system to adjust decision strategies in response to commercial scenarios dynamically, consistent with the core requirement of "business-driven technology and technology-empowered business" in digital transformation [1].

In addition, value alignment theory requires commercial systems to follow ethical norms and legal requirements in technical applications. By integrating industry compliance rules and ethical guidelines, large models enable intelligent BIS to achieve a dynamic balance between technological innovation and risk control in the decision-making process of scenarios such as inclusive finance and intelligent auditing [2, 9], making up for the shortcomings of traditional BIS in intelligent decision-making at the ethical and compliance levels.

The in-depth integration of these theories and large-scale modeling technologies has jointly constructed a comprehensive theoretical system for the research of large model-driven intelligent business information systems, laying a solid foundation for subsequent analysis of application scenarios and challenges.

3. Literature Review

3.1 Research on Large Model Technology and Vertical Domain Adaptation

The technological evolution of large models has provided core support for the intelligence of Business Information Systems (BIS). The iteration of its technical system and the breakthrough of vertical domain adaptation technology are even the key foundation for realizing the in-depth integration of computer technology and business management, and empowering intelligent decision-making in commercial scenarios [1, 5]. The Transformer architecture has broken through the limitations of traditional models in semantic understanding, laid the foundation for knowledge reasoning and multi-modal fusion of large models, and enabled large models to accurately parse unstructured data in commercial scenarios (such as financial texts, audit reports, engineering construction logs, etc.), realizing multi-source data docking with business information systems [8]. Parameter-Efficient Fine-Tuning (PEFT) technologies (such as LoRA, Adapter, prompt learning, etc.) have further solved the problem of scenario adaptation under resource constraints. By freezing the base model and training only a small number of parameters, they have achieved a balance between lightweight deployment and performance guarantees, providing technical support for the low-cost, easy implementation of large models in enterprise business information systems [6].

Li Xinyao et al. systematically sorted out five types of efficient transfer technology routes for large models in resource-constrained scenarios (such as modifying model structure, injecting adaptive parameters, etc.), pointing out that current research has achieved remarkable results in reducing training costs and improving deployment flexibility, providing technical possibilities for the popularization and application of large models in business information systems of small, medium and micro enterprises. However, there are still problems such as over-reliance on labeled data, imbalance between training and inference efficiency, and inconsistent evaluation standards [6].

In the field of vertical domain adaptation, in-depth exploration has been conducted into the construction of technical systems and the solution of core challenges. Gao Chaoyue et al. developed a technical system for verticalizing large models in digital intelligence business scenarios, covering five dimensions: computing power scheduling, algorithm optimization, data governance, architecture adaptation, and application operation and maintenance. They clarified the core challenges in integrating technology and business, such as distributed computing power scheduling bottlenecks, imperfect data governance systems, insufficient adaptability of basic model architectures, and a lack of full-life-cycle management, and proposed solutions such as dynamic scheduling based on computing power networks and modular architecture optimization [5].

Wang Limin et al. proposed that world models promote artificial intelligence to evolve from perception to decision-making. By enhancing large models' ability to understand complex commercial scenarios through dynamic prediction and physical consistency modeling, large models are upgraded from simple commercial data processing tools to the core of intelligent decision-making in business information systems, providing a new paradigm for upgrading business information systems' intelligence [8].

From the perspective of digital intelligence business theory, Xu Xin et al. emphasized the in-depth integration of technology and management, pointing out that current research still has obvious gaps in key areas of integration between business management and technology, such as cross-regional computing power collaborative scheduling, dynamic data ownership definition, and trusted human-machine collaboration mechanisms [1].

3.2 Research on the Evolution and Intelligence of Business Information Systems

The development of Business Information Systems (BIS) presents a clear evolutionary context: in the early stage, it mainly focused on static data processing. Tian Xin et al. built a business intelligence system based on retail big data to support operational decisions through data integration and rule-based analysis. However, its dependence on fixed logic makes it difficult to adapt to dynamic market changes [7].

With the integration of artificial intelligence technology, modern intelligent BIS has formed a four-layer architecture of “computing power layer - algorithm layer - data layer - application layer”. With technologies such as multi-modal data fusion and real-time reasoning optimization, it has achieved end-to-end intelligence from data collection to decision output [5].

In specific application scenarios, the value of large models has been fully verified. However, there are still pain points in scenario adaptation. Chen Wei noted that large models can automatically verify data and identify abnormal transactions in intelligent auditing, significantly improving auditing efficiency and compliance. However, there is still room for improvement in aspects such as audit evidence credibility verification, complex guideline adaptation, and interpretability [2]; Huang Baoju analyzed the application of generative AI in financial BIS, which has significant value in fields such as risk control modeling, customer service optimization, and marketing content generation, but problems such as data privacy leakage, algorithmic bias, and compliance risks have restricted its implementation process [3]; Lu Yujie et al. took the engineering construction field as the research object, verified the application potential of large models in project progress prediction, cost control, and supply chain collaboration, and proposed a modular integration scheme to solve the adaptation problems caused by industry data heterogeneity and complex business processes [4].

3.3 Research on the Theory and Practice of Integration between Large Models and BIS

The research on the integration of large models and business information systems draws on multidisciplinary theories. At the technical level, information fusion theory provides a methodological framework for integrating multimodal commercial data, including structured transaction data, unstructured text, and images. The cross-modal semantic alignment framework proposed by Jin Yan et al. has effectively improved the utilization efficiency of complex data [11].

At the organizational management level, digital transformation theory explains the internal mechanism by which Intelligent Business Information Systems (BIS) promote enterprise value creation. Xu Xin et al. pointed out that large, model-driven business information systems have become the core carrier for enterprises to cultivate new, high-quality productive forces by reconstructing business processes and optimizing resource allocation [1].

Research on risk governance and compliance is a key issue in integration practice. From a value alignment perspective, Liu Yinan explored the application logic of large models in inclusive finance business information systems, emphasizing the need to balance technological innovation and risk control by establishing a legal framework, ensuring algorithmic transparency, and promoting collaboration among stakeholders [9]. Yan Qiang et al. developed a multi-party participation response mechanism based on evolutionary game theory to address the “hallucination” problem in generative artificial intelligence, providing a theoretical basis for improving the credibility of output results from business information systems and reducing decision-making risks [10].

However, existing research still has three core shortcomings: in terms of technology, most vertical domain adaptation technologies are designed for specific industries, lacking a cross-industry integrated architecture that balances generality and flexibility; in terms of application, insufficient attention is paid to the heterogeneous needs of business information systems in different industries, and no reusable implementation paradigm has been formed; in terms of governance, the risk control system is relatively fragmented, lacking a full-chain governance framework covering technical security, organizational management, and laws and regulations.

3.4 Research Connection

Based on the above research gaps, this paper takes the “technology-application-governance” three-dimensional framework as the core to systematically sort out the research progress of large model-driven intelligent business information systems: at the technical level, it focuses on the integration and optimization of key vertical domain adaptation technologies; at the application level, it refines cross-industry general implementation paths; at the governance level, it constructs a full-chain risk control system. By integrating scattered research, a more complete theoretical system is built to address the deficiencies of current research in generality, systematicness, and practicality, and to provide a reference for subsequent academic research and industrial practice.

4. Discussion & Synthesis

4.1 Research Consensus and Consistent Trends

Existing research has formed three core consensuses regarding the integration of large models and Business Information Systems (BIS).

First, at the technical adaptation level, Parameter-Efficient Fine-Tuning (PEFT) and vertical domain architecture optimization are key to overcoming resource constraints and promoting scenario implementation

[5, 6]. The five-dimensional technical system ("computing power - algorithm - data - architecture - operation and maintenance") proposed by Gao Chaoyue et al. [5] and the five efficient transfer routes summarized by Li Xinyao et al. [6] both confirm the core value of lightweight and scenario adaptation.

Second, at the application level, the value of large models in finance, auditing, and engineering construction is widely recognized, with their empowering effects on automated processing, risk identification, and decision support, as supported by multiple literatures [2-4].

Third, at the risk governance level, "hallucination", data privacy, and compliance are priority common challenges in integration, requiring multi-disciplinary response mechanisms [9, 10].

Research trends are clearly focused: technical research has shifted from general large model optimization to vertical customization, emphasizing technology-commercial scenario alignment [1]; application research has moved from single-industry exploration to cross-domain adaptation, focusing on heterogeneous data and process integration [4]; governance research has advanced from single-risk response to full-chain control, highlighting coordination of technology, management, and law [9].

4.2 Research Disagreements and Contradictions

Core disagreements in existing research focus on two aspects.

The first is the conflict between the black-box nature of large models and commercial scenario-compliance requirements, centered on whether this nature violates the traceability principle in commercial auditing. Chen Wei noted that while large models enable automatic audit data verification and abnormal identification [2], their unexplainable decision-making fails to meet the stringent compliance requirements for full-process traceability and verifiability in highly regulated scenarios (e.g., finance, auditing), posing a core implementation obstacle. Although technical research attempts to address black-box defects through model deconstruction and decision logging [6, 8], no mature scheme balancing audit efficiency and traceability exists, and no academic consensus has been reached on its fundamental resolution.

The second is the cost-effectiveness dispute over technical routes for commercial applications, focusing on fine-tuning vs. Retrieval-Augmented Generation (RAG). Li Xinyao et al. [6] emphasized PEFT's value in resource-constrained settings, arguing that lightweight fine-tuning enables rapid adaptation and maximizes implementation efficiency. In contrast, Gao Chaoyue et al. [5] noted that fine-tuning's high data annotation and maintenance costs make it suitable for high-value, low-frequency decision-making scenarios. In contrast, RAG, with low transformation costs and real-time data updates, is better suited for high-frequency use cases (e.g., retail and financial customer service). No universal standard for technical route selection has been established due to unresolved cost-effectiveness boundaries.

Additionally, there is an underlying disagreement between technology-led and technology-management dual-drive implementation paths. Xu Xin et al. [1] advocated dual-drive, emphasizing organizational architecture and institutional design as prerequisites for integrating large models into BIS. In contrast, application-oriented studies (e.g., Chen Wei [2], Lu Yujie [4]) focus solely on technical module integration, prioritizing technical maturity over organizational adaptation, further intensifying technical route disputes.

4.3 Research Limitations

Comprehensive research reveals three significant limitations.

First, technical research is scenario-limited: most vertical adaptation technologies are industry-specific (e.g., finance, engineering), lacking a universal, flexible cross-industry architecture to meet heterogeneous BIS needs [4, 5]. Second, application research lacks depth: most studies only verify technical effects, with insufficient empirical analysis on in-depth issues such as business process reconstruction and organizational performance improvement [3, 7]. Third, governance research is fragmented: existing studies address single risks (e.g., hallucination, data privacy) without a full-chain framework covering technical security, organizational management, and laws [9, 10].

Furthermore, research methods are biased: technical studies focus on theoretical sorting and scheme design, while application studies lack long-term empirical tracking, leaving the practical applicability of some conclusions untested [1].

5. Conclusion

This paper systematically reviews research on large model-driven Intelligent Business Information Systems (BIS), summarizing existing consensus, disagreements, and deficiencies from three core dimensions: technical adaptation, application implementation, and risk governance. Large model technology is a key driver for upgrading BIS from data processing to intelligent decision-making. Parameter-Efficient Fine-Tuning (PEFT) and vertical domain architecture optimization are core to overcoming resource constraints and to scenario implementation, with significant application value in finance, auditing, and engineering construction. Still, they also face common challenges, including "hallucination", data privacy, and compliance.

Main contributions of existing research: establishing a vertical large-scale model technical framework and clarifying core scenario-adaptation paths; verifying large models' application potential in cross-industry BIS, providing preliminary practical references; proposing governance mechanisms for risks such as "hallucination", laying a theoretical foundation for trusted integration. However, limitations remain (poor technical generality, insufficient application depth, fragmented governance systems) that urgently need breakthroughs.

Future research can advance in three areas: first, building a cross-industry universal vertical adaptation architecture for large models, balancing flexibility and reusability; second, conducting long-term empirical research to quantify large models' impact on business processes and organizational performance; third, establishing a full-chain governance framework covering technical security, organizational management, and laws to realize coordinated development of technological innovation and risk control.

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The authors declare no conflict of interest.

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