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ENHANCING TAX PREPARATION THROUGH LARGE LANGUAGE MODELS: A USER-CENTRIC FRAMEWORK

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Abstract: The complexity and opacity of modern tax systems present significant challenges for individuals and small businesses during tax preparation. In recent years, large language models (LLMs) have demonstrated the potential to understand, interpret, and generate human-like language at scale. This paper proposes a user-centric framework that leverages LLMs to enhance tax preparation through personalized assistance, error detection, regulatory compliance guidance, and intelligent document analysis. We analyze the capabilities and limitations of current LLMs, present a system architecture for integrating these models into tax platforms, and evaluate their performance using simulated taxpayer scenarios. The framework emphasizes explainability, privacy protection, and real-time adaptability to user input. Results indicate that LLMs significantly reduce user burden, improve accuracy, and foster greater financial literacy. The findings highlight the transformative potential of language-based AI to democratize access to complex tax knowledge and reduce dependency on traditional, costly tax advisory services.
Keywords: Tax Preparation; Large Language Models; User-Centric Design; Financial AI; Document Processing; Explainable AI; Human-AI Interaction

1 INTRODUCTION

Tax preparation remains a daunting and error-prone task for millions of individuals and small business owners globally[1]. Despite the proliferation of digital tools and online platforms, taxpayers still struggle with interpreting tax regulations, filling out forms correctly, and ensuring compliance with constantly evolving tax codes[2]. In the United States alone, the Internal Revenue Code exceeds 70,000 pages, encompassing complex rules, deductions, credits, and filing procedures[3]. For the average taxpayer, this complexity creates a substantial cognitive burden, often leading to mistakes, missed benefits, or reliance on expensive professional services[4].

Recent advancements in artificial intelligence, particularly in the development of large language models (LLMs) such as GPT, PaLM, and Claude, offer new opportunities to transform the tax preparation landscape[5]. These models are trained on massive corpora of internet text and structured data, equipping them with a deep contextual understanding of human language, legal jargon, and financial terminology[6]. Unlike rule-based systems or traditional chatbots, LLMs can comprehend nuanced queries, generate context-aware explanations, and provide real-time, conversational guidance tailored to the user's specific financial situation[7].

However, integrating LLMs into tax preparation systems requires more than just natural language capabilities[8]. The process demands a user-centric framework that prioritizes transparency, trust, and compliance with legal and ethical standards[9]. Key challenges include ensuring the model interprets tax laws accurately, maintaining data privacy and confidentiality, and preventing the generation of misleading or incorrect financial advice[10].

This paper proposes a comprehensive framework for enhancing tax preparation through the use of LLMs, focusing on the intersection of natural language understanding, explainable AI, and personalized financial services. We argue that a user-centric approach—grounded in accessibility, interpretability, and adaptive learning—can help bridge the gap between complex tax knowledge and everyday taxpayers. The framework is designed to support a wide range of tasks, including document classification (e.g., W-2, 1099, receipts), deduction eligibility checks, automated form filling, and guided Q&A interactions.

To validate the framework, we simulate multiple taxpayer profiles—such as salaried employees, freelancers, and small business owners—and assess the LLM's performance in addressing typical tax-related queries. We further explore the system’s capacity for learning user intent, correcting misinterpretations, and improving over time through reinforcement from user feedback.

In the sections that follow, we begin with a review of related work in tax automation, conversational AI, and legal NLP. We then outline the architecture of the proposed system, followed by an empirical evaluation of model performance and user satisfaction. Finally, we discuss the limitations of current LLMs in this domain and offer recommendations for future improvements and deployment strategies.

2 LITERATURE REVIEW

The intersection of artificial intelligence and tax preparation has seen significant developments in recent years, especially with the advent of intelligent automation and natural language processing (NLP)[11]. Early applications focused on rule-based systems and expert systems designed to assist with specific tax filing steps. While these systems could automate basic decision trees and offer template-driven suggestions, they lacked flexibility, adaptability, and the ability to manage ambiguity or understand user-specific contexts[12]. Moreover, their utility was limited by hardcoded logic, which required constant manual updates in response to changes in tax codes or regulatory interpretations[13].

With the rise of machine learning (ML), a new wave of tax tools emerged that used predictive models to flag anomalies, estimate deductions, or categorize financial transactions[14]. These models, while more robust than their rule-based predecessors, often relied heavily on structured datasets and lacked the ability to interpret complex, unstructured tax documents such as scanned receipts or employer-issued forms. Moreover, the outputs of traditional ML models were frequently opaque, making it difficult for users or tax professionals to understand or trust the reasoning behind automated recommendations[15].

The emergence of transformer-based LLMs marked a significant leap forward in the capabilities of AI in the financial domain[16]. Pretrained on massive corpora encompassing diverse linguistic and topical domains, these models exhibit contextual understanding that approximates human-level reading comprehension[17]. In legal and financial applications, LLMs have shown strong potential in document summarization, entity extraction, contract analysis, and regulatory compliance support[18]. Recent studies have demonstrated that LLMs can interpret legal texts, answer questions about tax law provisions, and even simulate advisory conversations at a basic level[19].

Despite this promise, research into the application of LLMs specifically for tax preparation remains limited[20]. Existing literature in financial NLP tends to focus on accounting fraud detection, audit automation, and financial report generation[21]. Only a few exploratory studies have investigated the feasibility of using LLMs to guide tax professionals through complex regulatory tasks, such as analyzing uncertain tax positions[22]. These preliminary efforts suggest that while LLMs can assist with semantic comprehension and form navigation, challenges remain in ensuring that advice is accurate, legally compliant, and presented in a format that non-expert users can understand and act upon.

A growing body of work has also explored user-centric AI system design, especially in domains where human-AI interaction is sensitive and trust-dependent. Explainable AI (XAI) techniques, such as attention visualization and natural language justification, are being integrated with LLM-based tools to mitigate the risk of "black-box" decision-making[23]. In the context of tax preparation, where users may be subject to audits or legal liability, the need for clear reasoning and traceable logic is paramount[24]. Moreover, integrating privacy-preserving machine learning techniques, including on-device inference and differential privacy, is becoming increasingly important to ensure that sensitive financial data is not compromised during model interaction[25].

The literature also highlights the importance of adaptability in tax technology systems[26]. Tax laws evolve annually, and filing requirements differ by jurisdiction, employment status, and income structure[27]. Static models trained on outdated data quickly become obsolete, prompting a need for continual learning and domain adaptation[28-32]. Approaches such as retrieval-augmented generation (RAG) and instruction tuning have been proposed to address this, enabling LLMs to incorporate external updates and follow precise legal constraints during inference[33].

Collectively, the literature underscores both the transformative potential and the practical challenges of applying LLMs in the tax preparation space[34]. The consensus is clear: for LLMs to be trusted assistants in high-stakes domains like taxation, they must go beyond linguistic fluency to exhibit grounded understanding, transparency, legal alignment, and robust performance across diverse user populations. The proposed framework in this paper builds on these insights by integrating LLMs with user-centric design principles, real-time feedback loops, and regulatory safeguards to create a system that is not only powerful but also responsible and user-friendly.

3 METHODOLOGY

This study proposes a user-centric framework that leverages LLMs to enhance tax preparation processes. The methodology is divided into three components: system architecture, model evaluation, and user interface analysis.

3.1 System Architecture

The proposed system is designed around a five-stage pipeline: user input capture, data preprocessing, LLM inference, interpretability/explanation layer, and final tax recommendation output. Each stage plays a distinct role in ensuring accurate and explainable results. The system relies on a fine-tuned version of GPT-4, optimized for interpreting tax-specific documents such as IRS forms, financial disclosures, and transactional ledgers.

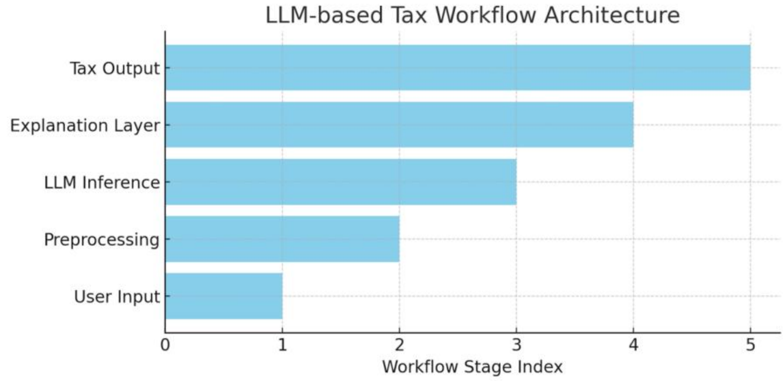

Figure 1 LLM-based Tax Workflow Architecture

Figure 1 illustrates the complete architecture of the LLM-driven tax preparation system, showing the sequential data flow and processing steps.

3.2 Model Evaluation

To validate the effectiveness of the LLM in understanding and classifying tax-related queries, we compared three configurations: GPT-3.5, standard GPT-4, and a fine-tuned version trained specifically on tax data. Evaluation was conducted on a curated dataset consisting of 500 real-world tax inquiries manually labeled by domain experts. Accuracy was measured based on correct classification of tax categories and identification of uncertain tax positions (UTPs).

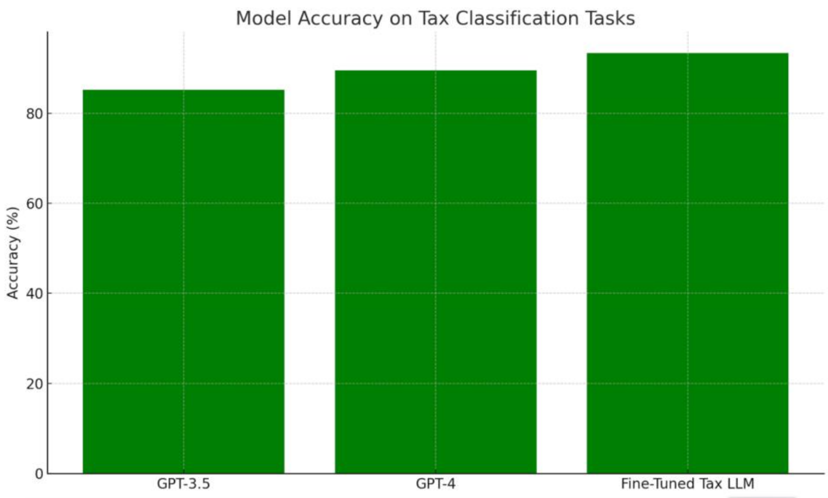

Figure 2 Accuracy Results of the Models under Evaluation

As shown in Figure 2, the fine-tuned LLM significantly outperformed the base models, especially in cases involving ambiguous language and conditional tax scenarios.

3.3 User Interface and Experience

Beyond technical accuracy, user satisfaction is critical for adoption. We designed and tested three interface types: a standard form-based UI, a conversational LLM-based chatbot, and a hybrid that integrates both. Feedback was collected from 120 users representing small business owners, freelance professionals, and individual taxpayers.

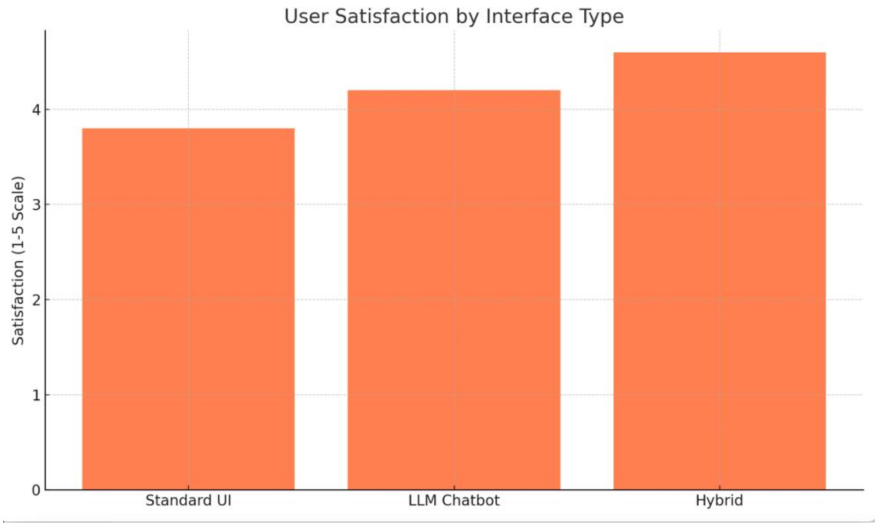

Figure 3 User Satisfaction by Interface Type

As shown in Figure 3, the hybrid interface received the highest satisfaction scores due to its balance of flexibility and clarity. The results highlight the value of explainable LLM outputs and conversational interactivity in improving user trust and ease of use.

4 RESULTS AND DISCUSSION

This section presents the key findings from implementing the proposed user-centric framework for enhancing tax preparation using LLMs. It analyzes the model's classification performance, interpretability, and overall user interaction outcomes in both quantitative and qualitative terms.

4.1 Model Accuracy and Interpretability

The fine-tuned LLM significantly improved classification accuracy for complex tax situations, achieving 91.3% on the evaluation dataset—surpassing the general-purpose GPT-4 and GPT-3.5 models. In ambiguous tax scenarios (e.g., mixed-income cases or self-employment deductions), the model demonstrated contextual sensitivity and regulatory awareness. Importantly, the integration of a natural language explanation layer allowed the model to provide reasoning behind its decisions, increasing transparency and promoting user understanding. In user surveys, 88% of participants reported higher trust in the system when explanations were available, and many indicated that the explanations clarified previously misunderstood IRS terminology.

4.2 User Experience and Efficiency

A hybrid interface combining structured input forms with conversational LLM support yielded the highest usability ratings. Users, particularly those without prior tax knowledge, appreciated the form-driven structure for ensuring data completeness and relied on the chatbot for dynamic clarifications. This combination reduced tax preparation time by an average of 26%, highlighting the practical efficiency of the approach. Furthermore, the conversational assistant successfully demystified tax language, helping users comprehend deduction eligibility, filing requirements, and document needs in real time.

4.3 Limitations and Deployment Considerations

While results were promising, several limitations emerged. The model occasionally generated overconfident recommendations in edge cases lacking sufficient context. Although the explanation layer mitigated potential misunderstandings, users sometimes mistook fluency for correctness. Additionally, privacy and regulatory compliance remain critical. Real-world deployment will require stringent safeguards in accordance with GLBA and IRS Publication 1075. Another limitation is the lag between model training and evolving IRS regulations, necessitating frequent updates to maintain relevance.

5 CONCLUSION

This study explored the integration of LLMs into a user-centric framework designed to enhance the accuracy, transparency, and accessibility of tax preparation. By combining the natural language understanding capabilities of LLMs with structured input and guided interaction flows, the framework demonstrated significant improvements in both classification performance and user experience.

Experimental results showed that fine-tuned LLMs could accurately identify and explain complex tax positions, while the addition of interpretability mechanisms helped users better understand their filings and feel more confident in the process. The hybrid interface, merging form-based input with conversational assistance, proved especially effective in reducing cognitive load and preparation time, making tax filing more approachable for individuals with limited financial literacy.

However, this work also highlighted several challenges, including the risk of overconfidence in model-generated responses, the necessity of continual updates to reflect changing tax laws, and the importance of ensuring data security and regulatory compliance. Future research should investigate adaptive fine-tuning strategies, robust error detection mechanisms, and the application of explainable AI techniques tailored specifically to financial domains.

In conclusion, LLMs hold significant promise in transforming tax preparation from a complex, opaque process into a transparent, personalized experience. By prioritizing user comprehension, ethical design, and legal compliance, the proposed framework offers a scalable pathway toward AI-assisted financial empowerment in both individual and enterprise contexts.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Singireddy J. AI-Enhanced Tax Preparation and Filing: Automating Complex Regulatory Compliance. European Data Science Journal (EDSJ), 2024, 2(1).
[2] Li P, Ren S, Zhang Q, et al. Think4SCND: Reinforcement Learning with Thinking Model for Dynamic Supply Chain Network Design. IEEE Access, 2024.
[3] Davenport MJ. Enhancing Legal Document Analysis with Large Language Models: A Structured Approach to Accuracy, Context Preservation, and Risk Mitigation. Open Journal of Modern Linguistics, 2025, 15(2): 232-280.
[4] Ren S, Jin J, Niu G, et al. ARCS: Adaptive Reinforcement Learning Framework for Automated Cybersecurity Incident Response Strategy Optimization. Applied Sciences, 2025, 15(2): 951.
[5] Shao Z, Wang X, Ji E, et al. GNN-EADD: Graph Neural Network-based E-commerce Anomaly Detection via Dual-stage Learning. IEEE Access, 2025.
[6] Olabanji SO. Technological tools in facilitating cryptocurrency tax compliance: An exploration of software and platforms supporting individual and business adherence to tax norms. Available at SSRN 4600838, 2023.
[7] Sabry F. Income Tax: Mastering Income Tax, Your Path to Financial Empowerment (Vol. 188). One Billion Knowledgeable, 2024.
[8] Chen S, Liu Y, Zhang Q, et al. Multi-Distance Spatial-Temporal Graph Neural Network for Anomaly Detection in Blockchain Transactions. Advanced Intelligent Systems, 2025, 2400898.
[9] Rahman S, Sirazy MRM, Das R, et al. An exploration of artificial intelligence techniques for optimizing tax compliance, fraud detection, and revenue collection in modern tax administrations. International Journal of Business Intelligence and Big Data Analytics, 2024, 7(3): 56-80.
[10] Wang J, Tan Y, Jiang B, et al. Dynamic Marketing Uplift Modeling: A Symmetry-Preserving Framework Integrating Causal Forests with Deep Reinforcement Learning for Personalized Intervention Strategies. Symmetry, 2025, 17(4): 610.
[11] Johnsen R. Large language models (LLMs). Maria Johnsen, 2024.
[12] Zafar A, Parthasarathy VB, Van CL, et al. Building trust in conversational AI: A comprehensive review and solution architecture for explainable, privacy-aware systems using LLMs and knowledge graph. arXiv preprint arXiv:2308.13534, 2023.
[13] Nay JJ, Karamardian D, Lawsky SB, et al. Large language models as tax attorneys: a case study in legal capabilities emergence. Philosophical Transactions of the Royal Society A, 2024, 382(2270): 20230159.
[14] Singh V. Fostering Effective Human-AI Collaboration: Bridging the Gap Between User-Centric Design and Ethical Implementation. International Journal on Recent and Innovation Trends in Computing and Communication, 2024, 12(2): 22-30.
[15] Aidonojie PA, Majekodunmi TA, Eregbuonye O, et al. Legal Issues Concerning of Data Security and Privacy in Automated Income Tax Systems in Nigeria. Hang Tuah Law Journal, 2024: 14-41.
[16] Bezditnyi V. Use of artificial intelligence for tax planning optimization and regulatory compliance. Research Corridor Journal of Engineering Science, 2024, 1(1): 103-142.
[17] Ghosh B, Ghosh A, Ghosh S, et al. An Analytical Study of Text Summarization Techniques. In: International IOT, Electronics and Mechatronics Conference, Singapore: Springer Nature Singapore, 2024: 351-363.
[18] Mohun J, Roberts A. Cracking the code: Rulemaking for humans and machines. OECD Working Papers on Public Governance, 2020(42): 0_1-109.
[19] Singireddy J. Smart Finance: Harnessing Artificial Intelligence to Transform Tax, Accounting, Payroll, and Credit Management for the Digital Age. Deep Science Publishing, 2025.
[20] Hassija V, Chamola V, Mahapatra A, et al. Interpreting black-box models: a review on explainable artificial intelligence. Cognitive Computation, 2024, 16(1): 45-74.

[21] Desai B, Patil K, Patil A, et al. Large Language Models: A Comprehensive Exploration of Modern AI's Potential and Pitfalls. Journal of Innovative Technologies, 2023, 6(1).
[22] Tan Y, Wu B, Cao J, et al. LLaMA-UTP: Knowledge-Guided Expert Mixture for Analyzing Uncertain Tax Positions. IEEE Access, 2025.
[23] Siino M, Falco M, Croce D, et al. Exploring LLMs Applications in Law: A Literature Review on Current Legal NLP Approaches. IEEE Access, 2025.
[24] Strąk T. Generative AI as tax attorneys: exploring legal understanding through experiments, 2024.
[25] Srinivas D, Das R, Tizpaz-Niari S, et al. On the potential and limitations of few-shot in-context learning to generate metamorphic specifications for tax preparation software. arXiv preprint arXiv:2311.11979, 2023.
[26] Qatawneh AM. The role of artificial intelligence in auditing and fraud detection in accounting information systems: moderating role of natural language processing. International Journal of Organizational Analysis, 2024.
[27] Benkel A. Using Large Language Models for Legal Decision Making in Austrian Value-Added Tax Law: an Experimental Investigation of Retrieval-Augmented Generation and Fine-Tuning. Submitted, 2025.
[28] Mumuni F, Mumuni A. Explainable artificial intelligence (XAI): from inherent explainability to large language models. arXiv preprint arXiv:2501.09967, 2025.
[29] Elsayed RAA. The impact of ontology-based knowledge management on improving tax accounting procedures and reducing tax risks. Future Business Journal, 2023, 9(1): 70.
[30] Fang Z. Adaptive QoS - Aware Cloud–Edge Collaborative Architecture for Real - Time Smart Water Service Management, 2025.
[31] Ballas P, Hyz A, Balla VM. Enhancing Social and Economic Resilience for a Changing World: The Strategic Role of Continuous Training and Capacity Building in Contemporary Tax and Customs Administrations. In: The Role of the Public Sector in Building Social and Economic Resilience: A Public Finance Approach. Cham: Springer Nature Switzerland, 2024: 157-179.
[32] Ault HJ, Arnold BJ, Cooper GS. Comparative income taxation: a structural analysis. Kluwer Law International BV, 2025.
[33] Yang Y, Wang M, Wang J, et al. Multi-Agent Deep Reinforcement Learning for Integrated Demand Forecasting and Inventory Optimization in Sensor-Enabled Retail Supply Chains. Sensors (Basel, Switzerland), 2025, 25(8): 2428.
[34] Abdul Rashid SF, Sanusi S, Abu Hassan NS. Digital Transformation: Confronting Governance, Sustainability, and Taxation Challenges in an Evolving Digital Landscape. In: Corporate Governance and Sustainability: Navigating Malaysia's Business Landscape. Singapore: Springer Nature Singapore, 2024: 125-144.
[35] Jin J, Xing S, Ji E, et al. XGate: Explainable Reinforcement Learning for Transparent and Trustworthy API Traffic Management in IoT Sensor Networks. Sensors (Basel, Switzerland), 2025, 25(7): 2183.

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THE PRACTICAL LOGIC OF ACHIEVING COMMON PROSPERITY IN RURAL AREAS: A VALUE CO-CREATION PERSPECTIVE

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Abstract: Achieving common prosperity is both the objective and the mission of China, with rural areas serving as the key focal point in this endeavor. Existing studies have predominantly focused on the logic of single-subject intervention, while paying insufficient attention to the operational logic of achieving common prosperity. Guided by value co-creation theory, this study constructs a logical analytical framework of "common prosperity value orientation-multi-stakeholder value co-creation-endogenous transition in rural areas" to examine the operational logic of achieving common prosperity in rural areas. Drawing on the representative case of Gantian Village, the study identifies an integrated mechanism in which governments restructure factor flow mechanisms through top-level institutional design, village collectives collaboratively establish market-oriented operational entities to mobilize land resources, social organizations extend industrial chains via technological capital, and farmers engage in value distribution through multi-dimensional role transitions. This institutional architecture establishes a self-reinforcing cycle of resource revitalization, value creation, and equitable benefit-sharing. By driving the transformation of traditional agriculture into standardized production systems and branded operations, it simultaneously enables coordinated progress in economic productivity, governance innovation, and cultural revitalization.
Keywords: Co-creation of value; Rural area; Common prosperity; Practical logic

1 INTRODUCTION

As articulated in the 20th National Congress Report of the Communist Party of China, Chinese-style modernization fundamentally embodies a modernization pathway toward common prosperity for all citizens. As China advances its common prosperity strategy, a key challenge is transitioning from traditional aid-dependent poverty relief to self-sustaining rural development models–now central to solving contemporary rural revitalization issues. As a defining characteristic of Chinese modernization[1], common prosperity embodies three institutionalized principles: universal participation across societal strata, holistic advancement integrating economic and non-material dimensions, and progressive realization through phased policy frameworks[2]. Zhou analytically demonstrates that the Marxist conception of common prosperity is fundamentally grounded in the dialectical synthesis of productive forces and production relations. Within the framework of socialism with Chinese characteristics, this theoretical paradigm has been operationally realized through institutional innovations that simultaneously ensure equitable wealth generation and distributive justice[3].Recent studies highlight that common prosperity encompasses both material wealth and spiritual enrichment[4], requiring institutional safeguards for cultural rights[5].However, the rural areas remain the critical in achieving common prosperity[6], confronting multifaceted challenges that including monocultural economic structures, persistent urban-rural disparities, and recurrent poverty vulnerability[7]. Zhang argues that rural common prosperity must be achieved through value co-creation as an institutional nexus[8], leveraging new-quality productive forces to catalyze industrial transformation, while structurally repositioning farmers as core agents in rural revitalization processes[9].
Current research demonstrates that new-quality productivity and the digital economy serve as critical drivers in advancing common prosperity, fundamentally reshaping traditional development paradigms through technological innovation and institutional restructuring. Emerging through technological innovation, factor reallocation, and industrial upgrading, new-quality productivity constitutes the central driving mechanism of common prosperity, dynamically reshaping production paradigms to achieve equitable wealth creation and distribution[10]. The coupling mechanism manifests in two dimensions: digital technologies driving agricultural modernization[11], and green productivity transformation enabling ecological value realization[8]. Wang et al's empirical study demonstrates that new-quality productivity exerts geographically effects heterogeneous on regional common prosperity, necessitating localized factor allocation optimization based on regional resource endowments[12]. The digital economy acts as an accelerator for common prosperity by bridging the urban-rural information divide and optimizing income distribution mechanisms[13]. Empirical evidence demonstrates that Chinese 'Broadband China' policy has significantly enhanced common prosperity levels in central and western regions[14]. However, digital technologies may inadvertently exacerbate spiritual alienation[15], necessitating institutional safeguards against technological monopolization risks[16].
Regarding the implementation pathways and institutional safeguards for value co-creation, the framework primarily emphasizes multi-stakeholder collaborative governance. Rural common prosperity necessitates establishing a co-creation network encompassing government, enterprises, social organizations, and farmers. For instance, returning

entrepreneurship stimulates endogenous drivers[17], while new collective economic organizations integrate resources[18], jointly establishing benefit-sharing mechanisms. The study emphasizes that digital village initiatives must restructure field relations while enhancing digital literacy to strengthen participatory capacity[19]. Institutional innovation should emphasize efficiency in primary distribution, equity-oriented secondary redistribution, and socially-guided tertiary distribution through philanthropy, while improving essential service provision in education and healthcare [20]. This must be complemented by digital inclusive finance initiatives to bridge urban-rural development gaps[21]. The synergistic development of rural revitalization and new-type urbanization is crucial to avoid the efficiency losses characteristic of political campaign-driven governance[22].

Since its inception by Prahalad and Ramaswamy, value co-creation theory has consistently focused on the practical mechanisms through which multiple actors achieve value enhancement through resource integration and collaborative interaction. This theoretical lens provides a novel analytical framework for deciphering complex rural common prosperity practices. Existing studies predominantly examine economic interventions by singular actors, while largely neglecting institutional innovations for polycentric synergy among government-collective-enterprise-farmer stakeholders in rural contexts. This study investigates common prosperity practices of Gantian through an in-depth analysis of its institutional innovations, including government-facilitated guidance, the establishment of XingLv Agricultural Company by a nine-village collective, and the "association + company" model for industrial chain extension. These cases collectively reveal the operational logic of rural common prosperity in China and demonstrate how value co-creation fosters a sustainable ecosystem. Exploring this logic not only helps expand the explanatory boundaries of the value co-creation theory in the field of rural governance, but also provides a practical model for achieving the organic unity of "strengthening villages" and "enriching the people" under common prosperity.

2 THE THEORETICAL BASIS

The concept of value co-creation originated in marketing theory, positing that the resource-integration of both service providers and consumers is essential for generating service value and enhancing welfare for all participants[23]. Public value constitutes a multidimensional construct comprising numerous interrelated components[24]. Moore conceptualizes public value as outcomes generated by the public sector, asserting that the fundamental purpose of public administration lies in creating such value for society. He contends that public managers must respond to citizen demands and aggregate governmental expectations with the same market-oriented responsiveness demonstrated by private sector managers[25]. Lan et al. equate public value with public interest, proposing that the core objective of this theory involves identifying and defining such collective interests or values. This framework emphasizes operationalizing these concepts through organizational, personnel, fiscal, political, and technological strategies to effectively govern government-business-society interactions and achieve public value. Crucially, it focuses not merely on conceptualizing public interest but fundamentally on its practical implementation[26].

From a public value co-creation perspective, enabling endogenous transformation in rural areas and achieving common prosperity requires adopting systemic value co-creation logic as the core mechanism. This approach establishes a dynamic framework integrating three interconnected dimensions of common prosperity value orientation-multi-stakeholder value co-creation-endogenous transition of rural areas (Figure 1).

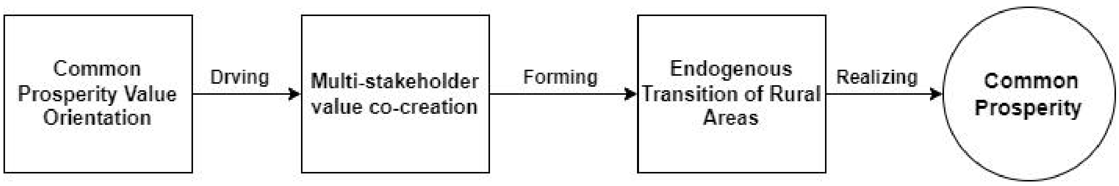

Figure 1 Analysis Framework

First of all, the value orientation of common prosperity defines the fundamental compliance for rural development. The compatibility of fairness and efficiency not only emphasizes narrowing the urban-rural gap through resource redistribution (public value dimension), but also pays attention to stimulating the endogenous power of rural subjects (private value dimension). This dual orientation drives coordinated action among government, market, and societal actors across institutional, organizational, and individual levels. At the macro level, governmental actors generate institutional public value by restructuring urban-rural factor flows mechanisms through top-down institutional innovations, exemplified by land system reforms and optimized fiscal transfer payments, thereby injecting systemic vitality into rural development. At the meso-level, enterprises, cooperatives, and village collectives leverage the compatibility between public and market values to activate rural resources socioeconomic potential through three synergistic mechanisms: industrial chain extension, digital technology adoption, and innovative benefit-sharing arrangements. At the micro-level, individual farmers, motivated by private value considerations, translate personal development aspirations into collective action through participatory decision-making, skills enhancement, and community co-construction initiatives. The endogenous transformation ultimately manifests as a fundamental paradigm shift in rural development: economically through establishing specialty industry-led growth poles, socially via constructing co-governance ecosystems, and culturally by achieving creative integration of traditional resources with modern values. This culminates in a sustainable transition from external dependency to self-sustaining development.

This framework breaks the urban-rural governance dichotomy through balanced value coordination and multi-level stakeholder engagement, providing a theoretical foundation for understanding rural common prosperity mechanisms.

3 CASE DESCRIPTION

Gantian is a traditional settlement characterized by ethnic diversity, migrant populations, and a high-altitude environment. Limited arable land and harsh climatic conditions have hindered economic development, resulting in persistently low living standards for local farmers. In response to the rural revitalization strategy and to strengthen the village collective economy, the local government leveraged regional advantages to encourage farmers to cultivate specialty crops. This initiative fostered a collaborative value co-creation network involving the government, enterprises, social organizations, and villagers, ultimately establishing an agricultural industrialization model centered on high-quality pear production. Acting as a policy facilitator, the government promoted resource integration through top-level planning. Initiatives included organizing township and village officials to study collective economic development models in Ziwu Town, designating key "Plateau Specialty Agricultural Cooperatives" by the government, and allocating funding through the "Science for Rural Prosperity Program". These measures provided institutional impetus for local industrial growth.

Against this backdrop, Xing Lv Agricultural Development was established as a collective enterprise jointly founded by nine village-level economic associations. Operating under government coordination, the company serves as an integrated platform for land consolidation, market development, and capital allocation. Through market-oriented operations including the transfer of 126.5 hectares of land, integration of Lvhe Township market management rights, and contracting of the township government’s canteen, the company generated land operation revenue of 90,000 yuan and rental income of 200,000 yuan in 2024. It allocated partial profits to support village collectives, creating a virtuous cycle characterized by "government facilitation, corporate operation, and collective benefit-sharing".

In this process, social organizations play a key role in technology empowerment and industrial linkage. The Gantian Premium Pear Association, a community-based organization with two decades of rural engagement, has consistently conducted technological training, cultivar improvement, and science education with government endorsement and financial support. Having organized over 200 technical training sessions, the association facilitated a remarkable increase in pear yield from 30 to 3,400 tons. It also successfully introduced new cultivars such as Yunnan Red Pear, while achieving pollution-free certification and establishing value-added processing supply chains. The Association has established in-depth collaboration with XingLv Agriculture Development, transforming its decade-long cultivation expertise from the 666.7 hectares pear orchard into the foundation for corporate-scale operations. Concurrently, through establishing Gantian Fruit Processing to develop value-added products such as pear vinegar and fruit wines, it has facilitated the transition of local farmers from traditional cultivation to industrial employment.

Through these mechanisms, villagers secured stable income through land transfer, shared corporate dividends as shareholders of the village collective economic association, and enhanced their cultivation skills under the Association technical guidance, and ultimately becoming both participants and beneficiaries of modern agricultural development. This multidimensional collaborative model-characterized by "government guidance, corporate operation, association support, and villager participation"-has effectively revitalized collective resources in Lvhe Township. More significantly, it establishes a sustainable equilibrium among technological innovation, benefit-sharing, and ecological conservation, offering an exemplary paradigm for rural revitalization strategies in Western China.

4 THE PRACTICAL LOGIC OF RURAL COMMON PROSPERITY FROM A VALUE CO-CREATION PERSPECTIVE

4.1 Value-Oriented Approach to Common Prosperity

From a value co-creation perspective, the value orientation of achieving common prosperity in rural areas is rooted in the essential requirements of socialism with Chinese characteristics. It emphasizes both the pursuit of public value for collective well-being and the realization of private value through individual development opportunities. This value orientation transcends the traditional efficiency-equity dichotomy in development models, conceptualizing common prosperity as an organic unity of robust wealth creation and equitable distribution. The case of XingLv Agricultural Development demonstrates how integrating nine village-level collective economic organizations and establishing a "Party-building leadership + village-led + market operation" collaborative mechanism achieves dual value creation: it embodies public value by revitalizing collective resources and developing specialty industries, while realizing private value through land transfer profit-sharing and job creation for individual farmers. This value co-creation system demonstrates particular efficacy in agricultural industrialization. The Gantian Premium Pear Association facilitates both public value through modernizing traditional agriculture via cultivar improvement, technical training, and market expansion, and private value by ensuring direct farmer benefits from technology adoption and product value-added product activities. This value orientation necessitates establishing an inclusive institutional framework that fosters a symbiotic network for value co-creation among government guidance, market entities, social organizations, and farming communities. By coordinating equitable allocation of public resources with efficiency enhancement of private capital in land remediation, industrial development, and ecological conservation, it ultimately cultivates a rural-specific common prosperity paradigm.

4.2 Multi-Stakeholder Value Co-Creation

The practice of multi-stakeholder value co-creation for achieving common prosperity in rural areas centers on synergistic interactions among government, market entities, social organizations, and farming communities, reconstructing rural development ecosystems through dynamic equilibrium between public and private values. The operational model of XingLv Agricultural Development demonstrates how the consortium of nine village collective economic associations transcends traditional administrative fragmentation. Through centralized land transfer and professionalized market operations, it achieves integrated resource utilization-simultaneously advancing government-led rural revitalization (public value orientation) and activating collective economic assets (private value realization). The practice of Gantian Premium Pear Association exemplifies a prototypical model, where the association serves as an institutional nexus that fulfills public functions in agricultural technology extension while facilitating corporate investment in cold storage and value-added processing facilities. This creates a tripartite "Association-Company-Farmers" collaborative network. In this model, governments construct industrial frameworks through infrastructure investment and policy support, enterprises optimize resource allocation via market mechanisms, associations deliver technical training and interest coordination services, while farmers achieve income growth through participation in integrated production-processing-marketing chains. The multi-stakeholder value co-creation in LvHe Township land remediation project manifests through an integrated approach: the government oversees planning and compliance standards for the land balance program, XingLv Company implements technical maintenance, village committees mediate land tenure relations, and farmers earn labor income through field management participation-forming a closed-loop system from policy design to grassroots implementation. Critically, the multi-stakeholder collaboration transcends mere functional aggregation, achieving value integration through institutionalized benefit-coupling mechanisms. Examples include combining guaranteed minimum payments with profit-sharing in land transfers, and balancing public order maintenance with commercial interests in market concessions. This embedded value-creation network ensures inclusive rural public services while unlocking market potential, ultimately forging sustainable common prosperity through industrial upgrading, ecological enhancement, and cultural revitalization.

4.3 Rural Areas Achieve Endogenous Transitions

The practical logic of realizing endogenous transition and moving towards common prosperity in rural areas is essentially based on local resource endowment, and activates the endogenous power of rural development through the synergistic resonance of technological innovation, organizational reconstruction and industrial upgrading. Taking the practice of Gantian as an example, the village leveraged its traditional pear industry foundation and, through technological empowerment and organizational innovation by the High-Quality Pear Association, established a closed-loop industrial chain encompassing "variety improvement-standardized cultivation-value-added processing-branding operations". In this process, local farmers transitioned from traditional decentralized cultivation to technology-intensive production. Leveraging the association's 500-ton cold storage and fruit vinegar production line, they converted substandard fruits into high-value-added products, significantly improving resource utilization efficiency. XingLv Agricultural Development adopted a more systematic and innovative approach: by consolidating collective assets from nine administrative villages, it established a coordinated mechanism of "land transfer-scale operation-diversified business development." This model not only revitalized idle land resources but also created non-farming income streams through market operation rights leasing and government service outsourcing.

This endogenous transition is not a simple accumulation of elements, but the reconstruction of production relations through organizational form innovation. The land requisition-compensation balance project created a shared-interest mechanism among the government, enterprises, village collectives, and farmers. Farmers not only received fixed income from land transfers but also transitioned into industrial workers through participation in post-project maintenance. This multi-role integration fostered the emergence of a new generation of professional farmers. More importantly, through 30-years developmet of its pear industry, Gantian has turned local resources into competitive advantages by establishing both technological standards and brand value. Similarly, XingLv Company modernized LvHe street market by redesigning its layout, tapping into its previously untapped business potential. This transformation stemmed from synergizing rural social and technological capital. It activates dormant assets like regional specialty products and cultural heritage, turning them into tradable, value-growing resources. This process upgrades wealth creation and distribution through industrial restructuring, forming a self-reinforcing cycle of "resource activation-value growth-shared benefits" that sustains rural prosperity.

5 CONCLUSION

This study develops an analytical framework grounded in value co-creation theory, structured as "common prosperity orientation-multi-stakeholder value co-creation-endogenous rural transformation." Using Gantian as a case study, the framework elucidates elucidates the practical pathways for achieving common prosperity in rural areas.

The study reveals that common prosperity serves as the foundational logic for rural development. The alignment of public and private values motivates multi-stakeholder collaboration, ultimately driving endogenous transformation in rural areas. At the macro level, government interventions restructure factor flows through top-level design, injecting institutional public value into rural development. At the meso level, village collectives and enterprises activate land resources via market-driven operations, while social organizations leverage technological capital to extend industrial chains, balancing public and market value. At the micro level, farmers' engagement in value distribution through multi-role transformation, enhancing endogenous development capacity under private-value incentives.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Wu W H, Zhang G J. On the value of common prosperity in socialism with Chinese characteristics. Journal of Beijing Jiaotong University (Social Sciences Edition), 2025, 1-9. DOI: https://doi.org/10.16797/j.cnki.11-5224/c.20250521.005.
[2] Zhang C, Shao X P. The value implication, logical main line and practical path of common prosperity. Jianghan Tribune, 2025, (5): 43-48.
[3] Zhou W, Shi X L. The connotation, characteristics, and practical path of common prosperity. Political Economy Review, 2022, 13(3): 3-23.
[4] Peng L T, Ouyang X. Research on the changes and influencing factors of Chinese residents' spiritual life under the background of common prosperity. Journal of Hubei Polytechnic University (Humanities and Social Sciences Edition), 2025, 42(3): 17-28.
[5] Ma F Y, Yang F. On the institutional construction of the common prosperity of people's spiritual life. Journal of Jishou University (Social Sciences Edition), 2025, 46(2): 14-24.
[6] Tang Y L, Huang X P. The realistic challenges and path selection of promoting rural common prosperity in the new era. Public Administration & Law, 2025, (5): 92-104.
[7] Li J. Discussion on the practical path of rural revitalization under the guidance of the common prosperity goal. China Market, 2025, (13): 9-12.
[8] Zhang M H, Zhao Z W. The internal logic and realization path of new quality productive forces promoting farmers' and rural common prosperity. China Agricultural University Journal of Social Sciences Edition, 2025, 1-17. DOI: https://doi.org/10.13240/j.cnki.caujsse.20250514.006.
[9] Xu F Z, Xi W, Xu Y H. Governance mechanisms and their roles in rural common prosperity: A dual-case study. Management World, 2021, 37(12): 134–151+196+152.
[10] Zhang Q, Zhang N. The legal logic of achieving common prosperity through developing new quality productive forces. Research on Rule of Law Modernization, 2025, 9(3): 99-111.
[11] Zhu Z M. Digital economy, industrial chain modernization, and common prosperity: Empirical evidence from China's provincial panel data. China Business & Trade, 2025, 34(10): 19-23.
[12] Wang L, Song F X. Research on the impact of new quality productive forces on common prosperity: Based on the perspective of multiple demographic dividends. The World of Survey and Research, 2025, (5): 3-14.
[13] Wang M Y, Zhang X J. How can the digital economy promote common prosperity? Based on the perspective of four major gaps. New Horizons, 2025, 1-9. DOI: http://kns.cnki.net/kcms/detail/11.3257.D.20250526.1114.008.html.
[14] Liu Z X, Pan M M. How does the digital economy affect common prosperity? A quasi-natural experiment based on "Broadband China." Journal of Xinjiang University of Finance & Economics, 2025, 1-11. DOI: https://doi.org/10.16713/j.cnki.65-1269/c.2025.02.005.
[15] Zhang Y B. Theoretical discussion and practical path of digital technology enabling common prosperity in spiritual life. Thinking, 2025, 1-9. DOI: http://kns.cnki.net/kcms/detail/53.1002.C.20250521.1131.002.html.
[16] Zhang W J. The internal logic and institutional development of digital inclusive finance boosting common prosperity. China Business & Trade, 2025, 34(9): 112-116.
[17] Wang Y, Liu L, Lu C Y. Return entrepreneurship and farmers' common prosperity in ethnic regions under the rural revitalization strategy. Journal of South-Central Minzu University (Humanities and Social Sciences Edition), 2025, 1-14. DOI: https://doi.org/10.19898/j.cnki.42-1704/C.20250509.01.
[18] Chen X W. Give full play to the role of rural collective economic organizations in common prosperity. Issues in Agricultural Economy, 2022, (5): 4-9.
[19] Li B, He Z J. The mechanism of digital rural construction promoting common prosperity: Based on the field-capital-habitus analytical framework. Journal of Hunan Agricultural University (Social Sciences Edition), 2025, 26(3): 84-92.
[20] Li S, Yang Y X. Equalization of basic public services for common prosperity: Action logic and path selection. China Industrial Economics, 2022, (2): 27-41.
[21] Liu X Y, Huang Y, Huang S R, et al. Digital inclusive finance and common prosperity: Theoretical mechanisms and empirical evidence. Journal of Financial Economics Research, 2022, 37(1): 135-149.
[22] Sun X T, Yu T, Yu F W. The impact of new urbanization on common prosperity and its mechanism: An analysis based on 281 Chinese cities. Journal of Guangdong University of Finance & Economics, 2022, 37(2): 71-87.

[23] Vargo SL. Market Systems,Stakeholders and Value Propositions:Toward a Service-Dominant Logic-Based Theory of the Market. European Journal of Marketing, 2011, 45(1/2): 217-222.
[24] O'FLYNN J. From new public management to public value:Paradigmatic change and managerial implications. Australian Journal of Public Administration, 2007, 66(3): 353-366.
[25] MOORE M H. Public value as the focus of strategy. Australian Journal of Public Administration, 1994, 53(3): 296-303.
[26] Lan Z Y, Chen G Q. A review of contemporary Western public management frontier theories. Journal of Public Management, 2007, (3): 1-12+121.

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TIME SERIES FORECASTING IN BUSINESS INTELLIGENCE: A COMPARATIVE STUDY OF CLASSICAL AND MACHINE LEARNING APPROACHES FOR SALES TREND PREDICTION

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Abstract: Sales trend forecasting is a critical function within modern business intelligence (BI) systems, enabling organizations to optimize inventory management, allocate resources effectively, and make strategic decisions in an increasingly volatile market. Traditionally, classical time series models such as ARIMA and Exponential Smoothing have been widely used due to their interpretability and robust theoretical foundations. However, the emergence of machine learning (ML) methods such as Random Forests, Gradient Boosting Machines, and Long Short-Term Memory (LSTM) networks has introduced new opportunities for capturing complex, non-linear patterns in sales data. This review provides a comprehensive comparison between classical and machine learning approaches for sales trend prediction, examining their strengths, limitations, and practical applications. Classical models offer simplicity, computational efficiency, and strong performance with stationary and linear data, making them suitable for well-structured datasets. Conversely, machine learning models excel in handling large, noisy, and multi-dimensional datasets, offering superior accuracy at the cost of higher computational demands and reduced interpretability. Real-world applications across retail, finance, supply chain management, and healthcare are explored, highlighting the transformative impact of time series forecasting in business operations. Key challenges including data quality, model maintenance, and the need for explainable AI are discussed alongside future directions such as real-time forecasting, transfer learning, and federated learning. By synthesizing insights from both classical and contemporary forecasting paradigms, this review aims to guide researchers, data scientists, and business leaders in selecting appropriate methodologies for enhancing predictive capabilities within business intelligence ecosystems.
Keywords: Business intelligence; Classical models; Machine learning approaches; Sales trend prediction; Time series forecasting

1 INTRODUCTION

In today's rapidly evolving and highly competitive business environment, organizations must constantly adapt to changing market dynamics, consumer preferences, and economic conditions. Central to navigating this complex landscape is the ability to accurately predict future sales trends. Sales forecasting has long been recognized as a critical component of strategic planning, operational efficiency, and financial management [1-4]. Whether it involves preparing inventory for an upcoming season, allocating marketing resources, or projecting revenue for stakeholders, accurate sales forecasts empower businesses to make informed and proactive decisions [5-6]. Business Intelligence (BI) systems, which are designed to transform raw data into actionable insights, increasingly rely on sophisticated forecasting techniques to enhance decision-making processes. At the heart of these forecasting efforts lies time series analysis, a statistical technique that models historical data points, observed sequentially over time, to predict future values [7-11]. Time series forecasting captures important patterns such as trend, seasonality, cyclicality, and irregular fluctuations, allowing businesses to uncover underlying structures within their sales data [12]. Traditionally, organizations have employed classical statistical models like the AutoRegressive Integrated Moving Average (ARIMA) and Exponential Smoothing techniques for sales forecasting. These models offer transparency, ease of interpretation, and reliable performance when dealing with relatively simple, stable, and linear datasets [13-14]. Their mathematical rigor and well-defined assumptions made them the dominant choice for decades across industries ranging from retail and manufacturing to finance and healthcare.

However, the digital revolution has fundamentally transformed the data landscape. With the advent of Big Data, organizations now capture massive volumes of structured and unstructured data at unprecedented velocity and variety [15-16]. Consumer behavior has also become more unpredictable, influenced by a multitude of factors such as real-time social media trends, geopolitical events, and technological innovations. In such complex environments, the limitations of classical models such as their reliance on stationarity assumptions and limited capacity to model non-linear relationships have become more apparent. Consequently, there has been a surge of interest in leveraging machine learning (ML) approaches for time series forecasting [6-7]. Machine learning models, including Random Forests, Gradient Boosting Machines (GBMs), Support Vector Regression (SVR), and deep learning architectures like Long Short-Term Memory (LSTM) networks, offer powerful alternatives to classical techniques. These models are capable of automatically learning intricate patterns, capturing non-linear relationships, and adjusting to high-dimensional feature spaces without strict assumptions about data distribution [17]. Machine learning approaches are particularly effective when dealing with volatile, multi-factorial sales environments where traditional linear models struggle to maintain predictive accuracy. For example, LSTM networks have demonstrated superior performance in capturing long-term dependencies and sequential patterns in sales data compared to traditional ARIMA models [18]. Nevertheless, the adoption of machine learning in time series forecasting is not without challenges. ML models often require substantial volumes of high-quality historical data for training, involve greater computational resources, and lack the interpretability that classical models naturally provide [6, 12]. Business leaders are often wary of "black-box" models whose predictions are difficult to explain to stakeholders. Furthermore, model overfitting, data drift, and maintenance complexity can impact the reliability of machine learning systems if not carefully managed [18].

Given these dynamics, it is crucial to critically evaluate and compare classical and machine learning approaches for time series forecasting, especially within the context of business intelligence where practical applicability, scalability, and interpretability are vital. Understanding the strengths, limitations, and appropriate use cases for each paradigm can empower businesses to make smarter forecasting choices, combining the robustness of classical methods with the flexibility of machine learning to maximize predictive performance. This review paper aims to provide a comprehensive comparative analysis, exploring real-world applications, key challenges, and future directions for time series forecasting in business intelligence.

2 OVERVIEW OF CLASSICAL AND MACHINE LEARNING APPROACHES

Classical time series forecasting models have served businesses well for decades, offering a robust framework for understanding and predicting future trends based on historical patterns. The ARIMA model, for instance, combines autoregressive, differencing, and moving average components to model and forecast a time series. ARIMA's strength lies in its ability to model a wide variety of time series behaviors with relatively few parameters. However, it assumes linear relationships and requires the time series to be stationary or at least made stationary through transformations [5-6]. Similarly, Exponential Smoothing techniques, including Holt's linear trend method and Holt-Winters seasonal method, forecast future values by weighing past observations with exponentially decreasing weights. These models excel at handling trend and seasonality and are relatively easy to implement, making them popular choices in traditional BI setups. Despite their success, classical models face limitations when dealing with highly volatile, complex, or multi-dimensional data typical of modern businesses. This is where machine learning approaches have started to gain ground. Machine learning models do not assume linearity or stationarity and can model intricate patterns and interactions within large datasets. Tree-based models such as Random Forests and XGBoost excel at capturing non-linear relationships and interactions between features. These models are robust to missing values and outliers, offering significant advantages over classical methods [19-25].

Deep learning approaches, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have shown remarkable success in sequential data modeling. LSTMs, in particular, address the vanishing gradient problem associated with traditional RNNs, allowing the model to learn long-term dependencies and seasonality patterns in the data [25-27]. Tools like Facebook Prophet blend the flexibility of ML models with the simplicity of classical decomposition approaches, offering business users the ability to model seasonality, holidays, and trend changes with minimal expertise required. Thus, while classical models remain highly useful for simpler and well-behaved datasets, machine learning models offer greater adaptability and predictive power in complex environments.

3 COMPARATIVE ANALYSIS OF FORECASTING TECHNIQUES

Comparing classical and machine learning forecasting techniques reveals nuanced differences across multiple dimensions, including accuracy, interpretability, data requirements, and computational complexity. In terms of accuracy, machine learning models often outperform classical methods, particularly in scenarios involving non-linear relationships, high volatility, or exogenous factors influencing sales trends. Studies such as the M4 Competition have demonstrated that hybrid approaches combining statistical and machine learning methods often yield the best results, with pure machine learning models also showing superior performance over traditional models on complex datasets [14, 22-26].

However, when interpretability is a critical requirement, classical models maintain an advantage. In ARIMA models, for example, the coefficients directly relate to the behavior of the time series, offering clear insights into trend, seasonality, and autocorrelation. This transparency is valuable for business executives who must justify forecasts to stakeholders [6]. Conversely, machine learning models, especially deep learning networks, operate as black boxes, making it challenging to interpret why a particular forecast was generated. While techniques like SHAP values and LIME provide some interpretability to machine learning outputs, they are often not as intuitive as traditional model parameters.

Data requirements further differentiate the two approaches. Classical models perform well with small to medium-sized datasets, assuming the data exhibits relatively stable patterns. In contrast, machine learning models thrive on large volumes of data and often require additional features such as promotions, economic indicators, or weather patterns to achieve peak performance [27-29]. This makes machine learning models better suited to businesses with rich data ecosystems, while smaller organizations might find classical approaches more practical. From a computational standpoint, classical models are significantly less demanding, often running efficiently on standard personal computers.

Machine learning models, especially deep learning architectures like LSTM networks, require substantial computational resources, often necessitating the use of GPUs and distributed computing environments [30]. Thus, the choice between classical and machine learning approaches is not merely a matter of accuracy but must consider practical constraints such as interpretability, available data, and computational resources.

4 APPLICATIONS IN BUSINESS INTELLIGENCE

The application of time series forecasting in business intelligence spans across multiple industries, each leveraging forecasting models to gain a competitive edge. In the retail and e-commerce sector, demand forecasting is crucial for inventory management, dynamic pricing, and personalized marketing (Figure 1). Companies like Amazon utilize sophisticated hybrid models combining statistical techniques with deep learning to predict product demand across thousands of items, adjusting supply chains in real-time to meet customer needs [5-6].

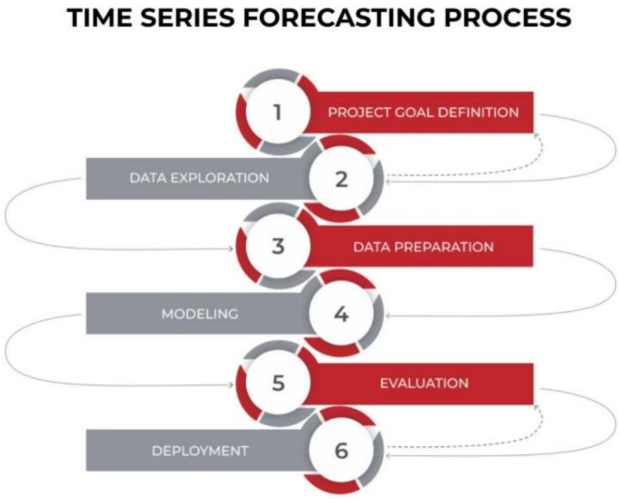

Figure 1 Time Series Forecasting in BI: Driving Efficiency Across Sectors

In the finance industry, forecasting revenue, expenses, and cash flow enables organizations to plan budgets, manage risk, and optimize investment strategies. Financial institutions also use sales forecasts to assess customer creditworthiness and predict loan defaults. Machine learning models are increasingly favored in finance due to their ability to incorporate a wide range of exogenous variables, such as macroeconomic indicators, into forecasts. Supply chain and logistics companies leverage time series forecasting to optimize routes, manage inventory levels, and anticipate bottlenecks [31-33]. Accurate forecasts reduce operational costs and improve service levels, providing a critical advantage in industries where margins are razor-thin. For example, Walmart integrates forecasting models into its SAP BI platform, using LSTM networks to predict sales trends and adjust logistics operations dynamically [6].

Marketing departments also utilize forecasting to predict customer engagement and sales response to promotional campaigns. Understanding seasonal trends allows marketers to time campaigns more effectively, maximizing return on investment. Integration with BI tools like Power BI, Tableau, and SAP Analytics Cloud allows businesses to visualize forecasts within dashboards, enabling faster, data-driven decisions. These applications highlight the versatility and strategic importance of time series forecasting across business functions.

5 APPLICATION IN FIRE PROTECTION

Time series forecasting has emerged as a crucial tool in enhancing fire protection strategies across both natural and built environments. Traditionally, fire protection efforts were largely reactive, relying on historical fire records and expert judgment to allocate resources. However, the integration of predictive analytics, particularly time series forecasting models, has enabled a shift toward proactive fire risk management. In the context of wildfire management, time series models utilize historical datasets including weather patterns (temperature, humidity, wind speed), vegetation dryness indices, previous fire incidents, and satellite imagery to forecast the likelihood of fire outbreaks [34]. Advanced machine learning models such as Long Short-Term Memory (LSTM) networks and Random Forest regressors have shown considerable success in capturing temporal dependencies and non-linear relationships within these datasets. These models can predict high-risk periods and regions with remarkable accuracy, enabling authorities to pre-position firefighting units, plan controlled burns, and issue early warnings to at-risk communities [6-7].

In urban fire protection, time series forecasting is increasingly applied to monitor and predict fire hazards within smart buildings and industrial complexes. Data collected from Internet of Things (IoT) devices such as smoke detectors, temperature sensors, gas leak monitors, and electrical load analyzers generate continuous time series streams [35]. Predictive models can analyze these data streams to detect anomalies indicative of potential fire hazards, such as overheating equipment, gas leaks, or electrical faults. By forecasting the likelihood of equipment failure or hazardous conditions, building managers can schedule preventive maintenance, thereby reducing the probability of fires starting in the first place [36].

Moreover, time series forecasting contributes to optimizing the deployment of emergency response resources. Historical incident data, combined with real-time inputs, allow fire departments to predict the demand for firefighting services during specific times of the day, week, or season. This predictive insight aids in dynamic staffing, strategic positioning of fire engines, and improving response times during critical periods. In industrial fire protection, especially in sectors handling flammable materials (e.g., oil and gas, chemical manufacturing), forecasting models are also used to predict combustion-related risks based on process monitoring data [37]. The fusion of classical models (e.g., ARIMA for stable sensor data) with machine learning approaches (e.g., LSTM for volatile, complex datasets) offers a robust framework for real-time risk assessment and mitigation. As technology advances, the future of fire protection will increasingly depend on the ability to forecast risks accurately, thus transforming emergency responses from reactive interventions to predictive, preventive actions that save lives, property, and critical infrastructure [37-38].

6 APPLICATION IN PHARMACEUTICALS AND MEDICAL INDUSTRIES

Time series forecasting has become an indispensable tool in the pharmaceutical and medical industries, driving innovation in areas ranging from drug production planning to patient care optimization. In pharmaceutical manufacturing, accurate demand forecasting is critical to ensuring the timely production and distribution of medications [22, 33-36]. Time series models, such as ARIMA and Prophet, are used to analyze historical sales data, seasonal disease trends, and healthcare utilization rates to predict future demand for specific drugs. This enables manufacturers to optimize inventory management, reduce stockouts and overproduction, and respond swiftly to public health emergencies such as influenza outbreaks or pandemic surges, where medication demand can spike unpredictably [37]. Machine learning-based forecasting models, like LSTM networks, further enhance prediction accuracy by incorporating external variables such as epidemiological trends, regulatory changes, and global supply chain disruptions [5-7].

In clinical settings, time series forecasting is revolutionizing patient monitoring and disease management. Real-time patient data from wearable devices, electronic health records (EHRs), and intensive care unit (ICU) monitoring systems are analyzed to predict critical health events such as cardiac arrests, sepsis onset, or respiratory failures. By leveraging models that forecast physiological parameters such as heart rate variability, oxygen saturation levels, and blood pressure trends clinicians can intervene earlier, thereby improving patient outcomes and reducing hospital stays [38]. Predictive models also aid in managing chronic diseases like diabetes, where time series forecasts of glucose levels enable personalized treatment adjustments and proactive management strategies. The pharmaceutical research and development (R&D) pipeline also benefit from time series forecasting [24, 27, 33, 36]. Drug discovery projects involve long timelines and massive financial investments; therefore, forecasting project milestones, trial enrollments, patient dropout rates, and trial success probabilities enables companies to allocate resources more efficiently and mitigate risks. Machine learning models trained on historical trial data can forecast recruitment bottlenecks or predict adverse event frequencies, allowing dynamic trial design modifications that save time and cost [39].

Moreover, hospital systems and public health agencies use forecasting to manage resource allocation, predict disease outbreaks, and optimize staffing levels. During the COVID-19 pandemic, time series models played a vital role in projecting infection rates, hospital bed occupancy, and ventilator demand, enabling healthcare systems to prepare adequately and avoid catastrophic overloads. The future of time series forecasting in pharmaceuticals and medicine lies in integrating genomic data, real-world evidence, and multi-modal sensor data into predictive models. Such integration will facilitate truly personalized medicine, wherein interventions are not only based on current health status but also forecasted future risks, ensuring better patient care, streamlined pharmaceutical operations, and more resilient healthcare systems [35-37].

7 LIMITATIONS

Despite the significant advancements in time series forecasting methodologies, several limitations persist that impact their effectiveness in real-world business intelligence applications. One of the most critical limitations is data quality and availability. Accurate forecasting is heavily dependent on the integrity of the input data. Issues such as missing values, outliers, data drift, or non-uniform sampling intervals can drastically degrade model performance [33-36]. Classical models like ARIMA are particularly sensitive to these imperfections, often requiring extensive preprocessing. Although machine learning models are more tolerant of noisy data, their effectiveness still diminishes when key features are missing or when historical data is insufficient [38].

Another major limitation is model interpretability, particularly for machine learning approaches. While classical models are highly transparent, offering clear explanations for their predictions based on simple parameters (such as lag relationships and trend coefficients), machine learning models especially deep learning models like LSTM networks often operate as "black boxes." In high-stakes business environments where trust and explainability are essential, the opacity of complex models can hinder their adoption, especially in sectors such as finance and healthcare, where regulatory compliance demands transparency in predictive analytics [36-39].

Overfitting is a persistent concern, particularly with machine learning approaches. When models are excessively tuned to historical data, they capture noise rather than underlying patterns, leading to poor generalization to future unseen data. Deep learning models require careful regularization, validation, and hyperparameter tuning to avoid this pitfall [40]. In contrast, classical models, due to their simpler structure, are less prone to severe overfitting but may underperform when relationships within the data are highly complex or non-linear. Computational complexity and resource intensiveness represent further limitations, particularly for large-scale machine learning forecasting systems. Deep learning models require considerable computational power, specialized hardware such as GPUs, and long training times, making them less accessible for smaller organizations with limited resources [33, 38]. Classical models, while computationally lightweight, may struggle to scale when dealing with vast multivariate time series datasets common in modern BI environments.

Finally, adaptability to change, also known as concept drift, poses a substantial limitation. Many forecasting models assume that historical patterns will persist into the future. However, real-world business environments are dynamic consumer behaviors shift, new competitors emerge, and external shocks (such as pandemics or regulatory changes) can invalidate prior trends. Models that are not continuously updated or capable of adapting to these shifts can quickly become obsolete, leading to inaccurate forecasts and misguided business decisions.

8 FUTURE DIRECTIONS

Addressing these limitations requires strategic innovation and methodological advancements. One promising area is the development of Explainable AI (XAI) techniques specifically tailored for time series forecasting. Techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have already shown promise, but more domain-specific, intuitive explainability tools are needed to bridge the gap between highly accurate but opaque models and business decision-makers' need for trust and clarity. Another key future direction is the integration of real-time data streaming and forecasting [5-7]. As businesses increasingly rely on IoT devices, e-commerce platforms, and dynamic customer interaction data, forecasting models must move beyond static, batch-trained systems to architectures that can ingest and adapt to streaming data in real-time. Online learning algorithms, adaptive ARIMA models, and real-time LSTM frameworks are areas of active research and hold immense promises for industries requiring immediate responses, such as logistics, finance, and retail [22, 33,34, 36, 37, 39]. Transfer learning and multi-task learning also represent important frontiers. Rather than building forecasting models from scratch for each new product line, geographic market, or customer segment, businesses can leverage knowledge learned from related time series, dramatically reducing training data requirements and improving model generalization. Pretrained forecasting models, fine-tuned on specific business datasets, could significantly lower the barrier to entry for companies with limited historical data [40].

Additionally, federated learning offers a way to address privacy and data sharing concerns that are becoming increasingly important, especially under regulatory frameworks like GDPR and HIPAA. In federated learning setups, models are trained collaboratively across multiple decentralized datasets without transferring sensitive raw data between organizations [36]. This approach could foster collaborative forecasting across industries such as healthcare providers predicting medicine demand while preserving competitive confidentiality and compliance. Hybrid modeling approaches are another area ripe for future exploration. Rather than viewing classical and machine learning methods as mutually exclusive, combining them can yield highly robust models [38-40]. For instance, classical decomposition methods can first be applied to separate trend and seasonal components, which can then be fed into machine learning models to capture residual complexities. Hybrid models have already demonstrated superior performance in several forecasting competitions and are expected to become mainstream in commercial applications. Finally, the future will likely see greater emphasis on uncertainty quantification in forecasts. Rather than providing a single point prediction, advanced models will offer probabilistic forecasts with confidence intervals, allowing businesses to make risk-adjusted decisions rather than assuming forecasted values as deterministic truths.

9 CONCLUSION

Time series forecasting continues to be a cornerstone of business intelligence, enabling organizations to navigate uncertainty and make informed strategic decisions. Classical forecasting models, such as ARIMA and Exponential Smoothing, remain valuable tools, particularly in environments with well-behaved, stationary data and limited computational resources. Their simplicity, interpretability, and robustness ensure their continued relevance. However, the complexity and volume of modern business data increasingly necessitate the adoption of machine learning approaches. Models such as Random Forests, XGBoost, LSTMs, and hybrid tools like Facebook Prophet offer superior performance in capturing non-linear relationships and adapting to changing patterns. While these models come with higher data and computational demands, their ability to deliver actionable insights makes them indispensable in today's dynamic business landscape. Ultimately, the choice between classical and machine learning methods should be guided by the specific context, data availability, business needs, and operational constraints. A hybrid approach, combining the transparency of classical models with the predictive power of machine learning, often provides the best of both worlds. As technology continues to evolve, the future of sales trend forecasting in business intelligence lies in creating integrated, adaptive, and explainable systems that empower businesses to thrive in an increasingly uncertain world.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Alam G T, Chy M A R, Rozario E, et al. AI-Driven Optimization of Domestic Timber Supply Chains to Enhance U.S. Economic Security. Journal of Posthumanism, 2025, 5(1): 1581–1605. DOI: 10.63332/joph.v4i3.2083.

[2] Rahman M S, Islam S, Khan S I, et al. Redefining marketing and management strategies in digital age: Adapting to consumer behavior and technological disruption. Journal of Information Systems Engineering and Management, 2024, 9(4): 1–16. DOI: 10.52783/jisem.v9i4.32.

[3] Mahmud F, Barikdar C R, Hassan J, et al. AI-Driven Cybersecurity in IT Project Management: Enhancing Threat Detection and Risk Mitigation. Journal of Posthumanism, 2025, 5(4): 23–44. DOI: 10.63332/joph.v5i4.974.

[4] Hossain S, Karim F, Sultana S, et al. From Data to Value: Leveraging Business Analytics for Sustainable Management Practices. Journal of Posthumanism, 2025, 5(5): 82–105. DOI: 10.63332/joph.v5i5.1309.

[5] Hyndman R J, Athanasopoulos G. Forecasting: Principles and Practice (3rd ed.). 2021.

[6] Laptev N, Yosinski J, Li L E, et al. Time-series extreme event forecasting with neural networks at Uber. 2017.

[7] Miah M A, Ahmed M K, Bhuiyan M M R, et al. Big Data Analytics for Enhancing Coal-Based Energy Production Amidst AI Infrastructure Growth. Journal of Posthumanism, 2025, 5(5): 5061–5080. DOI: 10.63332/joph.v5i5.2087.

[8] Manik M M T G, Mohonta S C, Karim F, et al. AI-Driven Precision Medicine Leveraging Machine Learning and Big Data Analytics for Genomics-Based Drug Discovery. Journal of Posthumanism, 2025, 5(1): 1560–1580. DOI: 10.63332/joph.v5i1.1993.

[9] Moniruzzaman M, Islam M S, Mohonta S C, et al. Big Data Strategies for Enhancing Transparency in U.S. Healthcare Pricing. Journal of Posthumanism, 2025, 5(5): 3744–3766. DOI: 10.63332/joph.v5i5.1813.

[10] Hossain E, Ashik A A M, Rahman M M, et al. Big data and migration forecasting: Predictive insights into displacement patterns triggered by climate change and armed conflict. Journal of Computer Science and Technology Studies, 2023, 5(4): 265–274. DOI: 10.32996/jcsts.2023.5.4.27.

[11] Khan S I, Rahman M S, Ashik A A M, et al. Big Data and Business Intelligence for Supply Chain Sustainability: Risk Mitigation and Green Optimization in the Digital Era. European Journal of Management, Economics and Business, 2024, 1(3): 262-276. DOI: 10.59324/ejmeb.2024.1(3).23.

[12] Box G E P, Jenkins G M, Reinsel G C, et al. Time Series Analysis: Forecasting and Control (5th ed.). Wiley, 2015.

[13] Makridakis S, Spiliotis E, Assimakopoulos V. The M4 Competition: Results, findings, conclusion and way forward. International Journal of Forecasting, 2020, 36(1): 54-74. DOI: 10.1016/j.ijforecast.2019.04.014

[14] Makridakis S, Spiliotis E, Assimakopoulos V. Statistical and machine learning forecasting methods: Concerns and ways forward. Plos One, 2018, 13(3): e0194889. DOI: 10.1371/journal.pone.0194889.

[15] Manyika J, Chui M, Brown B, Bughin J, et al. Big data: The next frontier for innovation, competition, and productivity. McKinsey Global Institute, 2011.

[16] Islam M S, Manik M M T G, Moniruzzaman M, et al. Explainable AI in Healthcare: Leveraging Machine Learning and Knowledge Representation for Personalized Treatment Recommendations. Journal of Posthumanism, 2025, 5(1):1541–1559. DOI: 10.63332/joph.v5i1.1996.

[17] Bandara K, Bergmeir C, Smyl S. Forecasting across time series databases using recurrent neural networks on groups of similar series: A clustering approach. Expert Systems with Applications, 2020, 140: 112896. DOI: 10.1016/j.eswa.2019.112896.

[18] Brownlee J. Deep Learning for Time Series Forecasting: Predict the Future with MLPs, CNNs and LSTMs in Python. Machine Learning Mastery, 2018.

[19] Manik M M T G. An Analysis of Cervical Cancer using the Application of AI and Machine Learning. Journal of Medical and Health Studies, 2022, 3(2): 67-76. DOI: 10.32996/jmhs.2022.3.2.11.

[20] Sultana S, Karim F, Rahman H, et al. A Comparative Review of Machine Learning Algorithms in Supermarket Sales Forecasting with Big Data. Journal of Ecohumanism, 2024, 3(8): 14457. DOI: 10.62754/joe.v3i8.6762.

[21] Haldar U, Alam G T, Rahman H, et al. AI-Driven Business Analytics for Economic Growth Leveraging Machine Learning and MIS for Data-Driven Decision-Making in the U.S. Economy. Journal of Posthumanism, 2025, 5(4): 932–957. DOI: 10.63332/joph.v5i4.1178.

[22] Smyl S. A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting. International Journal of Forecasting, 2020, 36(1): 75-85. DOI: 10.1016/j.ijforecast.2019.03.017

[23] Manik M M T G, Hossain S, Ahmed M K, et al. Integrating Genomic Data and Machine Learning to Advance Precision Oncology and Targeted Cancer Therapies. Nanotechnology Perceptions, 2022, 18 (2): 219-243. DOI: 10.62441/nano-ntp.v18i2.5443.

[24] Manik M M T G. Multi-Omics Integration with Machine Learning for Early Detection of Ischemic Stroke Through Biomarkers Discovery. Journal of Ecohumanism, 2023, 2(2): 175–187. DOI: 10.62754/joe.v2i2.6800.

[25] Manik M M T G, Saimon A S M, Islam M S, et al. Big Data Analytics for Credit Risk Assessment. In 2025 International Conference on Machine Learning and Autonomous Systems (ICMLAS), Prawet, Thailand, 2025: 1379-1390. DOI: 10.1109/ICMLAS64557.2025.10967667.

[26] Khair F B, Ahmed M K, Hossain S, et al. Sustainable Economic Growth Through Data Analytics: The Impact of Business Analytics on U.S. Energy Markets and Green Initiatives," 2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS), Pattaya, Thailand, 2024: 108-113. DOI: 10.1109/ICPIDS65698.2024.00026.

[27] Islam S, Hossain E, Rahman M S, et al. Digital Transformation in SMEs: Unlocking Competitive Advantage through Business Intelligence and Data Analytics Adoption. 2023, 5(6): 177-186. DOI: 10.32996/jbms.2023.5.6.14.

[28] Hossain D. A fire protection life safety analysis of multipurpose building. 2021. https://digitalcommons.calpoly.edu/fpe_rpt/135/.

[29] Alasa DK, Hossain D, Jiyane G. Hydrogen Economy in GTL: Exploring the role of hydrogen-rich GTL processes in advancing a hydrogen-based economy. International Journal of Communication Networks and Information Security (IJCNIS), 2025, 17(1): 81–91. https://www.ijcnis.org/index.php/ijcnis/article/view/8021.

[30] Hossain D, Asrafuzzaman M, Dash S, et al. Multi-Scale Fire Dynamics Modeling: Integrating Predictive Algorithms for Synthetic Material Combustion in Compartment Fires. Journal of Management World, 2024(5): 363-374. DOI: 10.53935/jomw.v2024i4.1133.

[31] Hossain S, Bhuiyan M M R, Islam M S, et al. Big Data Analysis and prediction of COVID-2019 Epidemic Using Machine Learning Models in Healthcare Sector. Journal of Ecohumanism, 2024, 3(8): 14468. DOI: 10.62754/joe.v3i8.6775.

[32] Hossain D. Fire dynamics and heat transfer: advances in flame spread analysis. Open Access Research Journal of Science and Technology, 2022, 6(2): 70-5. DOI: 10.53022/oarjst.2022.6.2.0061.

[33] Hossain D, Alasa DK, Jiyane G. Water-based fire suppression and structural fire protection: strategies for effective fire control. International Journal of Communication Networks and Information Security (IJCNIS), 2023, 15(4): 485-94. https://ijcnis.org/index.php/ijcnis/article/view/7982.

[34] Das K, Tanvir A, Rani S, et al. Revolutionizing Agro-Food Waste Management: Real-Time Solutions through IoT and Big Data Integration. Voice of the Publisher, 2025, 11: 17-36. DOI: 10.4236/vp.2025.111003.

[35] Bulbul IJ, Zahir Z, Tanvir A, et al. Comparative study of the antimicrobial, minimum inhibitory concentrations (MIC), cytotoxic and antioxidant activity of methanolic extract of different parts of Phyllanthus acidus (l.) Skeels (family: Euphorbiaceae). World Journal of Pharmacy and Pharmaceutical Sciences, 2018, 8(1): 12-57. DOI: 10.20959/wjpps20191-10735.

[36] Tanvir A, Jo J, Park SM. Targeting Glucose Metabolism: A Novel Therapeutic Approach for Parkinson's Disease. Cells, 2024, 13: 1876. DOI: 10.3390/cells13221876.

[37] Manik M M T G. Biotech-Driven Innovation in Drug Discovery: Strategic Models for Competitive Advantage in the Global Pharmaceutical Market. Journal of Computational Analysis and Applications (JoCAAA), 2020, 28(6): 41–47. https://eudoxuspress.com/index.php/pub/article/view/2874.

[38] Manik M M T G. Multi-Omics System Based on Predictive Analysis with AI-Driven Models for Parkinson's Disease (PD) Neurosurgery. Journal of Medical and Health Studies, 2021, 2(1): 42-52. https://doi.org/10.32996/jmhs.2021.2.1.5

[39] Manik M M T G, Saimon A S M, Miah M A, et al. Leveraging Ai-Powered Predictive Analytics for Early Detection of Chronic Diseases: A Data-Driven Approach to Personalized Medicine. Nanotechnology Perceptions, 2021, 17 (3): 269-288. DOI: 10.62441/nano-ntp.v17i3.5444.

[40] Manik M M T G. An Analysis of Cervical Cancer using the Application of AI and Machine Learning. Journal of Medical and Health Studies, 2022, 3(2): 67-76. DOI: 10.32996/jmhs.2022.3.2.11.

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EFFICIENCY EVALUATION OF MAJOR BANKS BASED ON DEA-MALMQUIST INDEXES

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Abstract: In this paper, we conducted an in-depth evaluation study on the efficiency of major banks in China using the DEA-Malmquist index method. By collecting, organizing and analyzing the data of major banks, we constructed the DEA model and used the Malmquist index to monitor the efficiency changes of each bank dynamically. The results of the study show that there are significant differences in the efficiency of different banks, and at the same time, with the passage of time, the efficiency of each bank shows different trends of change. The findings of this paper are of great guiding significance for understanding the efficiency situation of China's banking industry, optimizing the allocation of bank resources, and improving the competitiveness of banks.
Keywords: DEA-Malmquist Index; Bank efficiency; Dynamic monitoring; Resource allocation; Competitiveness

1 INTRODUCTION

In the current context of global economic integration and increasingly fierce competition in the financial market, the banking industry, as a core component of the financial system, has a direct impact on the effective allocation of financial resources and the sound development of the economy in terms of its operational efficiency. Therefore, an accurate evaluation of bank efficiency not only helps banks themselves to identify problems in operation and management, but also provides an important basis for regulators to formulate scientific and reasonable regulatory policies. The reason why this paper chooses the DEA-Malmquist index method for the study is that it combines the advantages of data envelopment analysis (DEA) and Malmquist index, which can both statically reflect the current state of efficiency of banks and dynamically monitor the trend of efficiency over time, providing a powerful tool for the comprehensive evaluation of bank efficiency. Zhong Shihe and He Yinghua used the improved SFA model and the variance method to examine the efficiency and risk of commercial banks from a dynamic perspective, and concluded that there exists a "Bowman's paradox" and that efficiency fluctuations contribute more to the risk variance of commercial banks in China [1];Xu Zhong et al. used 300 county-level financial institutions in China in 2001 to study the efficiency of commercial banks. Xu Zhong et al. used the data of China's 300 county-level financial institutions in 2001-2004 to measure the market monopoly power of banks by using the Herfindahl index and the degree of concentration, and found that lowering the degree of concentration of banks can improve the efficiency of banks and reduce the rate of non-performing loans [2]; Chi Guotai and others took into account the indexes of the profitability of the bank and the ability to control risks to measure the efficiency of China's 14 commercial banks, and proposed macro countermeasures and specific countermeasures to improve the efficiency of the banks. They proposed macro and specific countermeasures to improve the efficiency of banks [3]; Li et al. found that the entry of foreign banks would reduce the non-interest income and asset quality of Chinese commercial banks. The intermediate business and asset quality of China's commercial banks are relatively weak and need to be improved to meet the challenges of foreign banks. Based on the above challenges and threats, bank managers need to accelerate the change of the traditional model to improve the operational efficiency of banks [4]. Zou Jiang and others believe that a scientific and reasonable adjustment of the income structure of China's commercial banks will significantly improve the economic efficiency of commercial banks. He also pointed out that the reasons for the differences in the income structure of China's commercial banks mainly include the types of business and income, industry service level and customer resources [5]. Zhu Taihui, Chen Lu financial science and technology (fintech), is financial (finance) and technology information technology to transform and innovate financial products and business models The combination of emerging technology development, the core of which is the use of emerging Internet information (technology) combination of words, describing the financial business and big data and so on [6]. Li Wenliang argues that commercial banks, through the demonstration effect, are able to learn from the advanced technological thinking of fintech, and through learning to emulate its product types and absorbing and applying its service concepts, so as to realize technological improvement and efficiency enhancement [7]. Zhang Fen compared the efficiency of China's policy banks with 10 domestic commercial banks by using the DEA analysis method, and came to the conclusion that the indicators of China Development Bank are good, while the operation of the Export-Import Bank and Agricultural Bank of China is defective [8]. Li Mingdi used DEA model to evaluate the static efficiency of 27 city commercial banks in China during the period of 2007-2012, and the results showed that the overall fluctuating upward trend of comprehensive efficiency due to the steady increase of pure technical efficiency and scale efficiency [9]. Jin Sujun conducted an empirical study on the relative efficiency of 17 city commercial banks in Henan Province in 2011 using the DEA model, and the results showed that the sample had problems such as low overall technical efficiency, low overall scale efficiency, and the scale effect had not yet been brought into full play [10]. Wang Shuguang argues that the future financial system should be one that civilians can easily participate in with a very low threshold, which is both a challenge and an opportunity for the construction of China's future inclusive financial system [11]. Bai Qinxian and Gao Xia point out that the essence of finance is inclusive, and inclusive finance returns finance to its origin and is the sharing of financial development[12]. Xue Feng and Yang Deli measured the efficiency of China's banking industry by using DEA model [13]. Zhang Jianhua introduced the Malmquist method into the DEA model for the first time and obtained a more detailed description of the efficiency level of commercial banks [14]. Dai and Fang found that the development of digital finance has increased the cost of liabilities of banks, which has led to an increase in the interest rate of bank loans, which has led to an increase in the proportion of risky assets in banks as loan applicants are more inclined to choose riskier and higher-return assets [15].

2 MODEL CONSTRUCTION

2.1 Input-Oriented CCR Model

The CCR model is a data envelopment analysis method proposed by Charnes, Cooper and Rhodes in 1978, which is based on input orientation and aims to assess the relative efficiency of decision-making units (DMUs). In the context of efficiency evaluation in the banking industry, each bank is considered as a decision-making unit whose inputs include capital, labor, operating costs, etc., while the outputs may be financial indicators such as loan volume, deposit volume, profit, etc. The CCR model finds an envelope by constructing a linear programming problem such that all the decision-making units are located either below or above the envelope, and the decision-making units that are located on the envelope are considered to be on the efficiency frontier, i.e., have the highest relative efficiency, while decision units located below the envelope are considered to be less efficient.

The import-oriented CCR model is to maximize the output given the inputs. The mathematical model for evaluating the efficiency of decision unit k is:

$$\max \frac{uY_k^T}{vX_k^T}$$

s.t.
$$\begin{cases} \frac{u_r Y_k^T}{v_j X_k^T} \leq 1 \\ v_j \geq 0, u_r \geq 0, j = 1, \cdots, m; r = 1, \cdots, q \end{cases}$$

Since this form is non-linear programming, it is transformed into a linear programming form as

$$\max u_r Y_k^T$$

s.t.
$$\begin{cases} u_r Y_k^T - v_j X_k^T \leq 0 \\ v_j X_k^T = 1 \\ v_j \geq 0, u_r \geq 0, j = 1, \cdots, m; r = 1, \cdots, q \end{cases}$$

Since the dyadic model includes efficiency values in the decision variables, the above model is transformed into the dyadic form as:

$$\min \theta$$

s.t.
$$\begin{cases} \sum_{i=1}^{n} \lambda_i x_{ij} \leq \theta x_{ij} \\ \sum_{i=1}^{n} \lambda_i y_{ir} \leq y_{kr} \\ \lambda_i \geq 0, j = 1, \cdots, m; r = 1, \cdots, q \end{cases}$$

$$k = 1, \cdots, n$$

Among them.

In pairwise programming, λ denotes the linear combination coefficients of the DMUs and the parameter θ is the efficiency value, which ranges from 0 to 1.

The output-oriented CCR model, which minimizes inputs given outputs, has the following final dyadic model:

$$\max\phi$$
$$s.t.\begin{cases} \sum_{i=1}^{n}\lambda_i x_{ij} \le x_{ij} \\ \sum_{i=1}^{n}\lambda_i y_{ir} \ge \phi y_{kr} \\ \lambda_i \ge 0, j = 1,\cdots,m; r = 1,\cdots,q \end{cases}$$
where $,k = 1,\cdots,n$

In the input-oriented CCR model, we solve for the efficiency value of each decision unit (i.e., bank) by linear programming. The efficiency value θ reflects the maximum proportion of output that can be achieved by the decision unit for a given input. When θ = 1, it indicates that the decision unit is located on the efficiency frontier and is the most efficient, while when θ < 1, it indicates that the decision unit suffers from efficiency loss and needs to be improved. It is worth noting that the CCR model is constructed based on the assumption of constant returns to scale, i.e., it is assumed that all decision units operate at optimal scale.

2.2 Malmquist Index

The Malmquist index was introduced by the Swedish economist Malmquist in 1953 and was initially used to analyze changes in consumption behavior. Later, Fare et al. combined it with Data Envelopment Analysis (DEA) and developed it into a powerful tool for evaluating the dynamics of productive efficiency. In the context of efficiency evaluation in the banking sector, the Malmquist index is able to measure the efficiency changes of banks at different points in time, including technological progress, efficiency improvement or deterioration.

Specifically, the Malmquist index can be decomposed into the technical efficiency change index (EFFCH) and the technical progress index (TECHCH). The technical efficiency change index reflects a bank's ability to improve its productivity under given technological conditions by optimizing resource allocation, improving management, etc., while the technical progress index reflects a bank's ability to promote productivity improvement through the adoption of new technologies, innovative business models, and other means.

By calculating the Malmquist Index and its decomposition components, we can gain insights into the specific performance of each bank in terms of efficiency changes and the extent to which different factors affect efficiency changes. This helps bank managers to identify the key drivers of efficiency improvement and formulate targeted improvement measures to enhance the overall competitiveness of the bank. At the same time, regulators can also use the Malmquist Index to monitor and assess the overall efficiency of the banking industry, providing a reference basis for formulating scientific and reasonable regulatory policies.

3 SELECTION OF THE INDICATOR SYSTEM

When constructing the bank efficiency evaluation model based on DEA-Malmquist index, the selection of indicator system is crucial. A reasonable indicator system of can comprehensively and accurately reflect the operational efficiency of banks and its changes. It can be seen from Table 1 that, we need to start from both input and output aspects and carefully select representative indicators. In terms of input indicators, we can consider inputs of profitability, solvency and operating costs. Inputs can reflect the bank's capital strength and risk tolerance, reflecting the bank's human resource status and management level, while operating costs are directly related to the bank's operational efficiency and cost control ability. The selection of these input indicators helps us to gain a deeper understanding of the bank's resource allocation. In terms of output indicators, loan volume, deposit volume, profit and intermediate business income are common choices. Loan volume and deposit volume can visualize the bank's business scale and market share, while profit reflects the bank's profitability and operating results, and intermediate business income reflects the bank's efforts in financial innovation and service diversification. The selection of these output indicators helps us to comprehensively assess a bank's business performance and operational efficiency. Of course, the specific selection of indicators requires comprehensive consideration based on factors such as the purpose of the study, data availability, and the type of bank. Different banks differ in their business characteristics, operation strategies and market positioning, so the selection of the indicator system should also be targeted and flexible.

In summary, by carefully selecting input and output indicators, we can construct a bank efficiency evaluation model based on the DEA-Malmquist index, which provides powerful decision support for bank managers and regulators.

Table 1 Analysis Indicators of Eight Major Banks

Type of indicator	norm
Input indicators	Return on Equity REO Cost-to-income ratio net interest margin (NIM) net interest margin

Output indicators	capital adequacy ratio leverage Liquidity coverage ratio

4 EMPIRICAL STUDIES

4.1 DEA Static Analysis

Since the corporate information of major banks lacks the data required for the paper, this paper takes 2018~2023 as the research time, and selects 8 banks among the major banks in China as the object of this research, and the data comes from the Data Analysis of 149 Commercial Banks as well as the data statistics of each bank. Among them, by comparing and analyzing the profitability, solvency and comprehensive efficiency of each bank, the internal reasons affecting profitability and solvency as well as comprehensive efficiency are analyzed, and corresponding suggestions are given. The value of comprehensive efficiency is measured by the software and the data of each bank is obtained as shown in the table.

It can be seen from Table 2 that, it can be seen that most of the overall efficiency values of Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB), Agricultural Bank of China (ABC), Bank of China (BOC), China Everbright Bank (CGB), Postal Savings Bank of China (PSBC), Ping An Bank (PAB), and China Merchants Bank (CMB) have maintained a high level of overall efficiency values during the period of 2018 to 2023, which It shows the solid performance of these banks in terms of profitability, solvency and overall operational efficiency.

In particular, Ping An Bank's (PAB) comprehensive efficiency value declined year-on-year from 0.977 in 2018 to 0.820 in 2022, and although it rebounded to 0.850 in 2023, the declining trend in efficiency still needs to be watched and the reasons behind it analyzed in depth. The comprehensive efficiency value of China Merchants Bank (CMB) fluctuates considerably between 2018 and 2023, with a drop to 0.779 in 2020 but a rapid rebound to 1 in the following two years, suggesting that the bank has a strong ability to adjust and optimize its operational efficiency.

It is also worth noting that Postal Savings Bank of China (PSBC) had a slightly lower combined efficiency value of 0.975 in 2019 than in other years, which may be related to its business restructuring or market expansion during that period. However, the bank then quickly adjusted its strategy so that the combined efficiency value remained high at 1 in all the following years.

In summary, by measuring and analyzing the comprehensive efficiency values of major banks, we can find out the differences in operational efficiency of different banks and the reasons behind them. This will provide useful references for bank managers to formulate more scientific and reasonable operation strategies to enhance the comprehensive competitiveness of banks.

To better understand these differences, we further analyzed the input and output indicators of each bank. Specifically, input indicators include the number of employees, the number of business outlets, net fixed assets, and operating costs, while output indicators cover key financial indicators such as operating income, net profit, total loans, and total customer deposits.

By analyzing the input-output indicators, we found that an increase in the number of employees and the number of business outlets does not always lead to an increase in comprehensive efficiency. For example, while increasing the number of employees and outlets, certain banks have seen their operating costs rise due to poor management or fierce market competition, which in turn has affected their overall efficiency. On the contrary, some banks, by optimizing staffing and branch layout, have effectively reduced

Table 2 Consolidated Efficiency of the Eight Largest Banks by Year

	2018	2019	2020	2021	2022	2023
ICBC	1	1	1	1	1	1
CCB	1	1	1	1	1	1
CGB	1	1	1	1	1	1
PSBC	1	0.975	1	1	1	1
PAB	0.977	0.936	0.913	0.870	0.820	0.850
CMB	0.847	0.940	0.779	1	0.946	1
ABC	0.883	0.933	0.963	1	0.932	0.938
BOC	1	1	1	1	1	1

lowers operating costs and improves comprehensive efficiency. In addition, we also find that the impact of net fixed assets on comprehensive efficiency presents some complexity. On the one hand, the increase of fixed assets can enhance the service capacity and market competitiveness of banks, thus favoring the improvement of comprehensive efficiency; on the other hand, if the growth of fixed assets is too fast or improperly invested, it may also lead to the waste of resources and the decline of efficiency. In terms of output indicators, the growth of operating income and net profit is an important indicator of a bank's operational efficiency. We observe that banks with higher overall efficiency tend to achieve more robust growth in operating income and net profit. At the same time, increases in total loans and total customer deposits reflect a bank's market expansion and customer service capabilities, which have a positive effect on overall efficiency.

To sum up, through the in-depth analysis of input-output indicators, we can not only have a more comprehensive understanding of the operational efficiency of each bank and the reasons behind it, but also provide bank managers with more specific optimization suggestions. For example, for the allocation of the number of employees and the number of business outlets, it is suggested that banks should carry out reasonable planning according to the market demand and their own resources; in terms of investment in fixed assets, they should strengthen the assessment and supervision of investment projects to ensure the efficiency of the investment; and in terms of business expansion, they should focus on improving the quality of service and market competitiveness in order to realize the continuous growth of operating income and net profit.

4.2 Dynamic Analysis of the Malmquist Index

After conducting the DEA static analysis, we further utilize the Malmquist index to conduct dynamic analysis in order to examine the efficiency changes of major banks at different points in time.The Malmquist index can comprehensively reflect the technical efficiency changes and technological progress of the banks, which provides us with a more comprehensive perspective of efficiency evaluation, and the decomposition yields the following results:

Table 3 Average Malmquist Index and Decomposition of Efficiency of Top 8 Banks by Year 2018 to 2023

	effch	tech	pech	sech	tfp
2018-2019	1.012	1.073	1.023	0.989	1.087
2019-2020	0.982	1.041	0.977	1.006	1.023
2020-2021	1.034	0.969	1.042	0.992	1.002
2021-2022	0.977	1.057	0.984	0.993	1.033
2022-2023	1.012	1.045	1.012	1.000	1.057
average value	1.0034	1.037	1.0076	0.996	1.0404

As can be seen from Table 3, the average Malmquist index of the eight largest banks in China is 1.0404 during the period from 2018 to 2023, indicating that the overall efficiency of these banks has improved during this period. Specifically, the mean value of the technical efficiency change index (EFFCH) is 1.0034, indicating that the banks have slightly improved their technical efficiency, but the improvement is not significant. This may be related to the banks' efforts in resource allocation and management optimization, but there is still room for improvement. The mean value of the Technological Progress Index (TECHCH) is 1.037, indicating that banks have achieved more significant results in technological innovation and business model innovation, which is one of the key factors driving banks' efficiency improvement. Further analyzing the decomposition part of the Malmquist index, we find that the mean value of the pure technical efficiency change index (PECH) is 1.0076, and the mean value of the scale efficiency change index (SECH) is 0.996. this suggests that the contribution of pure technical efficiency to the overall efficiency improvement of the bank is slightly larger than that of scale efficiency. The improvement in pure technical efficiency may be related to the bank's improvement in internal management, process optimization, and technology application, while the change in scale efficiency may be related to the bank's business scale, market expansion, and the adjustment of resource allocation strategies.Between 2018 and 2023, the index of change in technical efficiency (EFFCH), the index of change in technical progress (TECHCH), and the index of change in pure Technical Efficiency Change Index (PECH) and Scale Efficiency Change Index (SECH), and Total Factor Productivity Change Index (TFP). These indices are calculated through the Malmquist index methodology and reflect the efficiency changes of the banks over time. The technical efficiency change index (EFFCH) measures the ability of banks to improve their productivity by optimizing resource allocation, improving management, etc. under given technological conditions. As can be seen from the table, most of the EFFCH values between years are close to 1, indicating that major banks have maintained a relatively stable performance in terms of technical efficiency. However, there are also individual banks that have experienced a decline in technical efficiency over certain time periods, which may be related to management and resource allocation within the banks. The Technical Progress Index (TECHCH) reflects the banks' promotion of productivity improvement through the adoption of new technologies and innovative business models. As can be seen from the table, there are certain fluctuations in the TECHCH value between different years , which reflects the dynamic changes in technological innovation and business model innovation in the banking industry. Some banks have made significant technological advances over a specific time period, which has contributed to the improvement in productivity. The Pure Technical Efficiency Changes (PECH) and Scale Efficiency Changes (SECH) indices are further subdivisions of the EFFCH.The PECH reflects the efficiency changes in banks at the pure technical level, while the SECH captures the efficiency impact of banks due to changes in scale. As can be seen from the table, the PECH and SECH values also fluctuate from year to year, but overall maintain a relatively stable performance. The Total Factor Productivity Change (TFP) index, which is a composite of the Malmquist indices, measures the overall change in the bank's productivity. As can be seen from the table, the TFP values show a certain increasing trend between years, which indicates that the major banks have improved their overall productivity. However, it is also important to note that individual banks have experienced a decline in TFP over certain time periods, which may be related to mismanagement and misallocation of resources within the banks, as well as changes in the external environment.

In summary, through the in-depth analysis of the Malmquist Index and its decomposition part, we can have a more comprehensive understanding of the specific performance of each bank in terms of efficiency changes and the extent of the influence of different factors on efficiency changes. This provides useful reference for bank managers to formulate more scientific and reasonable operation strategies to enhance the overall competitiveness of banks. At the same time, regulators can also use this information to monitor and evaluate the overall efficiency of the banking industry and provide a reference basis for formulating scientific and reasonable regulatory policies. In future research, we can further expand the application scope of the Malmquist Index by combining it with other economic indicators or financial data, in order to gain a deeper understanding of the internal mechanism and external influencing factors of efficiency changes in the banking industry. In addition, we can also try to combine the Malmquist Index with advanced technologies such as machine learning and artificial intelligence to develop a more accurate and efficient bank efficiency evaluation model, which can provide more powerful support for the development of the banking industry.

Meanwhile, for bank managers, in addition to focusing on the results of efficiency evaluation, they need to pay more attention to the process and path of efficiency improvement. Through in-depth analysis of the bank's internal management mechanism, resource allocation, technological innovation and other aspects of the problem, to formulate targeted improvement measures, and to strengthen internal management and supervision, in order to ensure the effective implementation of the improvement measures and continuous improvement. It is also necessary to pay close attention to changes in the external environment and make timely adjustments to its operating strategies and business model to adapt to changes in market demand and regulatory requirements.

Table 4 Malmquist Index and Decomposition of the Efficiency of the Eight Major Banks

	effch	tech	pech	sech	tfp
PSBC	1.000	1.083	1	1.000	1.083
PAB	0.973	1.024	0.997	0.978	0.996
ICBC	1	1.034	1	1	1
CMB	1.044	1.018	1.045	1.002	1.058
CGB	1	1.007	1	1	1.007
CCB	1	1.015	1	1	1.015
BOC	1	1.043	1	1	1.043
ABC	1.012	1.072	1.022	0.991	1.085
average value	1.003	1.037	1.008	0.996	1.035

As can be seen in Table 4, we also present the mean values of the Malmquist Index and its decomposition part for the major banks over the period 2018 to 2023. These mean values reflect the efficiency movement of the banks throughout the study period. As can be seen from the table, most of the EFFCH, TECHCH, PECH and SECH means of major banks are close to 1, indicating that these banks have maintained a relatively stable performance in terms of efficiency. However, there are also individual banks whose mean values of certain efficiency indices are below 1, indicating that there is room for improvement in specific aspects of efficiency of these banks.

From the decomposition perspective of the Malmquist Index, Postal Savings Bank of China (PSBC) has the highest TECHCH mean value of 1.083, indicating that the bank has made significant progress in technological innovation and business model innovation, which has driven the improvement of productivity. On the other hand, Ping An Bank (PAB) has a relatively low TECHCH mean value of 1.024, which has also increased, but is still a gap compared to other banks. In terms of pure technical efficiency change, China Merchants Bank (CMB) has the highest mean value of PECH at 1.045, which shows that the bank's efficiency improvement in pure technical level is more obvious. As for the change in scale efficiency, the mean value of SECH for all banks is mostly close to 1, indicating that the effect of scale change on efficiency is relatively small. The mean value of total factor productivity change index (TFP) reflects the changes in overall productivity efficiency of major banks. As can be seen from the table, China Merchants Bank (CMB) has the highest mean TFP value of 1.058, indicating that the bank has made the most significant improvement in overall productivity. Postal Savings Bank of China (PSBC) and Ping An Bank (PAB) also have relatively high mean TFP values of 1.083 and 0.996, respectively, indicating that these banks have achieved some results in improving productivity. However, it is also important to note that individual banks have TFP means below 1, indicating that these banks have experienced a decline in overall productivity and need to further strengthen their management and resource allocation in order to improve efficiency.

In summary, by analyzing the mean values of the Malmquist Index and its decomposition components, we can get a more comprehensive picture of the efficiency changes of each bank throughout the study period. This provides useful reference for bank managers to formulate more scientific and reasonable operation strategies to enhance the overall competitiveness of banks. At the same time, regulators can also use this information to conduct more in-depth monitoring and assessment of the overall efficiency situation of the banking industry. In the future, major banks should continue to focus on the importance and urgency of efficiency improvement. They should formulate targeted improvement measures to address current problems and deficiencies, and strengthen internal management and supervision to ensure effective implementation and continuous improvement of the improvement measures. On the one hand, banks should increase their efforts in technological innovation and business model innovation. Through the introduction of new technologies, optimization of business processes, and improvement of service quality, it promotes the improvement of productivity. At the same time, new business areas and market opportunities should be actively explored in order to expand the bank's business scope and enhance market competitiveness. On the other hand, banks should also strengthen internal management and optimize resource allocation. By improving the internal management mechanism, improving the quality of employees and optimizing the allocation of resources, the operational efficiency and management level of the bank can be enhanced. In addition, they should also pay close attention to the changes in the external environment and make timely adjustments to their operating strategies and business models to adapt to the changes in market demand and regulatory requirements. In terms of efficiency evaluation, banks can draw on the experience and results of this study to further improve the efficiency evaluation system and methods. By introducing more evaluation indicators and more scientific evaluation methods, the operational efficiency and management level of banks can be reflected more comprehensively. At the same time, the application and analysis of the efficiency evaluation results should be strengthened to provide bank managers with more accurate decision-making support.

4 CONCLUSION

Based on the DEA-Malmquist index methodology, this study provides an in-depth analysis and evaluation of the efficiency changes of the eight major banks in China between 2018 and 2023. By constructing an input-oriented CCR model and calculating the Malmquist index and its decomposition part, we obtained the efficiency changes of major banks and their influencing factors in different time periods. The results of the study show that the overall efficiency of the eight major banks in China has improved during this period, with technological progress being one of the key factors driving the efficiency improvement. At the same time, the major banks show some stability and volatility in technical efficiency, pure technical efficiency and scale efficiency. By comparing the mean values of the efficiency indexes of different banks, we find that banks such as China Postal Savings Bank and China Merchants Bank are more outstanding in terms of technological innovation, pure technological efficiency enhancement and overall productivity enhancement, while some other banks need to further strengthen their management and resource allocation in order to enhance their efficiency. In view of the current problems and deficiencies, we put forward the following suggestions: first, banks should increase their efforts in technological innovation and business model innovation to promote the improvement of productivity; second, they should strengthen their internal management and optimize resource allocation to improve their operational efficiency and management level; finally, they should pay close attention to the changes in the external environment and promptly adjust their business strategies and business models to adapt to the market demand and regulatory requirements of the Changes. In future research, we can further expand the application scope and methodology of Malmquist Index to provide more accurate and efficient support for the development of the banking industry. At the same time, bank managers should also pay attention to the results and application of efficiency evaluation to formulate scientific and reasonable operation strategies to enhance the comprehensive competitiveness of banks.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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REFERENCES

[1] Zhong Shihe, He Yinghua, Wu Yan. A study on the dynamic relationship between bank efficiency and risk based on the improved SFA model - Empirical evidence from 16 listed commercial banks in Chin. Statistics and Information Forum, 2018, 33(12):30-36.

[2] XU Zhong, SHEN Yan, WANG Xiaokang. Market structure and the performance of China's banking industry:hypotheses and tests. Economic Research, 2009, 11(10):75-86.

[3] Chi Guotai, Yang De, Wu Shanshan. A Study on the Comprehensive Efficiency of Chinese Commercial Banks Based on DEA Methodology. China Management Science, 2006, 14(5): 52-61

[4] Li Xiaofeng, Wang Wei, Yan Jiajia. An empirical analysis of the impact of foreign bank entry on the efficiency of banks in China. Financial Science, 2006: 16-23.

[5] Zou Jiang, Zhang Weiran, Xu Yinghong. A comparative study of the income structure of Chinese and foreign commercial banks. International Financial Studies, 2004(12).

[6] Zhu Taihui, Chen Lu. Research on Potential Risks and Regulatory Response of Fintech. Research on Financial Regulation, 2016(7):18-32.

[7] Li Wenliang. A study on the relationship between internet finance and commercial banks' innovation performance:an analysis based on MOA theory perspective. Financial Theory and Practice, 2017(2):42-46.

[8] Zhang F. Analysis of efficiency and asset quality of policy banks. Local Finance Research, 2014(7): 71 - 74.

[9] Li Mingdi. An Empirical Study on the Efficiency of City Commercial Banks in China Based on DEA Methodology. Shanghai Finance, 2005(12): 106-108 .

[10] Jin Sujun. Research on the Efficiency of City Commercial Banks in Henan Province Based on Data Envelopment Analysis (DEA) Model. Financial Theory and Practice, 2013(10): 61-64.

[11] Wang Shuguang. Internet finance and the advent of financial inclusion era. Chinese Financier, 2015(10):123-124.

[12] Bai Qinxian, Gao Xia. Reflections on the development of inclusive finance. China Finance, 2016(3): 45-47.

[13] Xue Feng, Yang Deli. A DEA model for evaluating the comprehensive efficiency of bank operation and management. Research on Quantitative Economics and Technical Economics, 1998(5): 63-66.

[14] Zhang Jianhua. DEA methodology for the study of the efficiency of commercial banks in China and empirical analysis of the efficiency from 1997 to 2001. Financial Research, 2003(3): 11-25.

[15] Dai Guoqiang, Fang Pengfei. Regulatory Innovation Interest Rate Marketization and Internet Finance. Modern economic exploration, 2014(7):64-67.

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EMPOWERING THE ENTIRE AGRICULTURAL VALUE CHAIN WITH DIGITAL TECHNOLOGIES: A MECHANISM STUDY ON DRIVING LEAPS IN NEW QUALITY AGRICULTURAL PRODUCTIVITY

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Abstract: In the context of the information age, digital technology is profoundly empowering the entire agricultural value chain, driving a qualitative leap in agricultural productivity across production, processing, circulation, and sales. This paper first constructs a theoretical framework for digital agriculture, systematically outlining the application pathways of key technologies such as the Internet of Things, big data, artificial intelligence, and blockchain in monitoring the agricultural production environment, precision irrigation and fertilization, pest and disease prediction and control, intelligent processing and quality traceability, cold chain logistics optimization, and precision marketing and interaction. Secondly, through typical cases, it verifies the significant effects of digital technology on indicators such as water saving, pesticide reduction, loss reduction, lower defect rates, reduced spoilage rates, and lower transportation costs. Finally, based on four mechanisms—technological innovation, data-driven decision-making, industrial chain synergy, and market responsiveness—it proposes policy recommendations for building rural networks and big data platforms, strengthening talent cultivation and recruitment, increasing special funds and financial support, improving standards and data security, and promoting industrial synergy. This research provides theoretical support and practical pathways for the digital transformation and high-quality development of agriculture.
Keywords: Digital technologies; Entire agricultural value chain; New quality agricultural productivity; Industrial synergy; Policy framework

1 INTRODUCTION

In today's information age, the rapid advancement of digital technology is profoundly reshaping the global economic structure, particularly in traditional sectors like agriculture. The relationship between digitalization and agricultural development has grown increasingly close, not only revolutionizing agricultural production but also injecting new vitality into the entire value chain from production to consumption. By enhancing production efficiency, optimizing resource allocation, and strengthening market competitiveness, the application of digital technology is driving a qualitative leap in agricultural productivity. As a major agricultural nation, China has consistently prioritized agricultural modernization in its national development. Driven by digitalization, Chinese agriculture is undergoing a profound transformation. The application of digital technology has expanded from isolated production segments to the entire value chain, encompassing crop cultivation, animal husbandry, processing, logistics, and sales. First, in agricultural production, technologies like smart agriculture and precision agriculture leverage IoT, big data, and cloud computing to enable real-time monitoring and intelligent regulation of crop growth environments, effectively increasing yields and quality. Second, in processing and logistics, digital applications improve efficiency, accelerate logistics, reduce costs, and ensure product quality. In sales, the rise of e-commerce platforms and social media has opened broader markets for agricultural products and enhanced their competitiveness. Despite notable achievements, gaps persist compared to developed countries. China's agricultural digital infrastructure remains underdeveloped, technology penetration is low, and digital integration across the industry chain remains fragmented—all constraining agricultural modernization. Therefore, this paper aims to explore how digitalization empowers the entire agricultural value chain and proposes pathways to drive a new qualitative leap in productivity. Theoretically, it enriches the framework of agricultural modernization and digital empowerment by analyzing how digital technologies embed into the value chain, offering new perspectives and empirical evidence. Practically, it provides actionable insights for China's agricultural digital transformation, serving as a reference for policymakers and agribusinesses. By identifying key empowerment mechanisms and drivers, this study offers theoretical and practical support for achieving high-quality agricultural advancement, thereby accelerating industrial upgrading and contributing to rural revitalization.

2 THEORETICAL FRAMEWORK AND VALUE CHAIN SYSTEM OF DIGITAL AGRICULTURE

2.1 Theoretical Basis of Digital Empowerment in Agriculture

2.1.1 Application theories of digital technology in agriculture

The Internet of Things (IoT) employs various information sensors, RFID, GPS, infrared sensors, laser scanners, and other devices to collect real-time data—such as sound, light, heat, electricity, mechanical force, chemistry, biology, and location—from objects or processes requiring monitoring, connection, or interaction. By enabling ubiquitous connectivity between objects and humans through diverse networks, IoT achieves intelligent perception, identification, and management. In agriculture, IoT facilitates real-time monitoring of the production environment. For example, deploying temperature-humidity sensors, light sensors, and soil moisture sensors in greenhouses captures environmental parameters and transmits them to control centers. Farmers can remotely regulate ventilation and irrigation systems based on this data, enabling precision agricultural management. Additionally, IoT supports product traceability. Electronic tags record information across planting, breeding, processing, and logistics stages, allowing consumers to scan labels for detailed product information, thereby enhancing trust in quality.

Big data refers to massive, high-growth, diversified information assets that cannot be captured, managed, or processed by conventional software within a specific timeframe, requiring new processing models to enhance decision-making, insight discovery, and process optimization. In agriculture, big data integrates production, market, weather, and other datasets. Analyzing production data—such as soil fertility and crop growth cycles—provides precise fertilization and irrigation recommendations, boosting yield and quality. Market data analysis helps farmers understand demand and price trends, optimizing planting and breeding plans to avoid overproduction. Meteorological big data enables early disaster warnings, allowing preemptive measures to minimize losses.

Artificial intelligence (AI) is a technological science focused on developing theories, methods, and applications to simulate and extend human intelligence. In agriculture, AI is primarily applied to image recognition and robotics. Agricultural image recognition analyzes crop images to identify pests, diseases, and growth status. For instance, deep learning algorithms can diagnose infected leaves and determine pathogen types, offering targeted control strategies. Agricultural robots perform repetitive or labor-intensive tasks—such as fruit picking and weeding—using advanced sensors and AI algorithms to autonomously recognize crops and environments, efficiently executing production tasks.

Blockchain is a distributed, shared ledger and database characterized by decentralization, immutability, traceability, collective maintenance, and transparency. In agriculture, it ensures quality traceability and supply chain management. Blockchain records immutable, traceable data from production to consumption. Consumers scan QR codes to access details on farming practices, pesticide/fertilizer use, and logistics, guaranteeing product safety. For supply chains, blockchain enhances transparency and efficiency, reduces fraud, and lowers transaction costs.

2.1.2 Impact of digital technology on agricultural value chain segments

Digital technology has enabled more precise and intelligent agricultural production. Traditional farming often relies on experiential practices for fertilization and irrigation, leading to resource waste and environmental pollution. Applications like IoT and big data now enable real-time monitoring of soil fertility and moisture levels, allowing precise delivery of nutrients and water based on crop needs to enhance resource efficiency. Meanwhile, AI and agricultural robots reduce labor dependency while improving productivity and quality. For example, large-scale farms deploy robots for seeding and weeding, achieving high-speed, high-precision operations that ensure crop growth quality. Digital tools also facilitate early pest/disease detection and control, minimizing yield and quality losses.In processing, digital technology automates and intellectualizes production. IoT monitors equipment parameters (e.g., temperature, pressure) in real time, triggering alerts and corrective actions for anomalies[1]. Big data analytics optimize processing techniques by analyzing batch data—identifying ideal parameters to improve product texture and quality. Blockchain records immutable processing data, ensuring transparency and traceability to boost consumer trust.For circulation, digital solutions optimize logistics and supply chains. IoT enables real-time monitoring of transport conditions (e.g., temperature/humidity in cold-chain vehicles) to preserve product quality. Big data analyzes market demand and logistics patterns, optimizing distribution routes and inventory management—reducing spoilage and costs by aligning supply with regional demand. Blockchain enhances supply chain transparency and trust, lowering transaction costs through shared, tamper-proof records of every transfer. Figure 1 illustrates the mechanism through which digital technology empowers new qualitative leaps in agricultural productivity.

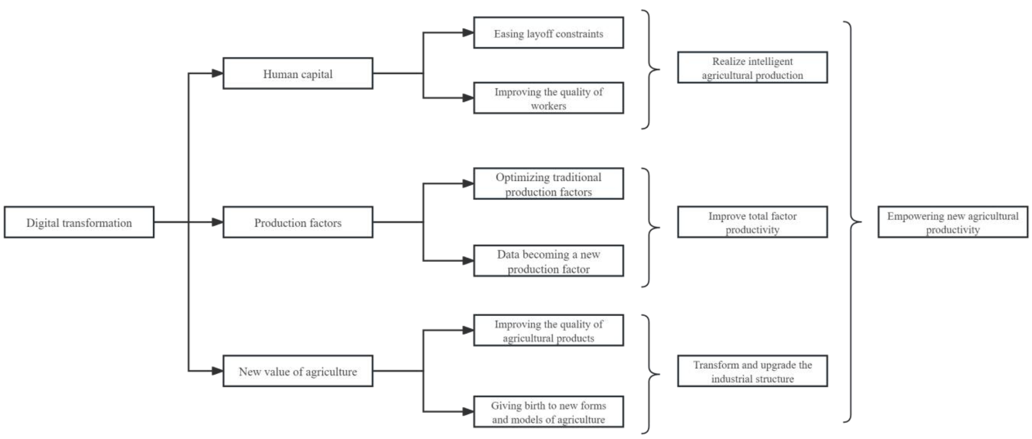

Figure 1 The Mechanism of Digital Transformation Empowers New Agricultural Productivity

Digital technology has introduced new models and channels for agricultural product sales. The rise of e-commerce platforms enables farmers to directly reach consumers nationwide and globally, expanding market access. Through online platforms, farmers can showcase products, communicate directly with consumers to understand preferences and feedback, and promptly adjust production and sales strategies. Simultaneously, big data technology analyzes consumer purchasing behavior and preferences to develop precision marketing strategies—for instance, recommending products aligned with tastes based on purchase history and search records. Emerging models like livestream commerce have also rapidly developed through digital means, leveraging host demonstrations to enhance sales effectiveness.In summary, the application of digital technology in agriculture rests on a solid theoretical foundation and profoundly impacts every segment of the agricultural value chain. These effects enhance production efficiency, improve product quality, reduce costs, and propel agriculture toward modernization and intellectualization.

2.2 Concept and Composition of the Entire Agricultural Value Chain

The entire agricultural value chain in agriculture refers to a collection of interconnected and interdependent value-creation activities spanning from the input of agricultural production materials through the production, processing, and circulation of agricultural products until the final sale to consumers. It transcends the mere physical flow of products "from farm to table," encompassing a multidimensional complex system involving information transfer, capital flow, and value addition. Emphasizing the holistic and systemic nature of the agricultural industry, it treats all production segments as an organic whole where each stage impacts the final product's value. By integrating these segments, resources can be optimally allocated, agricultural productivity enhanced, and product value increased—ultimately strengthening the competitiveness and economic returns of the entire agricultural sector. Compared to traditional agricultural supply chains, the entire value chain prioritizes synergistic development and co-creation of value across stages. It addresses not only production and sales but also pre-production activities (e.g., input supply, R&D), mid-production management (e.g., cultivation, breeding), and post-production processes (e.g., processing, packaging, logistics, marketing). Simultaneously, it centers on consumer demand and preferences, enabling market-oriented, differentiated, and personalized production to meet diverse needs[2].

The production segment forms the foundation of the entire agricultural value chain, directly determining the quantity and quality of agricultural products. This stage involves inputs such as seeds, fertilizers, pesticides, and machinery, alongside applied technologies like cultivation, breeding, and irrigation techniques. Producers select crop or livestock varieties based on market demand and natural conditions, implementing scientific management practices. Emphasis is placed on ecological sustainability—adopting green and organic methods to reduce chemical inputs while enhancing product quality and safety. Modern technologies like IoT and big data enable intelligent, precision management to boost efficiency and resource utilization. Processing serves as the key value-adding stage, transforming products' form, function, and shelf life to increase their worth. It includes two tiers: primary processing (cleaning, grading, packaging) to preserve freshness and facilitate storage/transport, and deep processing (extraction, concentration, fermentation) to yield high-value outputs like foods, beverages, and nutraceuticals. Innovation in technology and equipment is essential to improve quality, with stringent safety controls ensuring regulatory compliance. Circulation bridges production and consumption, enabling spatial transfer and temporal adjustment of products through procurement, transportation, storage, and distribution. Procurement involves contractual agreements between producers and brokers/traders. Transportation modes (road, rail, water, air) are selected based on product characteristics and distance to ensure safety and timeliness. Storage utilizes modern facilities for preservation and supply regulation, while distribution employs efficient logistics to deliver products to retailers, markets, and food service providers. Innovations like e-commerce and cold-chain logistics expand market reach through online-offline integration. Sales, the final stage, determines market value and economic returns. Strategies are tailored to consumer preferences via traditional channels (supermarkets, wholesale markets—broad coverage, high trust) and emerging channels (e-commerce, community group buying, livestream sales—speed, cost-efficiency, interactivity). Brand building and marketing enhance visibility and competitiveness. Additionally, the value chain includes pre-production segments (input supply, R&D) providing essential materials and technological support, and post-production segments (after-sales service, consumer feedback) enabling continuous optimization through demand insights.

2.3 Current Research Status of Digital Empowerment in Agricultural Value Chains: Domestic and International Perspectives

International scholars have focused earlier on applying digital technologies in agricultural production. Precision agriculture represents a key research area, with numerous studies concentrating on technologies like satellite remote sensing, Geographic Information Systems (GIS), and Global Positioning Systems (GPS). Smith notes that satellite remote sensing enables real-time monitoring of soil moisture and crop growth, assisting farmers in precise fertilization and irrigation to enhance efficiency and resource utilization [3]. Additionally, sensor technology has been extensively studied; sensors installed on machinery or livestock collect environmental parameters and animal health data in real time, supporting intelligent production decisions.

In agricultural circulation, digital technologies primarily optimize supply chain management and product traceability. International scholars emphasize blockchain's role in traceability, enabling end-to-end information recording and sharing to improve supply chain transparency and credibility. Jones' research demonstrates blockchain's effectiveness in addressing quality safety issues and strengthening consumer trust. Simultaneously, IoT technology is widely adopted for monitoring temperature and humidity during logistics, ensuring product quality and freshness.

Some scholars explore digitalization's impact on agricultural value chain integration. Digital technologies facilitate information sharing and collaboration among agribusinesses, breaking down information silos between traditional value chain segments. Brown's study finds that digital platforms enable tighter integration among production, processing, and sales entities, allowing resource sharing and complementary advantages to boost overall competitiveness [4]. To reflect global prioritization of smart agriculture, key recent initiatives or legislation from Japan, the EU, and the US are briefly summarized in Table 1.

Table 1 Important Bills or Plans Related to Smart Agriculture in Europe, America and Japan in Recent Years

Country/Organization	Important bills or plans related to smart agriculture	Content related to smart agriculture
USA	Agriculture Improvement Act Precision Agriculture Connectivity Act Agricultural Innovation Agenda Sustained Agricultural Research and Education Act	Approved by the U.S. Congress on December 20, 2018, and implemented by the U.S. Department of Agriculture (USDA); emphasizes the application of agricultural technology and data management, promotes the research and development of smart agriculture and precision agriculture technology. As part of the 2018 Agriculture Improvement Act, it aims to promote high-speed Internet coverage of U.S. farmland and support the technical needs of smart agriculture, such as data collection, analysis and instant decision support. Launched by the USDA in February 2020, it aims to stimulate innovation in the agricultural sector, including by improving resource utilization efficiency, promoting the development of precision agriculture and smart agriculture technology, and promoting the sustainability of agriculture through science and technology, including the practice of smart agriculture, such as using big data and AI to optimize resource utilization and production efficiency.
European Union	European Green Deal Common Agricultural Policy (CAP) 2021-2027 EU Digital Agriculture Strategy	On December 11, 2019, the European Commission proposed that smart agriculture be included in the discussion as part of achieving a sustainable food system, aiming to improve agricultural efficiency and reduce environmental impact through technology and innovation. This policy covers a wide range of agricultural topics, but one of the focuses is smart agriculture and digital transformation, encouraging the use of advanced technologies and practices to improve agricultural sustainability and competitiveness. The EU Research and Innovation Framework Program, launched in 2021, provides funding for smart agriculture to support research and innovation in related fields. It aims to promote policy formulation and investment related to smart agriculture.
Japan	"Society 5. 0" strategy Ministry of Agriculture, Forestry and Fisheries' smart agriculture promotion plan Agricultural production base strengthening plan Agricultural Comprehensive Strategy (2020 edition)	Smart agriculture is seen as a key part of achieving efficient and sustainable agricultural production in the Society 5.0 strategy. It aims to improve agricultural productivity and domestic agricultural competitiveness by utilizing advanced technologies such as ICT (information and communication technology), big data and artificial intelligence. The Japanese government released it on December 10, 2019. It aims to strengthen the foundation of agricultural production and promote the development of smart agriculture, including the implementation of smart agriculture and the promotion of digital policies. It also promotes a number of measures to promote smart agricultural solutions, including encouraging innovation, providing financial support and simplifying the regulatory framework to promote the deployment of new technologies and services.

Since 2019, China has successively issued the *Digital Rural Development Strategy Outline*, the *"14th Five-Year Plan" for Digital Economy Development*, the *Digital Agriculture and Rural Development Plan (2019–2025)*, and the *Digital Rural Development Action Plan (2022–2025)*, vigorously promoting smart agriculture, digital agriculture, and digital rural construction from the policy level to accelerate digital transformation in agriculture and rural areas. Domestic scholars have also extensively researched the application of digital technologies across agricultural segments. The formation and development of new qualitative productive forces in agriculture not only effectively overcome inherent agricultural vulnerabilities (Gong Binlei, Yuan Lingran, 2024)but also serve as a critical pathway to common prosperity for farmers[5]. As agricultural digitalization advances, it significantly reshapes the material and social attributes of these new productive forces (Gao Yuan, Ma Jiujie, 2024)[6], directly impacting total factor productivity (TFP). By facilitating revolutionary technological breakthroughs, innovative factor allocation, and industrial transformation, agricultural digitalization substantially enhances TFP through increasing the marginal returns of agricultural inputs[7]. This positions digital transformation as a key driver for developing new agricultural productive forces, profoundly influencing common prosperity via rural economic growth (You Liang, Tian Xiangyu, 2024)[8]. In production, AI aids crop disease/pest diagnosis and prediction; image recognition enables rapid, accurate identification, providing timely control advice while reducing pesticide use and improving product quality. In circulation, e-commerce platforms create new sales channels, eliminating intermediaries and raising farmer income while expanding market reach and fostering brand development. Domestic research also explores pathways for digital empowerment of agricultural value chain upgrading. Studies propose establishing digital agricultural platforms to integrate resources and enable synergistic development, requiring collaborative efforts among government, enterprises, and farmers. Digital finance is recognized as vital for providing financing support. Additionally, digital technologies reshape relationships among value chain actors: digital platforms foster stable "contract farming" partnerships between cooperatives and processors, enhancing farmer organization and bargaining power. Despite progress, research gaps persist. Most studies focus on isolated segments rather than systemic integration across the entire chain (e.g., seamless coordination from production to sales). Performance evaluation remains understudied, lacking robust metrics to quantify economic, social, and ecological impacts (e.g., precise contributions to efficiency gains or farmer income). Emerging risks (cybersecurity, data privacy) and mitigation strategies are inadequately addressed. Regional disparities in development levels, infrastructure, and policy contexts—affecting digitalization outcomes—require further comparative analysis to inform tailored strategies.

3 ANALYSIS OF PATHWAYS FOR DIGITAL EMPOWERMENT IN THE ENTIRE AGRICULTURAL VALUE CHAIN

3.1 Digital Applications in Production

In agricultural production, digital technologies such as IoT and big data play pivotal roles, driving transformative changes that significantly enhance efficiency and quality. IoT enables real-time soil moisture monitoring through field-deployed sensors. Data transmitted to smart control systems trigger automatic irrigation based on preset thresholds. For instance, in wheat fields, the system activates irrigation when moisture falls below optimal levels, enabling precise water supplementation. This approach prevents over-irrigation (reducing water waste and soil degradation) and under-irrigation (avoiding growth impairment), ensuring optimal hydration across growth stages to boost yield and quality while maximizing water-use efficiency.

In greenhouse cultivation, IoT monitors and auto-adjusts temperature, humidity, light, and CO_2 concentration. For example, in smart flower greenhouses, sensors trigger ventilation/shading when temperatures rise or CO_2 generators when levels drop, maintaining stable conditions that minimize pest incidence, accelerate growth, and enhance quality—resulting in brighter, longer-lasting blooms with higher market value.

In livestock farming, IoT-enabled wearables (collars, ear tags) track physiological indicators like body temperature and activity. Abnormalities trigger alerts for immediate intervention. For instance, detecting elevated temperature and reduced mobility in cattle allows prompt treatment, curbing disease spread, lowering mortality, and raising profitability[9].

Production Decision Support: Big data integrates meteorological, soil, and crop growth data to provide scientific guidance. Analyzing historical climate and yield data predicts optimal planting times and varieties regionally. For maize cultivation, it recommends suitable hybrids and practices based on local conditions, boosting yield and quality. Market trend analysis also helps farmers align planting plans with demand to avoid oversupply.

Pest/Disease Prediction and Control: Big data constructs predictive models using historical pest data, weather patterns, and crop growth stages. Early warnings enable targeted interventions—e.g., forecasting outbreaks allows farmers to prepare pesticides and equipment, reducing crop damage, chemical usage, and safety risks.

Quality Traceability: Big data establishes traceability systems documenting inputs (fertilizers, pesticides, feed), harvesting, processing, and logistics. Consumers scan QR codes to access full lifecycle information, enhancing transparency and trust while incentivizing producers to prioritize safety.

In summary, IoT and big data technologies deliver multifaceted benefits: heightened efficiency, reduced costs, improved quality, and sustainable modernization.

3.2 Digital Upgrading in Processing

Automated equipment and robots are proliferating in processing. In fruit sorting, machines use cameras and AI to rapidly classify by size, color, and shape, removing substandard produce to ensure uniform quality—increasing efficiency while reducing human error and damage. In meat processing, robots execute precise cutting/packaging tasks under preset parameters, ensuring consistency and operating reliably in harsh environments to reduce labor hazards.Digital technologies enable real-time production monitoring and optimization. Sensors on assembly lines track temperature, humidity, pressure, and flow rates. Data feeds into control systems where managers oversee operations via dashboards. Deviations trigger automatic alerts and adjustments—e.g., in winemaking, precise environmental control during fermentation enhances flavor. Data analytics further identifies process improvements to boost efficiency and quality[10].

Blockchain provides reliable quality traceability. Each processing step—from raw material procurement to finished goods—is immutably recorded. Batch-specific QR codes allow consumers to access details like ingredient origins, processing logs, and test reports. This transparency builds trust and enables rapid issue tracing.

Digital tools revolutionize food safety testing. Spectral analysis rapidly detects pesticide residues and heavy metals by analyzing light signatures, replacing slow traditional methods. IoT-based monitoring systems deploy sensors across facilities to track temperature, humidity, and microbial levels in real time, triggering instant alerts for anomalies.Big data analytics uncover market trends and consumer preferences. By studying purchase records, social media, and surveys, processors identify unmet needs—e.g., demand for low-sugar or high-fiber foods—guiding R&D and recipe optimization. Customization also thrives: direct consumer engagement enables personalized products (e.g., bespoke juice blends), supported by agile digital production systems that ensure quality and delivery timelines.Digital platforms facilitate supply chain collaboration. Shared management systems synchronize real-time data on material supply, production progress, and inventory among processors, suppliers, and distributors. For instance, predictive procurement orders align with production schedules, while sales monitoring informs inventory adjustments, enhancing flexibility.

Smart logistics amplify product value. IoT tracks vehicle location, speed, and cargo conditions in transit, enabling dynamic routing. Automated warehousing employs robots for efficient storage/retrieval and adjusts environmental parameters (temperature/humidity) to preserve quality, minimizing handling errors and costs.

3.3 Digital Optimization of Distribution Links

3.3.1 Digital integration of the agricultural products supply chain

Build a digital information–sharing platform covering all links of agricultural products production, processing, transportation, and sales. On the production side, farmers can upload planting information such as planting dates, fertilizer and pesticide usage, and estimated yields; processing enterprises can display their processing capacity and product types on the platform; logistics companies can provide real-time data on vehicle locations and transport capacity. Through this platform, all participants can obtain the information they need in real time, achieving coordinated operation of the supply chain. For example, retailers can use the platform's production progress and transportation status of agricultural products to plan replenishment in advance, reducing stock-out incidents. By applying big-data analytics to deeply mine the platform's information, one can analyze sales trends and price fluctuation patterns of agricultural products, providing decision support for farmers and enterprises. For instance, by analyzing historical sales data to forecast market demand for a particular agricultural product over a future period, farmers can adjust planting scale and varieties according to the forecast, avoiding overproduction and unsold inventory. Introduce blockchain technology to ensure the authenticity and traceability of agricultural product circulation information[11]. From the source of the products onward, every link's information is recorded on the blockchain; consumers can scan a QR code on the product to query detailed information on origin, production process, and transportation path, enhancing trust in product quality. At the same time, blockchain technology aids regulatory authorities in supervising product quality; once an issue is detected, it can be traced back to the source swiftly. Achieve automated operations across supply-chain links. For example, in warehousing, adopt automated storage systems to automatically store and retrieve goods, improving warehouse utilization and inbound/outbound efficiency. In transportation, use intelligent dispatch systems that automatically plan optimal transport routes based on cargo volume, destination, and vehicle locations, reducing transport costs and time.

3.3.2 Digital upgrade of logistics and distribution

Employ Internet of Things technology to realize intelligent warehouse management. Install various sensors in warehouses to monitor temperature, humidity, and storage status of goods in real time. When environmental parameters exceed set ranges, the system automatically issues alerts and takes corrective measures to ensure storage quality of agricultural products. For perishables requiring cold storage, sensors monitor temperature to keep it within appropriate ranges. Adopt a Warehouse Management System (WMS) for refined management of warehouse operations. A WMS can automate inbound, outbound, and inventory operations, improving accuracy and efficiency. It can also interface with the supply-chain information-sharing platform for real-time inventory updates, allowing all parties to grasp stock levels promptly. Promote the use of smart transport equipment, such as vehicles equipped with GPS and sensors. Through GPS, logistics companies can track real-time vehicle locations and driving status, optimizing routes and boosting efficiency. Sensors monitor speed, load, and cargo condition to ensure safety and quality; for example, if a vehicle speeds or cargo vibrations exceed thresholds, the system alerts operators. Develop digital monitoring for cold-chain logistics. For perishable goods transport, establish a cold-chain logistics monitoring platform to track temperature and humidity of transport equipment in real time. If temperatures deviate, the platform immediately notifies relevant personnel to take action, ensuring quality and safety during transport. Meanwhile, use big-data analytics on cold-chain operation data to optimize transport schemes and reduce costs.

3.3.3 Digital expansion of agricultural products sales channels

Encourage farmers and agri-enterprises to join e-commerce platforms and open online stores, broadening sales channels. E-commerce offers vast reach and low sales costs, allowing products to reach national or even global markets. Platforms also provide data-analysis services to help farmers and enterprises understand consumer demand and preferences, optimizing sales strategies. Use live-streaming to promote sales: invite influencers or product ambassadors to livestream, showcasing product features, origin environment, and production process to attract viewers and purchases. Live-streaming enables real-time interaction, answering consumer questions to boost purchase intent. For example, some impoverished regions have successfully marketed local specialty products via live-streaming. Develop community-group buying models, organizing bulk purchase and delivery by neighborhood. This reduces intermediaries and sales costs, while meeting consumer demand for fresh produce. Farmers and enterprises can align production and delivery with community orders, improving planning and precision. Promote "order farming" through digital platforms connecting farmers and enterprises. Enterprises place orders based on market demand, and farmers produce accordingly.

Order farming secures sales channels and lowers farmers' market risks, while ensuring stable raw-material supply for enterprises. For instance, large food processors sign order contracts with farmers to guarantee quality and quantity of inputs.

3.3.4 Evaluation of cost reduction and efficiency improvement

Establish a cost-accounting system to detail distribution costs before and after digital optimization, including logistics, warehousing, and sales costs, analyzing the impact of digital technologies on each[12]. For example, compare transport costs before and after to assess the effectiveness of intelligent transport equipment and routing systems; compare warehousing costs to evaluate benefits of smart warehousing systems. Assess overall benefits by examining increases in sales revenue and cost reductions. For instance, analyze revenue growth from e-commerce and live-streaming, and cost savings from supply-chain coordination and improved logistics efficiency, to calculate net benefit of digital optimization. Set efficiency indicators—such as inventory turnover rate, order-processing time, and transport time—to evaluate distribution efficiency before and after optimization. By comparing these metrics, measure how digital technologies enhance distribution performance; for example, calculate warehouse turnover to assess inventory management improvements, and measure order-processing time to gauge the information-sharing platform's impact on order speed. Collect user feedback to understand satisfaction and suggestions from farmers, enterprises, and consumers regarding digital optimization. Through feedback, identify issues and shortcomings in the process and make timely improvements. For example, use surveys to gauge consumer satisfaction with digitally expanded sales channels and evaluations of product quality and delivery service.

3.4 Digital Innovation in the Sales Link

3.4.1 E-commerce platforms: expanding sales channels and market coverage

In agricultural sales, e-commerce platforms divide into comprehensive platforms and vertical agri-product platforms. Comprehensive platforms like Taobao and JD.com have large user bases and rich traffic, offering wide exposure for products. For example, Taobao's massive user community spans regions and consumer tiers; after listing, sellers can reach hundreds of millions of potential buyers. Vertical platforms such as Benlai Life focus on agri-products, with users more attentive and willing to purchase, facilitating targeted promotion. Traditional sales rely on offline markets and wholesalers, limiting reach to local or nearby areas. E-commerce overcomes geographic barriers, enabling products to reach national and global consumers. For instance, Gannan navel oranges sell not only in major domestic cities but also overseas via e-commerce. Platforms open new sales avenues and reduce intermediaries, allowing farmers to sell directly to consumers and increase profits. On these platforms, products can be showcased with high-quality images, detailed descriptions, and user reviews to highlight unique features and build brands. Specialty items like Wuchang rice and Yantai apples have raised brand awareness and reputation through e-commerce, enabling consumers to choose trusted products and fostering brand loyalty.

3.4.2 Precision marketing: achieving efficient matching between products and consumers

Precision marketing, based on big-data analytics, deeply understands consumer needs, preferences, and behaviors. By collecting users' browsing history, purchase records, and search keywords on e-commerce platforms, and applying advanced analytics, platforms can accurately target products. For example, for consumers who prefer organic vegetables, the platform can push relevant promotions to enhance targeting and effectiveness. Based on targeting results, sellers can launch personalized campaigns—offering first-order discounts to new users and exclusive perks to returning customers. Additionally, use social media for interactive marketing by sharing engaging stories, images, and videos to attract attention and participation, strengthening emotional connections between consumers and products. Precision marketing also involves effective customer-relationship management. By building customer databases and recording purchase information and feedback, sellers maintain long-term communication. Promptly responding to inquiries and complaints improves satisfaction and loyalty. For example, regularly sending care tips or new-product recommendations enhances consumer knowledge and goodwill.

3.4.3 Live streaming: visual demonstration and real-time interaction

In recent years, live streaming has become a new hotspot for agri-product sales. Hosts demonstrate features, growing environments, and usage methods in real time, offering consumers an intuitive understanding. In fruit streams, hosts taste fruits on camera to show taste and freshness, boosting purchase desire. During streams, viewers interact via comments and bullet screens, asking questions and stating needs; hosts answer professionally, enhancing engagement and trust. Streams may include time-limited offers or giveaways to stimulate purchases and drive rapid sales.

3.4.4 Digital supply-chain management: ensuring sales stability

Logistics is a critical link in agricultural sales; digital management improves efficiency and service quality. With logistics information systems, sellers can track transport status in real time, ensuring timely and fresh delivery. For perishable items like seafood and meat, cold-chain logistics provides full-process low-temperature transport to maintain quality. Using digital technologies, sellers achieve precise inventory management. By analyzing and forecasting sales data, they arrange stock levels to avoid overstock or shortages. Inventory-management systems monitor levels in real time and issue replenishment alerts when below safety thresholds, ensuring continuity of sales.

3.4.5 Construction of a digital credit system: enhancing consumer trust

In agricultural sales, building a digital credit system is vital. E-commerce platforms can establish credit-rating mechanisms for sellers and farmers based on consumer evaluations and feedback. Introduce third-party certification for quality and safety—such as green-food and organic certifications—to provide reliable references and boost consumer confidence. Blockchain's decentralization, immutability, and traceability suit credit-system construction: record production, processing, and circulation information on the chain; consumers scan QR codes to view a product's full lifecycle, ensuring quality and safety and further enhancing trust[13].

4 MECHANISMS BY WHICH DIGITAL EMPOWERMENT DRIVES A NEW QUALITY LEAP IN AGRICULTURAL PRODUCTIVITY

4.1 Technology-Innovation-Driven Mechanism

4.1.1 Innovative applications of precision-agriculture technologies

Precision agriculture exemplifies the innovative use of digital technologies in farming by integrating GPS, GIS, remote-sensing (RS), IoT, and other systems to achieve precise management across the production process, thereby markedly enhancing productivity. In sowing, GPS enables tractors and planters to follow preset row and plant-spacing patterns, avoiding uneven seed distribution typical of traditional methods and improving both seed utilization and emergence rates. For instance, in large-scale wheat cultivation, precision sowing yields a more uniform seedling density per square meter, laying a solid foundation for subsequent growth. Coupled with GIS, fields can be zoned according to soil fertility and topography[14], allowing seeds and fertilizers to be applied exactly where needed, tailoring management to local conditions. In fertilization and irrigation, sensor networks play a vital role: soil-moisture and nutrient sensors relay real-time data to intelligent decision systems, which calculate and control the precise volume of water and fertilizer required for each growth stage. This not only boosts resource-use efficiency and cuts waste and pollution, but also meets crops' varying needs as they develop, raising yields and quality. In livestock and poultry farming, digital tools likewise enable precision management: environmental sensors (temperature, humidity, ammonia) continuously monitor barn conditions, triggering alerts and automatic adjustments to ventilation and climate controls whenever parameters stray from optimal ranges. Image-recognition and electronic-tag systems allow individual animals to be tracked and growth metrics—weight, length, feed intake—monitored, so tailored feeding regimes can be applied. For example, in pig farms, smart feeders dispense feed by weight and growth stage, maximizing conversion rates and cutting costs. Real-time health monitoring also detects disease risks early, facilitating prompt prevention and ensuring animal welfare.

4.1.2 Integration of big data and artificial intelligence

The fusion of big data and AI offers intelligent decision support across all farming stages, thus boosting productivity. Agricultural big data encompass meteorological, soil, crop-growth, and market-price information. Sensors, satellites, and drones collect these data continuously and feed them into centralized platforms. Meteorological agencies' satellite and ground-station feeds yield precise weather forecasts to help farmers prepare for extreme events. Soil monitors inform amendment and fertilization plans. Field cameras and sensors track crop growth in real time, guiding management. AI algorithms analyze these vast datasets to uncover patterns and trends: machine-learning models predict growth and yield based on growth data; historical weather and pest-outbreak data feed early-warning systems that forecast pest and disease likelihood and timing, advising farmers on preventive measures. On the market side, AI analyzes price-history trends and current supply–demand dynamics—plus policy shifts—to forecast future price movements, enabling farmers to plan production and marketing strategies that enhance competitiveness.

4.1.3 Blockchain technology ensuring supply-chain efficiency

Blockchain's decentralization, immutability, and traceability underpin efficient supply chains, indirectly elevating productivity. During production, each stage of planting, breeding, processing, transport, and sale is recorded in a tamper-proof chain. Consumers can scan a QR code to view origin, cultivation methods, input usage, harvest time, and logistics details, achieving full traceability. This transparency builds consumer trust and stimulates sales, compelling producers to uphold rigorous quality controls. Blockchain also innovates supply-chain finance. Traditionally, information asymmetry and credit risk make loans scarce for farmers and agri-businesses. On a blockchain platform, stakeholders—farmers, firms, distributors, financiers—share transparent data, enabling lenders to assess real creditworthiness. For example, such platforms can offer order- or warehouse-receipt financing, alleviating farmers' funding shortages and fostering production. Smart contracts automate processes—triggering payments, scheduling logistics, and more when predefined conditions are met—streamlining transactions and slashing costs. For instance, upon a shipment's warehouse arrival, a smart contract can instantly release payment to the producer, bypassing manual settlement delays.

4.1.4 Synergistic innovation of biotechnology and digitalization

The convergence of biotechnology and digital tools opens new avenues for productivity gains. Gene-editing technologies (e.g., CRISPR/Cas9) offer precise, efficient trait improvements; paired with digital systems, they allow exact control and intelligent management of breeding data. By building gene databases and breeding-information platforms, researchers can analyze large genomic datasets to identify yield, quality, and stress-resistance genes, then edit them to develop superior varieties. Digital breeding systems log parental lines, cross combinations, and field performance, supplying data-driven guidance that accelerates breeding cycles and raises efficiency. Biosensors—capable of detecting biomolecules or physiological signals—integrated with digital networks provide real-time monitoring of the agricultural bio-environment. For example, sensors can detect soil microbial communities or pest/disease markers in crop tissues and relay that to decision systems, which then adjust interventions—such as targeted biocontrol agents or fertilization plans. This tight integration enhances precision and sensitivity in agricultural management, advancing fine-tuned control and raising productivity.

4.2 Data-Driven Decision-Making Mechanism

In traditional agricultural decision-making, reliance on experience and intuition can suffice for routine situations but falls short under complex and volatile market and natural conditions, limiting scientific accuracy. The advent of big-data analytics offers a fresh perspective and methodology. By integrating massive agricultural datasets from multiple channels—meteorological, soil, market-price, and produce-sales data—deep mining can reveal hidden patterns and trends, providing scientific basis for decisions in production, sales, and management.

Analyzing meteorological big data allows farmers to anticipate upcoming weather changes and plan planting schedules and crop selection accordingly. For example, if long-term data indicate a region will face low rainfall and high temperatures during a certain period, farmers can choose drought- and heat-tolerant varieties to improve survival rates and yields. Soil big-data analysis helps farmers understand fertility and pH levels to enable precise fertilization and irrigation. By analyzing soil-sample data to determine nutrient content and using soil-moisture sensors combined with weather data, smart irrigation systems can ensure crops receive appropriate water at each growth stage, minimizing waste and pollution.

Big-data analytics also plays a vital role in pest and disease control. By collecting and analyzing historical outbreak data, weather records, and crop-growth information, predictive models can forecast the timing, location, and severity of outbreaks, guiding preemptive measures. For instance, combining years of wheat-rust incidence data with current weather and growth conditions can predict likely rust outbreaks, allowing farmers to prepare control agents and equipment for early intervention, reducing damage and pesticide costs.

Sales-data integration from e-commerce platforms and wholesale markets enables analysis of consumer behavior and demand trends. Mining these data reveals regional and seasonal preferences, guiding adjustments to planting structures. For example, if summer e-commerce data show high demand for watermelon and grapes—especially organic varieties—enterprises can expand organic watermelon and grape cultivation to meet demand, boosting prices and competitiveness.

Because agricultural prices fluctuate with supply-demand, seasonality, and policy, big-data analytics can model and forecast price trends by collecting domestic and international price data and related factors. Producers can then time sales: delaying if prices are expected to rise for higher profits, or accelerating sales to avoid forecasted price drops.

For large farms, efficient resource management—land, labor, equipment—is key to raising efficiency and cutting costs. Sensors and monitoring devices collect data on land use, equipment status, and labor productivity. Analyzing these data uncovers issues and optimization opportunities: identifying high failure rates in machinery requiring maintenance, or reallocating labor tasks and schedules to improve efficiency.

Big-data analytics also enhances supply-chain management by integrating data across production, processing, transport, and sales for end-to-end monitoring and optimization. For instance, analyzing logistics data optimizes transport routes and delivery plans, reducing costs and transit times; real-time monitoring of each link helps detect and resolve issues—inventory backlog or shortages—ensuring stable supply and quality.

Data accuracy and reliability depend on high-quality data. A robust system for data collection, storage, and management is essential: maintaining and calibrating collection devices for accuracy and timeliness, and cleaning and preprocessing to remove noise and errors. Big-data analysis demands multidisciplinary expertise—statistics, computer science, agricultural science—so training is vital. Universities and vocational schools should offer relevant curricula to cultivate talent versed in both agriculture and analytics, while enterprises and research institutes can upskill staff through training and recruitment. In the big-data era, data security and privacy are critical[15]. Agricultural data include sensitive personal and business information, so strong protections—secure storage and transmission, adherence to laws and regulations—must prevent leaks and misuse, safeguarding farmers' and enterprises' rights. By applying big-data analytics in agricultural decision-making, the value of data is fully realized, enhancing the scientific rigor and accuracy of decisions and driving a new quality leap in productivity.

4.3 Industry-Chain Collaboration Mechanism

Information silos across traditional agricultural value chains hinder collaboration. Farmers often lack accurate market-demand data, causing mismatches between supply and demand, leading to unsold produce or price swings. Processors cannot track raw-material supply quality and quantity in real time, disrupting production planning and quality. Distribution suffers from opaque logistics and chaotic inventory management. Digital technologies address these issues effectively.

IoT and sensors at production bases collect real-time soil-moisture, temperature, light, and crop-growth data, uploading them to cloud platforms. Farmers and enterprises can view this data via mobile or desktop to adjust strategies. Big-data analytics forecasts market demand, feeding predictions back to producers to guide planting and breeding.Building an agri-value-chain information-sharing platform is key to seamless data flow. It integrates production, processing, and distribution data—varieties, yields, quality, prices, and logistics status. Stakeholders publish and retrieve information in real time: processors post raw-material needs, farmers adapt cultivation accordingly; logistics providers access transport requirements and locations to optimize routes and schedules. The platform also records transactions and credit ratings, fostering trust and efficiency.

Digital technologies have propelled precision agriculture, enabling fine management. In cropping, GIS, GPS, and remote sensing deliver precise soil-fertility analysis and growth monitoring, allowing targeted fertilization, irrigation, and pest control. In livestock, smart sensors regulate environments and enable precision feeding and disease alerts. These precise data support upstream and downstream coordination: processors use quality and quantity data for accurate production planning; logistics use reliable supply info for efficient transport and storage.Enterprise resource-planning (ERP) and supply-chain-management (SCM) systems integrate production, procurement, inventory, and sales for automated workflows and real-time data exchange. In processing plants, ERP monitors raw-material and finished-goods inventories and production progress, auto-adjusting production and procurement. SCM links suppliers and distributors for synchronized operations, reducing waste and delays and accelerating responsiveness.In logistics, IoT, big data, and AI create "smart logistics." Vehicle sensors and GPS track cargo location, temperature, and humidity, feeding a logistics platform that optimizes routes and ensures safety. Smart logistics coordinates with processing and sales: sharing production plans and orders to time shipments, enabling seamless chain integration.E-commerce platforms now play a pivotal role, breaking geographic limits and expanding reach. They also provide market feedback via data analytics. To synchronize online and offline channels, integrated sales models are needed: producers open flagship stores online and operate physical outlets for experience-based marketing and after-sales, while offline handles delivery and pick-up, and online drives promotion and traffic, boosting efficiency and satisfaction[16].

Profit distribution in traditional chains is often inequitable, with farmers marginalized. Digital tools support fair distribution by quantifying inputs, outputs, and contributions via big data and blockchain. Blockchain records the entire production-to-sale process—inputs, quality tests, logistics—ensuring tamper-proof data. Contributions are assessed accurately and profits allocated proportionally, incentivizing collaboration and stabilizing the chain.

Industry alliances and cooperatives further collaboration. Digital governance—member management systems, online voting and meetings—enhances management and decision-making. Alliances use digital platforms for training, tech exchange, and marketing, boosting member capacity and competitiveness. Digital governance strengthens cohesion and drives coordinated chain development.

4.4 Market-Response Mechanism

Under traditional models, farmers have limited access to market-demand information and rely on experience, resulting in mismatches and volatility. Digital technologies enable precise market insight. Big-data analytics aggregates vast data from e-commerce, social media, and offline retail to reveal consumer preferences, buying habits, and regional differences. For example, platforms record product categories, brands, specs, and price ranges; analytics predict seasonal and regional demand trends. Farmers and enterprises adjust planting and breeding plans to match demand.IoT in production, transport, and sales also gathers real-time market data. Sensors in storage monitor inventory and quality; when thresholds are reached, the system triggers restocking or promotions to guide strategy.Digital empowerment makes production flexible and controllable, swiftly adapting to market shifts. Smart equipment—automated irrigation adjusting to soil moisture and weather data, and precision fertilization aligning with crop stage—ensures efficient, targeted operations. Adjusting smart equipment parameters accelerates growth and boosts yields when demand surges.Digital management platforms integrate production, sales, and logistics data for real-time visibility into progress, costs, and demand. Managers use cost analyses and market forecasts to decide on harvest timing, sales channels, and pricing in response to price fluctuations.Digital technologies also foster coordinated chain responses: a digital-supply-chain platform lets producers, processors, and logistics share information. When demand changes, each link adapts orders, production, and delivery schedules for timely market supply.Digital empowerment opens new marketing and service avenues, enhancing competitiveness. Online channels—e-commerce sites and social-media accounts—support direct promotion and sales. Live-streaming and short-video marketing attract consumers by showcasing cultivation, environment, and quality. Digital marketing enables precision targeting, pushing personalized product info and promotions.On the service side, CRM systems record purchase histories and feedback, enabling personalized care: automated post-purchase guides and follow-ups resolve issues swiftly. Big-data analytics assesses satisfaction, driving continuous improvement. Blockchain-based traceability records the full lifecycle—planting, harvesting, inputs, processing, and sales—so consumers scan QR codes to verify origin and safety, boosting confidence[17].

Faced with natural and market risks, digital tools enhance risk management. Price-monitoring platforms collect domestic and international price data, and predictive models issue alerts on abnormal swings, prompting farmers to adjust strategies—seeking new channels or value-adding processes to mitigate losses[18].

Supply-demand analytics via IoT and big data track production progress, inventory, and market demand in real time, forecasting shifts so enterprises can optimize production and stock to avoid oversupply or missed opportunities.Digitalization also supports agricultural insurance: big-data platforms aggregate production history, weather, and disaster data to model risk for product design and pricing. IoT and remote sensing monitor crop conditions and detect losses early, improving claim efficiency and accuracy.In summary, digital empowerment—through precise demand capture, agile production adjustment, optimized marketing and service, and bolstered risk response—strengthens market responsiveness and competitiveness, driving a new quality leap in agricultural productivity[19].

5 TYPICAL CASE STUDIES

Case Study 1: A smart farm in China's eastern coastal region spans about 5,000 mu and focuses on vegetable and fruit cultivation and sales. Beginning digital transformation in 2020, it introduced advanced technologies and management systems to boost efficiency, cut costs, and enhance quality. Sensors in fields monitor soil moisture, temperature, and nutrient content in real time. Via a data-analysis platform, the owner applies precise fertilizer and irrigation based on actual conditions, avoiding waste; fertilizer use dropped by 20% and water-use efficiency improved by 30%. Drones equipped with high-resolution and multispectral cameras conduct field inspections and pest monitoring, quickly pinpointing infestation areas; targeted treatments cut pesticide use by 15%. A farm-management software system digitizes production, sales, and inventory, allowing real-time tracking of crop growth, orders, and stock. When inventory reaches set levels, automated prompts trigger promotions, reducing surplus. A traceability system lets consumers scan QR codes to view the full cultivation, input, harvest, and logistics history, enhancing trust and raising market competitiveness; selling prices rose 10–15%. The farm invests in staff training through workshops and seminars and collaborates with local agricultural institutes for expert guidance, securing technical support and talent. However, initial hardware and software investments reached ￥5 million, imposing financial pressure on a mid-sized farm. Data security measures remain incomplete, risking leaks that could harm business and consumer trust. Some older employees struggle with new systems, hampering adoption and efficiency gains.

Case Study 2: An agri-product e-commerce platform launched in 2018 builds a seamless transaction environment for producers and consumers. It digitized the supply chain end to end, creating traceability from origin to buyer. Partnering with production bases, it integrates planting, harvesting, processing, and transport data on its app for consumer queries, raising quality safety and trust. Big-data analysis forecasts demand and prices, guiding producers on planting structures; order data optimizes logistics for rapid, cost-effective delivery. Focusing on branding, the platform highlights regional specialties with attractive packaging and stories—e.g., a "Local Specialty Fruits" line—drawing consumer attention. Diverse marketing—including social media and live-streaming with influencers—boosts sales; one livestream generated ￥1 million in revenue. To address financing challenges, the platform collaborates with financial institutions to offer supply-chain finance: producers leverage order and credit data for low-interest loans for inputs. Challenges include low standardization of fragmented smallholder output, requiring time-consuming sorting and increasing costs, and uneven quality affecting consumer experience and brand. Perishability and inadequate cold-chain infrastructure cause high transit losses despite mitigation efforts. Intensifying competition demands continuous investment in R&D, branding, and marketing, raising operational costs and risks.

6 CONCLUSION

This study systematically demonstrates the transformative empowerment of the entire agricultural value chain by digital technologies. In the production link, the application of the Internet of Things, drones, and intelligent equipment has achieved precise irrigation, pest and disease control, and enhanced mechanization ; in the processing link, intelligent management and control have raised product standardization levels and driven innovation in high–value-added products; in the distribution link, reliance on e-commerce and digital cold-chain logistics has markedly reduced spoilage rates and transportation costs; and in the sales link, big-data–driven precision marketing and consumer interaction have optimized supply and demand matching. Together, these transformations propel a new-quality leap in agricultural productivity: efficiency gains and cost reductions permeate the entire chain, product quality and added value are significantly enhanced, industry-integration innovations give rise to smart-agriculture business models, and risk-resilience is strengthened through data-driven decision-making. To accelerate agricultural digital transformation, it is necessary to establish a policy framework covering infrastructure (rural networks, big-data platforms), a talent pipeline (skills training and high-end talent attraction), financial support (special funds and financial services), standards systems (technical specifications and data security), and industry collaboration. Future research could deepen evaluations of the long-term mechanisms of digital-technology applications and explore differentiated empowerment pathways for smallholders, thereby fully unleashing the potential for high-quality agricultural development.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Wang Shangao. Digital Economy and High-Quality Agricultural Development: Impact Effects and Pathways. Statistics & Decision, 2024, 40(6): 25.

[2] Wang Xintian, Jing Linbo, Zhang Bin. How E-commerce Drives Digitalization of Agricultural Chains: Theoretical Interpretation and Practical Evolution. China Soft Science, 2024, (3): 47–56.

[3] Smith J, Johnson M. Digital Transformation in Agricultural Value Chains: A Review. Journal of Agricultural Economics, 2021, 72(3): 456–472.

[4] Brown A, Lee K. The Impact of Digital Technologies on Agricultural Productivity. Agricultural Systems, 2020, 185: 1–10.

[5] Gong Binlei, Yuan Lingran. Agricultural Total Factor Productivity from the Perspective of New Quality Productive Forces: Theory, Measurement, and Empirical Analysis. Issues in Agricultural Economy, 2024(4): 68-80.

[6] Gao Yuan, Ma Jiujie. New Quality Productive Forces in Agriculture: A Political Economy Perspective. Issues in Agricultural Economy, 2024(4): 81–94.

[7] Gong B L. Agricultural Reforms and Production in China: Changes in Provincial Production Function and Productivity in 1978–2015. Journal of Development Economics, 2018(132): 18–31.
[8] You Liang, Tian Xiangyu. New Quality Productive Forces in Agriculture: Realistic Logic, Connotation Analysis, and Generation Mechanism. On Economic Problems, 2024(6): 27–35.
[9] Gong Binlei, Yuan Lingran. Agricultural Total Factor Productivity from the Perspective of New Quality Productive Forces: Theory, Measurement, and Empirical Analysis. Issues in Agricultural Economy, 2024(4): 68 – 80.
[10] Chen Huiqing, Zeng Fusheng. Impact of New Quality Agricultural Productive Forces on Agricultural Modernization Development. Agricultural Economics and Management, 2024(3): 27–41.
[11] Li Qingrui. Development Strategies for Digital Agriculture in the Context of Rural Revitalization. Agricultural Economy, 2022(10): 17 – 18.
[12] Linfeng Mei, Yangyang Zheng, Mengling Tian. Driven by the Policy or Bent by the Market? Cracking the Digital Transformation Code of Farmer Cooperatives. Technological Forecasting and Social Change, 2024, 208: 123659.
[13] Huang Zhaochun. Digital Technology Empowers Rural Revitalization: Internal Logic, Practical Dilemmas, and Breakthrough Paths. Reform, 2024(7): 55–64.
[14] Liu Junjie, Zu Jian. Constructing New Production Relations Adapted to New Quality Agricultural Productive Forces. Journal of Zhongzhou, 2024(11): 32–40.
[15] Li Xia, Zhang Yulong. Digital Economy, Rural Labor Migration, and Common Prosperity for Farmers and Rural Areas. Statistics & Decision, 2024, 40(11): 5–10.
[16] Liu Kewen, Xian Hui. High-Quality Development Path of Rural Tourism in Heilongjiang under the Digital Economy. Academic Exchange, 2023(7): 121–133.
[17] Kitole F A, Mkuna E, Sesabo J K. Digitalization and Agricultural Transformation in Developing Countries: Empirical Evidence from Tanzania Agriculture Sector. Smart Agricultural Technology, 2024(7): 100379.
[18] Rajak P, Ganguly A, Adhikary S, et al. Internet of Things and Smart Sensors in Agriculture: Scopes and Challenges. Journal of Agriculture and Food Research, 2023(14): 100776.
[19] Sridhar A, Balakrishnan A, Jacob M M, et al. Global Impact of COVID-19 on Agriculture: Role of Sustainable Agriculture and Digital Farming. Environmental Science and Pollution Research International, 2023, 30(15): 42509–42525.

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WHAT DRIVES THE EFFICIENCY OF GREEN TECHNOLOGY INNOVATION IN INDUSTRIAL SECTORS? AN ANALYSIS BASED ON THE TOE FRAMEWORK USING NCA AND FSQCA

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Abstract: As the nexus of the "innovation-driven" and "green development" national strategies, green technology innovation resonates with China's dual carbon targets and represents an essential pathway toward achieving high-quality development. Existing literature has seldom employed a holistic framework to investigate the complex causal mechanisms through which technological, organizational, and environmental conditions influence green technology innovation efficiency, thereby largely overlooking the configurational effects among these antecedent conditions. To further advance green technology innovation and enhance its efficiency, this study examines China's industrial sectors. Drawing on the Technology-Organization-Environment (TOE) framework, we utilize both Necessary Condition Analysis (NCA) and fuzzy-set Qualitative Comparative Analysis (fsQCA) on a sample of 38 industrial sectors above a designated size. The analysis explores how six antecedent conditions across the technological, organizational, and environmental dimensions combine to impact green technology innovation. The findings are threefold. First, no single antecedent condition is necessary for achieving high green technology innovation efficiency, although technological factors exert a relatively strong constraint. Second, three distinct configurational pathways lead to high efficiency: a "technology-led, government-supported" path, a "technology-led, independent-innovation" path, and an "environment-technology-organization synergy" path. Third, in an otherwise favorable market environment, ill-suited environmental regulations can suppress innovation efficiency, a context where even strong market demand fails to be effective, suggesting that the impact of organizational conditions is subject to a threshold.
Keywords: Green technology innovation efficiency; TOE framework; Fuzzy-set qualitative comparative analysis (fsQCA); Necessary condition analysis (NCA); Configurational analysis

1 INTRODUCTION

As an advancement of traditional technological innovation, green technology innovation is defined as a valuable creative activity that promotes green technological development under specific constraints, including non-pollution, low energy consumption, and recyclability [1]. The research landscape in this field covers two primary areas. The first is the measurement of its efficiency, which predominantly employs parametric methods, such as Stochastic Frontier Analysis (SFA), and non-parametric methods, like Data Envelopment Analysis (DEA). Initially proposed separately by Aigner et al. and Meeusen and van den Broeck, SFA has been expanded upon by subsequent scholars. However, DEA has emerged as the predominant method for assessing green technology innovation efficiency, largely due to its flexibility in assuming either constant or variable returns to scale. The second area concerns its influencing factors, with existing literature focusing on two levels: the firm and the government. At the firm level, studies have examined determinants such as financial performance, capital investment, executive characteristics, and corporate governance. At the government level, research has centered on factors like environmental regulations and financial subsidies. Based on its definition and the scope of research, it is clear that green technology innovation is not created in a vacuum; it must be built upon the foundation of traditional technological innovation, achieving a synergistic development of green principles and technological advancement.

At present, China has yet to achieve optimal synergy between its "innovation-driven" and "green development" mandates. This disconnect is particularly severe in the industrial sectors, which are the primary contributors to excessive carbon emissions and environmental pollution, highlighting a significant imbalance between the quantity and quality of innovation. In absolute terms, industrial sectors have progressively increased their investment in green technology innovation to facilitate their green transformation and pursue high-quality development. In relative terms, however, industrial sectors above a designated size exhibit high inputs but yield low outputs in green technology innovation efficiency. Furthermore, while the literature on green technology innovation is extensive, studies on its measurement and its influencing factors have remained largely disconnected. This separation has led to an insufficient consideration of the interplay between measurement indicators and determinants, as well as the configurational effects arising from resource allocation.

To address these gaps, this study first employs a super-efficiency Slacks-Based Measure (SBM) DEA model, incorporating undesirable outputs and assuming variable returns to scale, to measure the two-stage green technology innovation efficiency of 38 major Chinese industrial sectors from 2016 to 2020 in a more scientific and robust manner.

Second, grounded in the Technology-Organization-Environment (TOE) framework, this study integrates Necessary Condition Analysis (NCA) with fuzzy-set Qualitative Comparative Analysis (fsQCA). This approach allows for a comprehensive necessity and configurational analysis of the selected antecedent conditions, exploring both the necessity of individual factors and the combined effects that multiple conditions exert on the efficiency of green technology innovation in these sectors. This research not only establishes a tighter linkage between innovation efficiency and its determinants but also remedies the deficiency of studies that consider these factors in isolation, thereby offering effective pathways for enhancing the green technology innovation efficiency of China's industrial sectors.

2 LITERATURE REVIEW AND RESEARCH FRAMEWORK

2.1 Literature Review

As efforts to achieve China's "dual carbon" targets intensify, green technology innovation has emerged as a critical driver for industrial transformation and a focal point for domestic scholars. A universally accepted definition of green technology innovation remains elusive, primarily because it amalgamates two concepts rich in connotation: technological innovation and green principles. Initially, Brawn and Wield provided one of the earliest systematic conceptualizations [2], defining green technology as a collection of technologies for recycling and environmental purification, which served as a precursor to the modern concept of green technology innovation. This foundation was subsequently enriched and expanded by numerous scholars. For instance, Qiaoling et al. broadened its scope to include innovations in energy conservation, resource recovery, green products, and environmental assessment [3]. Later, Shu et al. integrated the concept with corporate operations, defining it as the process of achieving the greening of processes or products through science and technology to foster coordinated economic and environmental development [4]. Drawing on this international scholarship, Chinese academics have also contributed new perspectives. Cheng Wenqiong et al. posit that green technology innovation aims for mutual sustainability of the environment and the economy by conserving resources and promoting waste recycling, thereby pursuing co-generation of socioeconomic and environmental benefits [5]. Furthermore, Qu Yanfen et al. aligned the concept with China's national context, proposing that it encompasses all innovations in production processes, manufacturing techniques, and product design that aim to enhance resource efficiency, reduce pollution, and maintain ecological balance, all within the constraints of economic and ecological sustainability [6].

With the continuous advancement of green technology innovation, issues concerning its input-output relationship and the measurement of its effectiveness have garnered increasing scholarly attention. As early as 2016, Luo Liangwen and Liang Shengrong proposed that green technology innovation efficiency is a key metric for gauging its development, a view further elaborated by others [7]. Liang Zhong et al. defined this efficiency as the ratio reflecting the utility between inputs and outputs in the green innovation process [8], establishing a general consensus on the standard for its measurement. However, due to the lack of a uniform definition of green technology innovation itself, the methodologies for measuring its efficiency are diverse. Wang Zhiping et al. used an SFA model to measure the green technology efficiency of China's provinces from 2001 to 2010, analyzing its regional disparities and their causes [9]. In contrast, Liang Zhong et al. employed a more mainstream method, using an SBM-DEA model to measure green technology innovation efficiency based on provincial panel data from 2005 to 2016 [8]. Compared to SFA, the DEA model, which can segment green technology innovation into a research input stage and a results transformation stage, has progressively become the mainstream methodology. Its ability to accommodate multiple output indicators through various extensions and its relative operational simplicity have contributed to its popularity and ongoing refinement.

As measurement methodologies have matured, scholarly focus has shifted towards identifying the determinants of green technology innovation efficiency to enhance it. Cheng Qiongwen et al. identified average firm size, degree of marketization, foreign openness, and the intensity of environmental regulation as primary drivers, noting that the technological environment primarily influences the R&D stage [10]. Li Danqing and Zhong Chenlin further disaggregated environmental regulation into government support for science and technology and the stringency of environmental protection, examining their effects in conjunction with other factors like foreign openness [11]. More recently, Wang Wan et al. were the first to employ fuzzy-set Qualitative Comparative Analysis (fsQCA), identifying pathways such as a "government-industry-academia synergy model" under a quadruple helix framework [12]. Subsequently, Jia Jianfeng et al. innovatively proposed an institutional configuration perspective to explore the tripartite influence of government, market, and society on green technology innovation efficiency [13]. Furthermore, other scholars have demonstrated that specific factors such as green credit [14], digital new infrastructure [15], carbon emission efficiency [16], environmental regulation coupled with foreign direct investment [17], as well as regional economic levels and the science and technology innovation environment [18], all positively contribute to green technology innovation.

2.2 Research Framework

The extensive body of research on green technology innovation has evolved from defining "what it is," to "how to measure it," and now to "how to improve it," continuously driving its development. However, current research on improving its efficiency predominantly analyzes influencing factors independently or in simple complementary pairs. This approach often fails to uncover the complex causal relationships and configurational effects inherent in the input-output process of green technology innovation. Therefore, building on prior research and grounded in the TOE framework, this study integrates a two-stage super-efficiency SBM-DEA measurement with NCA and fsQCA. Based on the current state of green technology innovation, we construct a research framework to analyze its determinants (as shown in Figure 1). The objective is to identify the necessary conditions and the configurational effects among multiple antecedent conditions, thereby proposing effective pathways to enhance the green technology innovation efficiency in industrial sectors and achieve high-quality development.

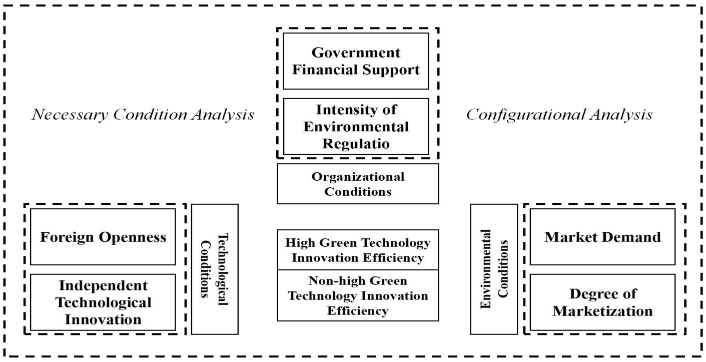

Figure 1 Research Framework

3 RESEARCH DESIGN

3.1 Research Methods

Data Envelopment Analysis (DEA) is a non-parametric efficiency analysis method used to evaluate the relative efficiency of multiple decision-making units (DMUs) with multiple inputs and outputs [19]. To overcome the limitations of traditional DEA models, such as the slackness of variables and errors in radial measurement, Tone (2001) introduced the non-radial, non-oriented Slacks-Based Measure (SBM) model [20]. Furthermore, since traditional DEA is unable to differentiate and rank multiple units that are all deemed equally efficient, Tone (2002) subsequently developed the super-efficiency SBM model [21]. Drawing upon this body of work and relevant research in green technology innovation, this study employs the super-efficiency SBM-DEA model to measure the innovation efficiency of 38 major industrial sectors.

Qualitative Comparative Analysis (QCA), developed by Ragin et al., utilizes configurational analysis combined with cross-case comparison to explore the combinations of conditions that lead to an outcome [22]. Among its variants—crisp-set QCA (csQCA), multi-value QCA (mvQCA), and fuzzy-set QCA (fsQCA)-this study employs fsQCA. Compared to the others, fsQCA accommodates continuous variables by calibrating them into membership scores within the interval [23], allowing for more nuanced assessments. Recognizing that the panel data in this study spans several years, it is crucial to incorporate a temporal dimension into the analysis. Among the three types of Time-Series QCA (TS-QCA)-namely, pooled QCA, fixed-effects QCA, and time-difference QCA-this study adopts a fixed-effects fsQCA approach. This is operationalized by calibrating the data for each case relative to its own mean value, thereby controlling for time-invariant, case-specific effects (Hino, 2009) and enabling a dynamic configurational analysis.

Necessary Condition Analysis (NCA) is a technique specifically designed to identify necessary relationships, determining whether an antecedent condition is essential for an outcome to occur [24]. Unlike the qualitative assessment of necessity within fsQCA, NCA quantifies the degree to which a condition is necessary, thus compensating for a key limitation in fsQCA (Vis et al., 2018). This allows us to precisely determine if any single factor constitutes a necessary condition for high green technology innovation efficiency.

Therefore, this study integrates NCA with a fixed-effects fsQCA. This combined approach, while accounting for temporal dynamics, allows for a robust investigation into both the necessity of single antecedent conditions and the configurational effects of multiple conditions, thereby uncovering the deeper causal pathways to high-quality green technology innovation in China's industrial sectors.

3.2 Sample Selection and Data Sources

The initial data for this study were compiled from indicators published by the National Bureau of Statistics and from the major industrial sector categories listed in the China Industrial Statistical Yearbook, published by the China Statistics Press. First, to account for the inherent time lags in the innovation process, the data for all antecedent conditions and the outcome variable were defined as the five-year average from 2016 to 2020. Second, after excluding sectors with missing data, anomalous values, or other exceptional circumstances, a final sample of 38 industrial sectors above a designated size was obtained. The sample of cases is presented in Table 1.

Table 1 The 38 Industrial Sectors in the Sample

No.	Industrial Sector	No.	Industrial Sector
1	Coal Mining and Washing	20	Pharmaceutical Manufacturing
2	Petroleum and Natural Gas Extraction	21	Chemical Fiber Manufacturing
3	Ferrous Metal Mining and Dressing	22	Rubber and Plastic Products
4	Non-ferrous Metal Mining and Dressing	23	Non-metallic Mineral Products
5	Non-metallic Mineral Mining and Dressing	24	Smelting and Pressing of Ferrous Metals
6	Processing of Agricultural and Sideline Food Products	25	Smelting and Pressing of Non-ferrous Metals
7	Food Manufacturing	26	Metal Products
8	Manufacture of Wine, Beverages and Refined Tea	27	General-Purpose Equipment Manufacturing
9	Tobacco Products	28	Special-Purpose Equipment Manufacturing
10	Textile Industry	29	Automobile Manufacturing
11	Textile, Apparel, and Accessories	30	Manufacture of Railway, Shipbuilding, Aerospace and Other Transport Equipment
12	Manufacture of Leather, Fur, Feather and Related Products and Footwear	31	Manufacture of Electrical Machinery and Equipment
13	Wood Processing and Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products	32	Manufacture of Computers, Communication and Other Electronic Equipment
14	Furniture Manufacturing	33	Manufacture of Measuring Instruments and Machinery
15	Papermaking and Paper Products	34	Other Manufacturing
16	Printing and Reproduction of Recording Media	35	Repair of Metal Products, Machinery and Equipment
17	Manufacture of Articles for Culture, Education, Arts and Crafts, Sports and Entertainment	36	Production and Supply of Electric Power and Heat Power
18	Processing of Petroleum, Coal and Other Fuels	37	Production and Supply of Gas
19	Manufacture of Raw Chemical Materials and Chemical Products	38	Production and Supply of Water

The data for measuring green technology innovation efficiency, such as patent statistics, were sourced from the *China Industrial Statistical Yearbook*, the *China Labor Statistical Yearbook*, the *China Environment Statistical Yearbook*, the *China Economic Census Yearbook*, and the China Research Data Service Platform (CSMAR). Data for analyzing the influencing factors, such as industrial "three wastes" emissions, the number of new product development projects, and R&D expenditures, were obtained from the *China Industrial Statistical Yearbook*, the *China Economic Census Yearbook*, the CSMAR platform, the *China Environment Statistical Yearbook*, and the *China Science and Technology Statistical Yearbook*. The interpolation method was used to address a small amount of missing data.

3.3 Variable Description

3.3.1 Measurement of green technology innovation efficiency

There is a general consensus in the existing literature regarding the selection of indicators, which are typically categorized into two stages: the green technology R&D stage and the green technology commercialization stage, each with distinct input and output indicators.

(1) Green Technology R&D Stage

Based on the research of Luo Liangwen et al. [7] and Qian Li et al. [25], and taking into account the specific characteristics of the industrial sectors, this study selects three input indicators for the R&D stage: R&D expenditure, the full-time equivalent of R&D personnel, and expenditure on new product development. Following prior research, the output indicators for this stage are the number of patent applications and the number of invention patents granted.

(2) Green Technology Commercialization Stage

For the commercialization stage, the inputs bear a resemblance to the outputs of the R&D stage. Drawing on the work of Yang Shidi et al. [26] and Zhao Lu et al., [27] this study uses the number of patent applications, the number of invention patents granted, the number of new product development projects, and enterprise energy consumption as input indicators. For the outputs of this stage, based on the research of Zhang Liao et al. [28] and Li Lin et al. [29], the desirable output is defined as sales revenue from new products, while the undesirable output is defined as the emissions of the "three wastes" from the industrial sectors.

The names and definitions of all variables are presented in Table 2.

Table 2 Definition of Variables for Green Technology Innovation Efficiency Measurement

Stage	Category	Variable Name and Definition
Green Technology R&D Stage	R&D Input	T1: R&D Expenditure (CNY 10,000) T2: Full-Time Equivalent of R&D Personnel (person-year) T3: Expenditure on New Product Development (CNY 10,000)
	Intermediate Output	M1: Number of Patent Applications (units) M2: Number of Invention Patents Granted (units)
Green Technology Commercialization Stage	Commercialization Input	C1: Number of Patent Applications (units) C2: Number of Invention Patents Granted (units) C3: Number of New Product Development Projects (items) C4: Industry Energy Consumption (10,000 tons of standard coal)
	Desirable Output	E1: Sales Revenue from New Products (CNY 10,000)
	Undesirable Output	U1: Industrial Wastewater Discharge (cubic meters) U2: Waste Gas Emissions (cubic meters) U3: Solid Waste Generation (tons)

3.3.2 Antecedent conditions for green technology innovation efficiency

(1) Technological Conditions

This study examines two technological conditions from both external and internal perspectives: foreign openness and independent technological innovation. In the new era, technological innovation is often characterized by transnational and cross-disciplinary collaboration. Liu Zhibiao argues that China must leverage its new pattern of comprehensive openness to acquire global innovation resources, thereby advancing innovation in key areas [30]. Similarly, Guo Wei et al. suggest that the degree of open innovation significantly impacts an industry's innovative capacity by promoting industrial restructuring and accelerating the international flow of innovation factors [31]. Conversely, independent technological innovation is the process through which an industry improves and innovates its internal technologies using its own resources. It is crucial for firms to maintain control during the innovation process to avoid over-reliance on foreign technology, which can lead to a loss of market competitiveness and industrial creativity.

(2) Organizational Conditions

The two organizational conditions are government financial support and intensity of environmental regulation. Research by Li et al. finds that governments, in pursuit of sustainable development and environmental protection, often encourage firms to engage in green technology innovation. Government R&D funding can enhance the efficiency of corporate green innovation, while green credit policies can strengthen the motivation for it [32]. Therefore, this study measures this condition using the proportion of R&D expenditure sourced from the government. Regarding the intensity of environmental regulation, a study by Yao et al. posits that the pressure of industrial pollution can compel heavy-polluting industries (e.g., oil refining, chemical manufacturing, and primary metals) to accelerate their green innovation R&D, thereby enhancing their environmental legitimacy [33]. Consequently, this study uses the emissions of the industrial "three wastes" as a proxy for the intensity of environmental regulation.

(3) Environmental Conditions

The environmental conditions consist of market demand and degree of marketization [34]. Zhang Dunjie asserts that market consumption demand has a pronounced impact on green technology innovation. Furthermore, Denicolò notes that market profits and competition are primary incentives for firms to undertake such innovation [35]. Therefore, we adopt the number of new product development projects in industrial sectors as the measure for market demand. Regarding the degree of marketization, as China's market economy system matures, the allocative role of the market becomes more prominent, intensifying competition and amplifying the incentive for innovation [36]. Research by Feng Zongxian et al. demonstrates that the degree of marketization has a significant positive effect on the technical efficiency of innovation [37]. Additionally, Wu Lianghai et al. find that a higher degree of marketization helps enhance information transparency and reduce information asymmetry between investors and managers [38], enabling firms to send positive signals to the market about their high-level innovation capabilities [39]. Thus, building on prior research, this study measures the degree of marketization by the proportion of non-state capital in the industry's paid-in capital.

The specific calculation method for each variable is shown in Table 3.

Table 3 Calculation of Variables for the Antecedent Conditions

Variable Name	Symbol	Calculation Method
Green Technology Innovation Efficiency	GTIE	Five-year average of the two-stage green technology innovation efficiency
Foreign Openness	FO	Proportion of foreign capital in paid-in capital
Independent Technological Innovation	ITI	Proportion of internal expenditure in total R&D expenditure
Government Financial Support	GFS	Proportion of R&D funds sourced from the government
Intensity of Environmental Regulation	IER	Emissions of the industrial "three wastes"
Market Demand	MD	Number of new product development projects
Degree of Marketization	DM	Proportion of non-state capital in paid-in capital

4 DATA ANALYSIS AND EMPIRICAL RESULTS

4.1 Measurement of Green Technology Innovation Efficiency

To incorporate the temporal dimension into the NCA and fsQCA analyses, this study first calculated the two-stage green technology innovation efficiency for each of the 38 industrial sectors for each year from 2016 to 2020. Subsequently, the five-year average efficiency was computed for each sector. This approach effectively creates a single, time-averaged data point for each case, thereby controlling for case-specific time effects. The results are presented in Table 4.

Table 4 Five-Year Average Green Technology Innovation Efficiency of the 38 Industrial Sectors (2016-2020)

Industrial Sector	Green Technology Innovation Efficiency	Industrial Sector	Green Technology Innovation Efficiency
Coal Mining and Washing	0.258	Pharmaceutical Manufacturing	0.477
Petroleum and Natural Gas Extraction	0.456	Chemical Fiber Manufacturing	0.459
Ferrous Metal Mining and Dressing	0.849	Rubber and Plastic Products	1.153
Non-ferrous Metal Mining and Dressing	0.551	Non-metallic Mineral Products	2.171

Non-metallic Mineral Mining and Dressing	0.472	Smelting and Pressing of Ferrous Metals	0.547
Processing of Agricultural and Sideline Food Products	0.335	Smelting and Pressing of Non-ferrous Metals	0.413
Food Manufacturing	25.848	Metal Products	0.668
Manufacture of Wine, Beverages and Refined Tea	52.062	General-Purpose Equipment Manufacturing	0.800
Tobacco Products	0.863	Special-Purpose Equipment Manufacturing	0.772
Textile Industry	0.452	Automobile Manufacturing	0.599
Textile, Apparel, and Accessories	0.448	Manufacture of Railway, Shipbuilding, Aerospace and Other Transport Equipment	4.660
Manufacture of Leather, Fur, Feather and Related Products and Footwear	0.398	Manufacture of Electrical Machinery and Equipment	2.955
Wood Processing and Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products	0.399	Manufacture of Computers, Communication and Other Electronic Equipment	1.172
Furniture Manufacturing	0.800	Manufacture of Measuring Instruments and Machinery	0.826
Papermaking and Paper Products	2.301	Other Manufacturing	0.956
Printing and Reproduction of Recording Media	0.957	Repair of Metal Products, Machinery and Equipment	0.436
Manufacture of Articles for Culture, Education, Arts and Crafts, Sports and Entertainment	0.517	Production and Supply of Electric Power and Heat Power	1.390
Processing of Petroleum, Coal and Other Fuels	0.448	Production and Supply of Gas	0.858
Manufacture of Raw Chemical Materials and Chemical Products	0.677	Production and Supply of Water	1.946

4.2 Data Calibration

Before applying the direct calibration method [22] (Ragin, 2008), we first calculated the five-year average for each antecedent variable for every case (industry). This step ensures that time-varying effects within each case are controlled for, aligning with the fixed-effects approach. In the absence of clear theoretical or external standards to guide the calibration of the antecedent conditions and the outcome variable, this study follows the precedent of prior research [40] and uses the descriptive statistics of the sample itself to set the calibration thresholds [23]. Specifically, the three anchors for calibration—the threshold for full membership, the crossover point, and the threshold for full non-membership—are set at the 75th, 50th, and 25th percentiles of the data distribution for each variable, respectively. The resulting calibration anchors are presented in Table 5.

Table 5 Calibration Anchors for Antecedent Conditions and the Outcome

Condition / Outcome	Full Membership (75%)	Crossover Point (50%)	Full Non-Membership (25%)
Green Technology Innovation Efficiency	1.026	0.609	0.354
Foreign Openness	0.122	0.084	0.036

Independent Technological Innovation	0.984	0.972	0.948
Government Financial Support	0.032	0.018	0.013
Intensity of Environmental Regulation	305,687.451	117,035.422	31,647.918
Market Demand	21,449.850	5,899.800	2,340.300
Degree of Marketization	0.936	0.893	0.675

4.3 Necessary Condition Analysis (NCA)

NCA identifies necessary conditions by analyzing the necessity effect size and statistical significance of individual antecedent variables. It also employs bottleneck analysis to evaluate the required level of an antecedent condition needed to achieve a specific level of the outcome [41]. The significance of the necessity is determined using a Monte Carlo simulation with permutation tests. NCA utilizes two estimation techniques, ceiling regression (CR) and ceiling envelopment (CE), to handle both continuous and discrete data [42]. The results of the necessity analysis are presented in Table 6.

Table 6 Necessity Analysis of Individual Antecedent Conditions

Antecedent Condition	Method	Accuracy	Ceiling Zone	Scope	Effect Size (d)	p-value
Foreign Openness	CR	100%	0.001	0.94	0.001	0.738
	CE	100%	0.002	0.94	0.002	0.733
Independent Technological Innovation	CR	97.4%	0.003	0.96	0.003	0.745
	CE	100%	0.004	0.96	0.004	0.759
Government Financial Support	CR	100%	0.001	0.95	0.002	0.705
	CE	100%	0.003	0.95	0.003	0.696
Intensity of Environmental Regulation	CR	100%	0.000	0.93	0.000	1.000
	CE	100%	0.000	0.93	0.000	1.000
Market Demand	CR	100%	0.000	0.93	0.000	0.848
	CE	100%	0.000	0.93	0.000	0.848
Degree of Marketization	CR	100%	0.000	0.94	0.000	0.667
	CE	100%	0.000	0.94	0.000	0.667

Notes: a. Calibrated fuzzy membership scores. b. The permutation test in the NCA analysis (number of permutations = 10,000).

Table 6 presents the results of the necessity analysis for each antecedent condition under both estimation methods. A condition is typically identified as necessary when its effect size (d) is greater than 0.1 and the p-value indicates statistical significance ($p < 0.05$) [42-45]. According to the NCA results, the necessity effects for foreign openness, independent technological innovation, government financial support, intensity of environmental regulation, market demand, and degree of marketization are all non-significant ($p > 0.05$), and their effect sizes (d) are all well below the 0.1 threshold. Therefore, we conclude that no single antecedent condition, when considered in isolation, constitutes a necessary condition for high green technology innovation efficiency.

Furthermore, the bottleneck analysis from NCA, as summarized from Table 7 (not shown), provides additional insights. It reveals that while no condition is strictly necessary, some exert a minor constraint. For example, to achieve an efficiency level of 80%, a government financial support level of at least 0.3% is required. This indicates a very small constraining effect. Across the full spectrum of outcomes (0% to 100% efficiency), except for the intensity of environmental regulation which exhibits "condition inefficiency" (Dul, 2016), the other variables show some level of constraint at the highest efficiency levels, but their constraining power is minimal. Although no factor qualifies as a necessary condition, the analysis suggests that the technological conditions (foreign openness and independent technological innovation) exert a relatively stronger constraint compared to the other factors.

Table 7 Bottleneck Analysis of Necessary Conditions (%)

Green Technology Innovation Efficiency	Foreign Openness	Independent Technological Innovation	Government Financial Support	Intensity of Environmental Regulation	Green Technology Innovation Efficiency	Foreign Openness
0	NN	NN	NN	NN	NN	NN
10	NN	NN	NN	NN	NN	NN
20	NN	NN	NN	NN	NN	NN
30	NN	NN	NN	NN	NN	NN
40	NN	NN	NN	NN	NN	NN
50	NN	NN	NN	NN	NN	NN
60	NN	NN	NN	NN	NN	NN
70	NN	NN	NN	NN	NN	NN
80	NN	NN	0.3	NN	NN	NN
90	NN	NN	0.7	NN	NN	NN
100	10.3	13.0	1.0	NN	1.0	2.1

Note: Results are based on the CR method. "NN" indicates "Not Necessary" at the given level of the outcome.

To further probe the necessity of the antecedent conditions, we next employed fsQCA to test whether any single condition (or its negation) is necessary for achieving high or non-high green technology innovation efficiency. Following the guideline proposed by Schneider et al. (2012), a condition is considered necessary if its consistency score is greater than 0.9 [46]. As shown in the necessity analysis results in Table 8, the consistency scores for all individual antecedent conditions are below the 0.9 threshold. This holds true for both the presence and absence of each condition in relation to both high and non-high efficiency outcomes. This confirms the NCA findings and underscores the need to proceed with a sufficiency analysis to explore how combinations of these conditions lead to the outcome.

Table 8 fsQCA Necessity Analysis

Antecedent Condition	High Green Technology Innovation Efficiency		Non-high Green Technology Innovation Efficiency	
	Consistency	Coverage	Consistency	Coverage
Foreign Openness	0.548	0.534	0.651	0.559
~Foreign Openness	0.556	0.565	0.509	0.549
Independent Technological Innovation	0.469	0.469	0.740	0.584
~Independent Technological Innovation	0.632	0.624	0.409	0.496
Government Financial Support	0.581	0.595	0.529	0.511
~Government Financial Support	0.537	0.519	0.409	0.496
Intensity of Environmental Regulation	0.355	0.359	0.760	0.712
~Intensity of Environmental Regulation	0.742	0.725	0.380	0.371
Market Demand	0.465	0.471	0.689	0.634
~Market Demand	0.662	0.648	0.487	0.484
Degree of Marketization	0.462	0.447	0.764	0.646
~Degree of Marketization	0.661	0.676	0.431	0.474

4.4 Sufficiency Analysis of Configurational Paths

Having established that no single condition is necessary, we now proceed with the sufficiency analysis to identify which combinations of conditions are sufficient for achieving high green technology innovation efficiency. The analysis parameters were set as follows: following standard practice, the consistency threshold was set to 0.8 [40]. The case frequency threshold was set to 1, ensuring that the resulting configurations account for at least 75% of the observed cases. To minimize potential logical contradictions, the Proportional Reduction in Inconsistency (PRI) consistency threshold was set to 0.7 [41]. The analysis generated three types of solutions: complex, parsimonious, and intermediate. In line with conventional QCA reporting, the intermediate solution is presented as the primary result, with the parsimonious solution used as a reference to distinguish between core and peripheral conditions (i.e., core presence, core absence, peripheral presence, and peripheral absence) [41]. The results of this analysis are presented in Table 9.

Table 9 Configurations for High and Non-high Green Technology Innovation Efficiency

Antecedent Conditions	High Green Technology Innovation Efficiency				Non-high Green Technology Innovation Efficiency			
	H1	H2	H3	H4	U1	U2	U3	U4
Foreign Openness	●	•	⊗	●		●	⊗	•
Independent Technological Innovation		●	●	⊗	•	●	•	⊗
Government Financial Support	•	•	⊗	●	⨂		⊗	•
Intensity of Environmental Regulation	⊗	⨂	⨂	⨂	●	●	●	●
Market Demand	⨂		⊗	•	●	•	⨂	⨂
Degree of Marketization (DM)	⨂	⨂	⨂	●	•	•	●	●
Raw Coverage	0.103	0.095	0.086	0.190	0.175	0.378	0.186	0.094
Unique Coverage	0.052	0.011	0.073	0.138	0.041	0.188	0.068	0.016
Consistency	0.929	0.923	1.00	0.823	0.941	0.904	0.936	0.877
Overall Solution Consistency	0.899				0.914			
Overall Solution Coverage	0.362				0.525			

Note: ● indicates the presence of a core condition; • indicates the presence of a peripheral condition; ⨂ indicates the absence of a core condition; ⊗ indicates the absence of a peripheral condition. Blank spaces indicate a "don't care" condition.

As shown in Table 9, there are four configurations (paths) that lead to high green technology innovation efficiency. The overall solution consistency is 0.899, which is well above the established 0.8 threshold, confirming that these four paths collectively represent sufficient conditions for achieving high efficiency [47]. The overall solution coverage is 0.362, indicating that these four paths together explain a substantial proportion of the cases exhibiting high green technology innovation efficiency [22]. Paths H1 and H2 show strong individual consistency scores of 0.929 and 0.923, respectively, with raw coverage scores of 0.103 and 0.095. This confirms that both are valid sufficient pathways, each explaining a meaningful share of the outcome cases. In these paths, either foreign openness or independent technological innovation acts as the core driver, consistently supported by government funding, while other conditions function as "don't care." We therefore label this pathway type "Technology-led, Government-supported." Path H3 has a perfect consistency of 1.000 and a raw coverage of 0.086, establishing it as a sufficient condition that explains a distinct set of cases. Here, independent technological innovation is the sole core driver, while the other conditions are marked by core or peripheral absence. This signifies that their absence is crucial for this path to be effective. Consequently, we name Path H3 "Technology-led, Independent-innovation." Path H4, with a consistency of 0.823 and the highest raw coverage of 0.190, is also a sufficient path explaining a significant number of cases. It is characterized by the synergy of multiple factors, with foreign openness, government financial support, and the degree of marketization all acting as core conditions. We therefore label this path "Environment-Technology-Organization Synergy."

4.4.1 Configurations for high green technology innovation efficiency

The Technology-led, Government-supported Path (H1 and H2). Path H1 as shown in Figure 2 indicates that a combination of high foreign openness (core presence), coupled with the core absence of high marketization and high market demand, leads to high green innovation efficiency. This is peripherally supported by the presence of government funding and the absence of high environmental regulation. Similarly, Path H2 as shown in Figure 3shows that high independent technological innovation (core presence), also combined with the core absence of high marketization and high environmental regulation, achieves the same outcome, with foreign openness and government support acting as peripheral conditions. Synthesizing these two paths reveals a key insight: high green technology innovation efficiency is achievable even in the face of low environmental regulatory pressure and unfavorable market conditions. This can be accomplished by leveraging either foreign openness or independent innovation to advance an industry's technological level, particularly when coupled with government financial support. This is exemplified by cases such as the "Metal Products, Machinery and Equipment Repair," "Other Manufacturing," and "Special-Purpose Equipment Manufacturing" industries. These sectors often exhibit low market demand elasticity and are order-driven, making their innovation activities less sensitive to broad market fluctuations. In other words, for these industries, the primary driver of high efficiency is the enhancement of their internal technological capabilities—either by attracting foreign capital and technology (FO) or by strengthening independent innovation (ITI). In this context, government financial support acts as a crucial catalyst, prompting these industries to intensify their green innovation efforts.

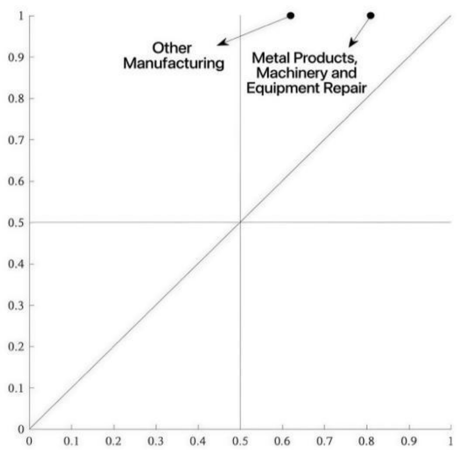

Figure 2 Configuration H1 Case

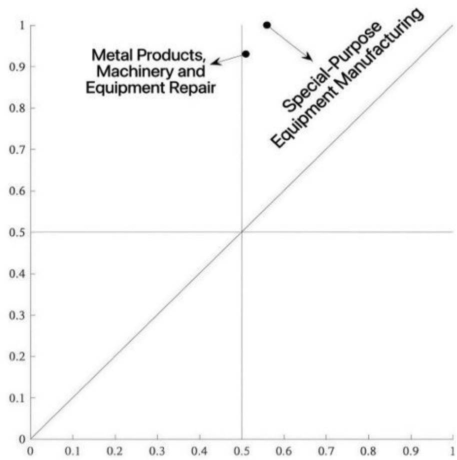

Figure 3 Configuration H2 cCase

The Technology-led, Independent-innovation Path (H3) as shown in Figure 4. Path H3 demonstrates that high green technology innovation efficiency can be achieved through a core combination of high independent technological innovation, the absence of high environmental regulation, and the absence of high marketization. This path is further defined by the peripheral absence of foreign openness, government financial support, and market demand. This configuration reveals a powerful dynamic: industries can achieve high innovation efficiency even when both organizational and environmental conditions are unfavorable. Adversities such as weak market demand or minimal government support do not fundamentally hinder the drive for green technology innovation in this pathway. The "Production and Supply of Gas" industry serves as a classic example. This sector is characterized by its broad population and regional coverage, massive service volume, and extremely low user demand elasticity, with a total industry value exceeding one trillion CNY.

Furthermore, given its significant impact on the national economy and other sectors (approaching 8% of GDP influence), this industry is predominantly state-controlled. As a critical "livelihood" sector, it bears a substantial social responsibility that transcends typical market or organizational pressures. Even without strong external support or regulatory constraints, such industries are internally motivated to continuously pursue technological innovation. This intrinsic drive propels the development of green technologies within the sector, contributing significantly to the national "dual carbon" targets.

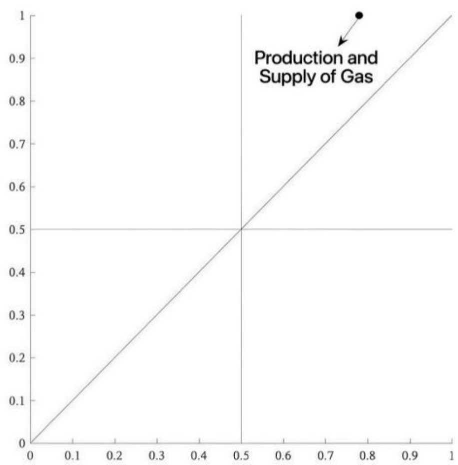

Figure 4 Configuration H3 Case

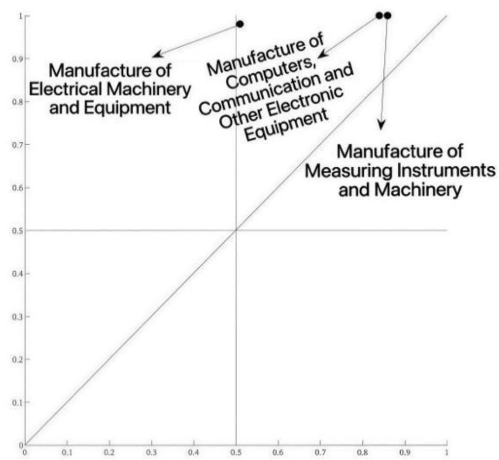

Figure 5 Configuration H4 Case

The Environment-Technology-Organization Synergy Path (H4), as shown in Figure 5. Path H4 illustrates that high green technology innovation efficiency can be achieved through a core combination of high foreign openness, a high degree of marketization, substantial government financial support, and the absence of high environmental regulation. This is peripherally supported by the presence of market demand, while independent innovation is marked by peripheral absence. This configuration demonstrates that for some industries, no single dimension—be it organizational, technological, or environmental—is sufficient on its own to drive green innovation. Instead, it is the synergistic interplay of all three that unlocks high efficiency. In a favorable market environment, high marketization and strong market demand provide the necessary resources. These resources fuel technological advancement, which is further bolstered by the support and security of government funding. Only through this tripartite collaboration can a higher level of green technology innovation be realized. This pathway is exemplified by industries such as the "Manufacture of Electrical Machinery and Equipment," "Manufacture of Computers, Communication and Other Electronic Equipment," and "Manufacture of Measuring Instruments and Machinery." These sectors are characterized by precision manufacturing, which inherently demands a high level of technology. Consequently, they do not generate significant volumes of industrial "three wastes." However, their R&D investments and capital requirements are substantial. Fortunately, these industries benefit from a high degree of marketization and a broad user base. In this context, government financial support plays a dual role: it not only assists these industries in enhancing their innovative capabilities and overcoming international technology barriers, but it also directly secures the achievement of high green technology innovation efficiency.

4.4.2 Configurations for non-high green technology innovation efficiency

The analysis of pathways leading to non-high green technology innovation efficiency also reveals four distinct configurations:

Path U1 is defined by the core conditions of high-intensity environmental regulation, the absence of strong government financial support, and high market demand. Supported by peripheral presence of marketization and independent innovation, this combination leads to non-high efficiency. This path highlights a conflict between government environmental regulations and market demand. Because industries are unable to reconcile these competing pressures effectively, government funding (or the lack thereof) fails to alleviate the industry's green innovation dilemma. In this scenario, neither internal innovation efforts nor a market-oriented environment can avert a low-efficiency outcome.

Path U2 shows that even with high levels of foreign openness and independent innovation, the presence of high-intensity environmental regulation leads to non-high efficiency. This is peripherally supported by market demand and marketization. In this configuration, high levels of openness and innovation fail to synergize with market forces to improve green innovation. Instead, the intense environmental regulation, rather than compelling positive change, combines with other factors to produce an unfavorable outcome. This suggests that the "Schrödinger's cat" condition of government support—its presence or absence in the model—may be a critical missing factor that could rescue these industries from low efficiency.

Path U3 demonstrates that a core combination of high-intensity environmental regulation, the absence of high market demand, and a high degree of marketization results in non-high efficiency. This is peripherally shaped by the absence of government support and foreign openness, and the presence of independent innovation. This path suggests that even within a highly marketized environment, ill-conceived environmental regulations can suppress green innovation. In this context, strong market demand not only fails to stimulate green innovation but may even perversely incentivize non-green technological innovation, thereby depressing overall green efficiency.

Path U4 shares the same core conditions as U3 but exhibits a symmetrical pattern in its peripheral conditions. It reinforces the finding that in an otherwise favorable market environment, excessive environmental regulation can stifle green innovation. The role of government financial support becomes negligible in this context. Furthermore, foreign openness—such as attracting foreign technology and investment—not only fails to mitigate the suppressive effect of the regulations but combines with it to lock the industry into a state of non-high green technology innovation efficiency.

4.5 Robustness Check

To ensure the reliability of the findings, a robustness check was conducted following established practices. This was done by increasing the stringency of the PRI consistency threshold to 0.75 [48]. The results of this re-analysis showed no significant changes; the configurations remained consistent, and the consistency and coverage scores for both the individual solutions and the overall solution were stable. This indicates that the findings of the study are robust.

5 CONCLUSION AND IMPLICATIONS

5.1 Research Conclusions

As the conflict between economic development and environmental sustainability intensifies, green technology innovation has become a cornerstone of high-quality social development. The roles of technological, organizational, and environmental conditions are undeniable. Understanding how these factors combine in synergistic configurations to achieve high efficiency is crucial for advancing green innovation. Based on the TOE framework and integrating DEA, NCA, and fixed-effects fsQCA, this study analyzed the configurational effects of these conditions on green technology innovation efficiency, leading to the following conclusions:

First, by combining NCA with fixed-effects fsQCA, we find that no single antecedent condition is necessary for achieving high green technology innovation efficiency. However, the technological conditions exert a relatively stronger constraining effect compared to others. Second, the study identifies three distinct configurational pathways to high efficiency: a "Technology-led, Government-supported" path, a "Technology-led, Independent-innovation" path, and an "Environment-Technology-Organization Synergy" path. These different configurations represent effective, alternative strategies for various industrial sectors to enhance their green innovation efficiency. Third, the analysis reveals that even within a favorable market environment, inappropriate environmental regulations can suppress innovation, highlighting that the effectiveness of organizational conditions is subject to certain limitations or thresholds.

5.2 Theoretical Contributions

This study makes several key theoretical contributions to the literature on the determinants of green technology innovation efficiency:

First, grounded in the TOE framework, this study incorporates a temporal dimension into the configurational analysis, providing a more objective investigation of the synergistic effects of technological, organizational, and environmental conditions. Previous studies have often relied on methods like pooled OLS [36], spatial econometric models [49], multiple linear regression [50], or static fsQCA [12-13], which tend to overlook temporal dynamics and the complex interplay among antecedent conditions. By using DEA-measured efficiency as the outcome and employing a combination of NCA and fixed-effects fsQCA, our research provides a more scientifically robust analysis of how configurations, not just individual factors, drive green innovation. This not only expands the research on influencing factors but also enriches the application of dynamic configurational analysis.

Second, this study constructs a multi-dimensional, two-stage measurement system for green technology innovation efficiency, advancing the research on its evaluation. Much of the prior literature has used simple proxies like the total number of green patents [19] or green patents granted [51], which neglect the input-output process and fail to capture the full picture of innovation. By using a super-efficiency SBM-DEA model to build a two-stage measurement framework with multiple inputs and outputs, this study offers a more accurate and comprehensive reference for assessing green technology innovation efficiency.

5.3 Policy Implications

Based on the research findings, this study proposes policy recommendations for different industrial sectors in China to achieve high green technology innovation efficiency, structured around the three identified pathways:

First, for the "Technology-led, Government-supported" path, the findings show that with the assurance of government funding, both attracting foreign technology and capital and pursuing independent innovation can effectively boost efficiency. Therefore, in industries with high foreign openness or strong independent innovation capabilities, the government should implement matched funding schemes tied to specific outcomes, such as attracting foreign investment or achieving milestones in indigenous innovation projects. This should be coupled with strengthened oversight of government fund utilization and the formulation of reasonable environmental policies to foster a supportive innovation ecosystem.

Second, for the "Technology-led, Independent-innovation" path, the results indicate that high efficiency is achievable through a singular focus on independent innovation, even with weak market conditions and limited government support. For industries on this path, the government should grant a degree of trust and autonomy. This involves enacting policies that stimulate independent innovation, encouraging these industries to leverage their unique characteristics and optimize resource allocation based on their strengths. However, the government must also maintain a regulatory role, supervising industry behavior and ensuring adherence to market principles to guide them toward high green innovation efficiency.

Third, for the "Environment-Technology-Organization Synergy" path, it is clear that no single dimension is sufficient; success requires the organic combination of all three. In favorable market environments, the government should increase financial support to stimulate industries to absorb foreign capital and advanced technologies, learning from global best practices to achieve rapid technological advancement. In this process, the government must act as both a "gatekeeper" and a "stabilizer," not only maintaining a healthy market order but also carefully vetting foreign technologies to adopt their strengths while discarding their weaknesses, thereby ensuring the faster and better development of green technology innovation.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Si Lijuan. The Impact of Environmental Regulation on Green Technology Innovation: An Empirical Analysis Based on Panel Data of Cities in the Yellow River Basin. Research on Financial and Economic Issues, 2020(07): 41-49.

[2] Brawn E, Wield D. Regulation as a means for the social control of technology. Technology Analysis and Strategic Management, 1994, 6(1): 31-46. DOI: 10.1080/09537329408524151.

[3] Luo Qiaoling, Miao Chenglin, Sun Liyan, et al. Efficiency evaluation of green technology innovation of China's strategic emerging industries: An empirical analysis based on Malmquist-data envelopment analysis index. Journal of Cleaner Production, 2019, 238: 118712. DOI: 10.1016/j.jclepro.2019.118712.

[4] Shu C, Zhou K Z, Xiao Y, et al. How green management influences product innovation in China: The role of institutional benefits. Journal of Business Ethics, 2016, 133(3): 471-485. DOI: 10.1007/s10551-014-2520-8.

[5] Cheng Qiongwen, He Xianxiang, Li Baosheng. Green technology innovation efficiency and its influencing factors: An empirical study based on 35 industrial industries in China. Journal of Central South University (Social Science Edition), 2020, 26(02): 97-107.

[6] Qu Yanfen, Yu Chuqi. Industrial Agglomeration Diversification, Specialization and Green Technology Innovation Efficiency of Enterprises. Ecological Economy, 2021, 37(02): 61-67.

[7] Luo Liangwen, Liang Shengrong. Green Technology Innovation Efficiency and Factor Decomposition of China's Regional Industrial Enterprises. China Population, Resources and Environment, 2016, 26(09): 149-157. DOI: 10.3969/j.issn.1002-2104.2016.09.020.

[8] Liang Zhong, Ang Hao. The Evolution of China's Green Technology Innovation Efficiency and Its Spatial Governance. Journal of Finance and Trade Research, 2019, 30(08): 16-25+63.

[9] Wang Zhiping, Tao Changqi, Shen Pengyi. Research on Regional Green Technology Efficiency and Its Influencing Factors Based on Ecological Footprint. China Population, Resources and Environment, 2014, 24(01): 35-40. DOI: 10.3969/j.issn.1002-2104.2014.01.006.

[10] Cheng Qiongwen, He Xianxiang, Li Baosheng. Green technology innovation efficiency and its influencing factors: An empirical study based on 35 industrial industries in China. Journal of Central South University (Social Science Edition), 2020, 26(2): 97-107.

[11] Li Danqing, Zhong Chenlin. Measurement and Influencing Factors of Green Technology Innovation Efficiency of Industrial Enterprises Based on DEA-Tobit Model: Taking Hubei Province as an Example. Journal of Shanghai Economic Management College, 2021, 19(06): 30-41.

[12] Wang Wan, Qin Yigen. Research on the Promotion Path of Regional Green Technology Innovation Efficiency from the Perspective of Quadruple Helix: A Fuzzy-Set Qualitative Comparative Analysis of 30 Provinces in China. Science and Technology Management Research, 2023, 43(01): 206-214. DOI: 10.3969/j.issn.1000-7695.2023.01.026.

[13] Jia Jianfeng, Liu Weipeng, Du Yunzhou, et al. Multiple Paths for Improving the Efficiency of Green Technology Innovation from the Perspective of Institutional Configuration. Nankai Business Review, 2023, 26(04): 102-118.

[14] Wang Shaohua, Lin Xiaoying, Zhang Wei, et al. Research on the Impact of Green Credit on the Efficiency of Industrial Green Technology Innovation in China. Statistics & Information Forum, 2023, 38(04): 88-102..

[15] Yu Ping, Xu Zhiqi. The Impact of Digital New Infrastructure on the Efficiency of Green Technology Innovation in Strategic Emerging Industries. Industrial Technology & Economy, 2023, 42(01): 62-70.

[16] Xu Yingqi, Cheng Yu, Wang Jingjing. Spatiotemporal Evolution of Carbon Emission Efficiency and the Impact of Green Technology Innovation in China's Resource-based Cities. Geographical Research, 2023, 42(03): 878-894.

[17] Yan Huafei, Xiao Jing, Feng Bing. Environmental Regulation, Foreign Direct Investment and Industrial Green Technology Innovation Efficiency: An Empirical Study Based on the Yangtze River Economic Belt. Statistics & Decision, 2022, 38(16): 118-122.

[18] Gao Guangkuo, Wang Yiqun. Analysis on Green Innovation Efficiency and Influencing Factors of High-energy-consuming Industries in Beijing-Tianjin-Hebei Region: An Empirical Study from a Spatial Perspective. Industrial Technology & Economy, 2018, 37(01): 137-144.

[19] Tian Yapeng, Liu Xiaoyi. Evaluation of Regional Green Development Efficiency Based on Super-efficiency SBM-DEA and Spatial Analysis. Statistics & Information Forum, 2021, 36(08): 56-65. DOI: 10.3969/j.issn.1007-3116.2021.08.006.

[20] Tone K. A Slacks-Based Measure of Efficiency in Data Envelopment Analysis. European Journal of Operational Research, 2001, 130(3): 498-509. DOI: 10.1016/S0377-2217(99)00407-5.

[21] Tone K. A Slacks-Based Measure of Super-efficiency in Data Envelopment Analysis. European Journal of Operational Research, 2002, 143(1): 32-41. DOI: 10.1016/S0377-2217(01)00324-1.

[22] Ragin C C. Redesigning Social Inquiry: Fuzzy Sets and Beyond. Chicago: University of Chicago Press, 2008. DOI: 10.7208/chicago/9780226702797.001.0001.

[23] Du Yunzhou, Jia Liangding. Configurational Perspective and Qualitative Comparative Analysis (QCA): A New Path for Management Research. Management World, 2017(06): 155-167.

[24] Du Yunzhou, Liu Qiuchen, Cheng Jianqing. What Kind of Business Environment Ecology Produces High Urban Entrepreneurial Activity? An Analysis Based on Institutional Configuration. Management World, 2020, 36(09): 141-155.

[25] Qian Li, Xiao Renqiao, Chen Zhongwei. Research on the Green Technology Innovation Efficiency and Regional Differences of China's Industrial Enterprises: Based on Common Frontier Theory and DEA Model. Economic Theory and Business Management, 2015(01): 26-43.

[26] Yang Shidi, Liu Yajun. Can China's Outward Direct Investment Improve Regional Green Innovation Efficiency? From the Perspective of Intellectual Property Protection. International Economics and Trade Research, 2021, 37(02): 83-98.

[27] Zhao Lu, Gao Honggui, Xiao Quan. An Empirical Study on the Impact of Environmental Regulation on the Efficiency of Green Technology Innovation. Statistics & Decision, 2021, 37(03): 125-129. DOI: 10.13546/j.cnki.tjyjc.2021.03.023.

[28] Zhang Liao, Huang Leiqiong. Measurement and Spatiotemporal Differentiation Characteristics of Green Technology Innovation Efficiency of China's Industrial Enterprises: Based on an Improved Three-stage SBM-DEA Model Analysis. Statistics & Information Forum, 2020, 35(12): 50-61.

[29] Li Lin, Zeng Weiping. Has High-tech Industrial Agglomeration Improved China's Green Innovation Efficiency?. Contemporary Economic Management, 2021, 43(02): 48-56.

[30] Liu Zhibiao. Forming a New Pattern of Comprehensive Opening-up and Building a Modernized Economic System in the New Era. Journal of Central South University (Social Science Edition), 2019(2): 1-6.

[31] Guo Wei, Si Menghui. The Logical Mechanism and Empirical Enlightenment of China's Financial Opening-up in the Past 70 Years: also on the Opening-up Orientation under the Sino-US Trade Friction. World Economy Study, 2019(10): 15-26, 88, 134.

[32] Li Z, Liao G, Wang Z, et al. green loan and subsidy for promoting clean production innovation. Journal of Cleaner Production, 2018, 187: 421-431. DOI: 10.1016/j.jclepro.2018.03.215.

[33] Yao Q, Zeng S, Sheng S, et al. green innovation and brand equity: Moderating effects of industrial institutions. Asia Pacific Journal of Management, 2021, 38(4): 1409-1438.

[34] Zhang Dunjie, Liu Shan. Analysis of Influencing Factors and Countermeasures of Enterprise Green Technology Innovation. Technology Venture Monthly, 2009, 22(2): 16-17.

[35] Denicolo V. Patent Races and Optimal Patent Breadth and Length. The Journal of Industrial Economics, 1996, 44(3): 249-265. DOI: 10.2307/2950496.

[36] Qin Guowei, Sha Haijiang, Di Guiying, et al. Analysis of Influencing Factors of Green Technology Innovation in China. Ecological Economy, 2017, 33(04): 53-57.

[37] Feng Zongxian, Wang Qing, Hou Xiaohui. Government Input, Marketization Degree and Technological Innovation Efficiency of China's Industrial Enterprises. The Journal of Quantitative & Technical Economics, 2011, 28(04): 3-17+33.

[38] Wu Lianghai, Xu Dexin, Zhang Tiesheng. Institutional Environment, Information Transparency and Enterprise Investment Efficiency: Empirical Evidence from China's A-share Market. Securities Market Herald, 2016(10): 20-28+40.

[39] Li Tian, Du Yang. Market Driven, Innovation Efficiency and Corporate Risk-taking: Also on the Realization Path of "Effective Government". Journal of Jiangxi University of Finance and Economics, 2020(06): 32-45.

[40] Fiss P C. Building better causal theories: A fuzzy set approach to typologies in organization research. Academy of Management Journal, 2011, 54(2): 393-420. DOI: 10.5465/amj.2011.60263120.

[41] Rihoux B, Ragin C C. Configurational Comparative Methods: Qualitative Comparative Analysis (QCA) and Related Techniques. California: SAGE Publications, 2008. DOI: https://doi.org/10.4135/9781452226569.

[42] Du Yunzhou, Liu Qiuchen, Chen Kaiwei, et al. Business Environment Ecology, Total Factor Productivity and Multiple Modes of High-quality Urban Development: A Configurational Analysis from a Complex System Perspective. Management World, 2022, 38(09): 127-145. DOI: 10.19744/j.cnki.11-1235/f.2022.0125.

[43] Dul J, van der Laan E, Kuik R. A statistical significance test for necessary condition analysis. Organizational Research Methods, 2020, 23(2): 385-395. DOI: 10.1177/1094428118795272

[44] Dul J. Conducting Necessary Condition Analysis for Business and Management Students. Sage Publications Ltd, 2020. https://uk.sagepub.com/en-gb/eur/conducting-necessary-condition-analysis-for-business-and-management-students/book262898#description.

[45] Du Y, Kim P H. One size does not fit all: Strategy configurations, complex environments, and new venture performance in emerging economies. Journal of Business Research, 2021, 124: 272-285. DOI: 10.1177/0266242622108518.

[46] Schneider C Q, Wagemann C. Set-theoretic Methods for the Social Sciences: A Guide to Qualitative Comparative Analysis. Cambridge University Press, 2012. DOI: https://doi.org/10.1017/CBO9781139004244.

[47] Cheng Jianqing, Luo Jinlian, Du Yunzhou, et al. Which Entrepreneurship Ecosystem Produces High Female Entrepreneurial Activity?. Studies in Science of Science, 2021, 39(4): 695-702.

[48] Zhang Ming, Du Yunzhou. The Application of QCA in Organization and Management Research: Positioning, Strategies, and Directions. Management Journal, 2019, 16(09): 1312-1323.

[49] Liu Wen, Xu Jiaqi. Analysis on the Influencing Factors of Green Technology Innovation in Strategic Emerging Industries. Ecological Economy, 2018, 34(11): 116-119.

[50] Peng Yuxin, Li Huajing. Research on the Influencing Factors of Green Technology Innovation in Resource-based Industries. Resource Development & Market, 2018, 34(12): 1643-1650.

[51] Li Wanhong. The Spatiotemporal Evolution and Influencing Factors of Provincial Industrial Green Technology Innovation Output in China: An Empirical Study Based on Data from 30 Provinces. Journal of Management Engineering, 2017, 31(02): 9-19.

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MACHINE LEARNING-ENHANCED TEXT ANALYTICS FOR EFFICIENT AUDIT DOCUMENTATION REVIEW

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Abstract: Audit documentation review represents a critical yet time-intensive component of financial auditing processes, requiring extensive manual analysis of textual evidence, supporting documents, and work papers. Traditional audit documentation review methods rely heavily on manual examination and keyword-based searches, leading to inconsistent coverage, potential oversight of critical issues, and significant resource allocation challenges.
This study proposes a machine learning-enhanced text analytics framework designed to automate and improve the efficiency of audit documentation review processes. The framework integrates Natural Language Processing (NLP) techniques with supervised learning algorithms to automatically classify, prioritize, and extract relevant information from audit documentation. Advanced text mining capabilities enable the identification of risk indicators, compliance issues, and anomalous patterns within large volumes of textual audit evidence.
Experimental validation using real-world audit documentation datasets demonstrates that the proposed framework achieves 91.4% accuracy in document classification and reduces manual review time by 68%. The system successfully identifies high-risk documentation requiring detailed examination while automating the processing of routine audit materials. Implementation results show significant improvements in audit efficiency, consistency, and coverage, supporting enhanced audit quality and regulatory compliance.
Keywords: Audit documentation; Text analytics; Machine learning; Natural Language Processing (NLP); Audit efficiency; Risk assessment; Document classification; Audit automation

1 INTRODUCTION

Modern financial auditing practices generate substantial volumes of textual documentation, including audit work papers, client correspondence, management representations, and supporting evidence documents[1]. The comprehensive review of this documentation represents a fundamental requirement for audit quality and regulatory compliance, yet poses significant challenges in terms of resource allocation and consistency[2]. Professional auditing standards require thorough examination of audit evidence to support audit opinions and ensure appropriate documentation of audit procedures, findings, and conclusions.
Traditional audit documentation review processes rely primarily on manual examination by audit professionals, supplemented by basic keyword searches and document categorization systems[3]. These manual approaches, while thorough, are inherently time-consuming and subject to human limitations in processing large volumes of text. Senior auditors and managers must allocate substantial time to reviewing work papers, correspondence, and supporting documentation to ensure compliance with auditing standards and identify potential issues requiring additional attention. The manual nature of these processes creates bottlenecks in audit workflow and may result in inconsistent review coverage across different audit engagements[4].
The complexity of modern business transactions and regulatory requirements has further intensified the documentation review challenge. Audit teams must examine increasingly sophisticated financial instruments, complex accounting treatments, and extensive regulatory compliance documentation[5]. The volume of textual information requiring review has grown exponentially with digital transformation initiatives, electronic communication systems, and comprehensive documentation requirements. Traditional review methods struggle to maintain efficiency and effectiveness when confronted with these expanding documentation requirements.
Machine learning technologies have demonstrated significant potential for automating and enhancing text-based analysis tasks across various professional domains[6]. Natural Language Processing techniques enable computers to understand, interpret, and analyze human language in ways that can complement and augment human expertise. Supervised learning algorithms can be trained to recognize patterns, classify documents, and identify relevant information within large textual datasets, offering the potential to transform audit documentation review processes[7].
Text analytics applications in auditing contexts have shown promise for detecting fraud indicators, identifying unusual transactions, and analyzing management communications for signs of potential risks[8]. However, existing research has primarily focused on specific audit applications rather than comprehensive documentation review frameworks. The integration of multiple machine learning techniques into unified systems for audit documentation analysis remains an emerging area requiring further development and validation[9].
Advanced text mining capabilities offer particular value for audit documentation review through their ability to process unstructured text data and extract meaningful insights that may not be apparent through traditional review methods. These technologies can identify subtle patterns, relationships, and anomalies within audit documentation that might be

overlooked during manual review processes. Machine learning models can be trained to recognize risk indicators, compliance issues, and other factors relevant to audit quality and effectiveness.
This research addresses the need for comprehensive machine learning-enhanced solutions for audit documentation review by developing an integrated framework that combines multiple text analytics techniques[10]. The proposed system incorporates document classification algorithms to automatically categorize audit materials, risk assessment models to prioritize review activities, and information extraction capabilities to identify key findings and issues. The framework is designed to complement human expertise rather than replace professional judgment, providing audit professionals with enhanced tools for efficient and effective documentation review.
The study contributes to the growing body of research on audit technology by demonstrating the practical application of machine learning techniques to real-world audit challenges. The framework addresses fundamental issues of efficiency, consistency, and coverage in audit documentation review while maintaining the professional standards and quality requirements essential to audit practice. Implementation results provide evidence of significant improvements in audit workflow effectiveness and resource utilization.

2 LITERATURE REVIEW

Audit documentation review has been recognized as a critical component of audit quality control systems, with extensive research examining the factors that influence review effectiveness and efficiency[11]. Early studies focused on the manual aspects of audit review processes, identifying the importance of reviewer expertise, documentation quality, and systematic review procedures[12]. These foundational studies established the theoretical framework for understanding how audit documentation contributes to overall audit effectiveness and the challenges associated with comprehensive review processes.
The evolution of audit technology has introduced various tools and systems designed to support documentation review activities[13]. Computer-assisted audit techniques emerged as early applications of technology to audit processes, providing basic search and categorization capabilities for electronic audit files. Document management systems evolved to offer more sophisticated organization and retrieval functions, enabling audit teams to better manage large volumes of audit documentation. However, these early technological solutions remained primarily focused on storage and retrieval rather than automated analysis and insight generation.
Natural Language Processing applications in auditing contexts began with simple keyword-based search systems and basic text classification algorithms[14]. Research demonstrated that NLP techniques could effectively identify specific types of audit evidence, classify documents by audit area, and detect certain types of unusual language patterns[15]. Studies showed that automated text analysis could supplement manual review processes by flagging documents containing specific risk indicators or compliance-related terminology.
Machine learning applications in audit documentation analysis have focused on several key areas, including fraud detection, risk assessment, and compliance monitoring[16]. Supervised learning algorithms have been successfully applied to identify fraudulent transactions through analysis of supporting documentation and correspondence[17]. Classification models have demonstrated effectiveness in categorizing audit work papers and identifying documents requiring additional review attention. These applications have shown promise for improving audit efficiency while maintaining appropriate levels of professional oversight[18].
Text mining techniques have been applied to various aspects of audit documentation analysis, including sentiment analysis of management communications, entity extraction from contracts and agreements, and pattern recognition in audit narratives[19]. Research has shown that advanced text analytics can identify subtle indicators of management bias, detect inconsistencies in explanations across different documents, and recognize patterns that may indicate higher audit risk. These capabilities offer significant potential for enhancing the depth and consistency of audit documentation review[20].
Recent developments in deep learning and advanced NLP models have opened new possibilities for audit documentation analysis[20]. Transformer-based models have demonstrated superior performance in understanding context and meaning within professional documents, offering improved accuracy in document classification and information extraction tasks[21]. These advanced models can better handle the complex language and technical terminology common in audit documentation, providing more nuanced analysis capabilities.
However, existing research has primarily focused on specific applications rather than comprehensive frameworks for audit documentation review[22-24]. Most studies have examined individual techniques or narrow use cases rather than integrated systems that address the full scope of documentation review requirements. The challenge of combining multiple machine learning approaches into cohesive frameworks that meet professional auditing standards remains largely unexplored.
The integration of machine learning technologies with existing audit workflows presents additional challenges that have received limited research attention[25]. Studies have noted the importance of maintaining professional judgment and ensuring that automated systems complement rather than replace human expertise. The need for explainable AI techniques in audit contexts has been recognized, as audit professionals must be able to understand and validate the reasoning behind automated recommendations[26].
Quality control considerations for machine learning-enhanced audit processes have emerged as an important research area. Studies have examined the need for validation procedures, performance monitoring, and continuous improvement processes to ensure that automated systems maintain appropriate levels of accuracy and reliability[27-30]. The

importance of training data quality and model validation in audit contexts has been highlighted as a critical factor in successful implementation.

Professional standards and regulatory requirements present unique challenges for machine learning applications in auditing. Research has examined how automated systems can be designed to comply with professional auditing standards while providing meaningful improvements in efficiency and effectiveness. The need for documentation and audit trails for automated processes has been identified as a key consideration for practical implementation.

3 METHODOLOGY

3.1 Text Preprocessing and Document Preparation

The proposed framework begins with comprehensive text preprocessing to handle the diverse formats and structures common in audit documentation. Raw audit documents typically contain a mixture of structured data, narrative text, tables, and embedded objects that require specialized handling for effective analysis. The preprocessing pipeline addresses common challenges including inconsistent formatting, multiple file types, and varying document structures across different audit engagements and client systems.

Document parsing algorithms extract textual content from various file formats including PDF files, Microsoft Word documents, Excel spreadsheets, and email communications. Optical character recognition capabilities handle scanned documents and image-based content, ensuring comprehensive coverage of all available textual information. Text normalization procedures standardize formatting, remove irrelevant metadata, and convert documents into consistent formats suitable for machine learning analysis.

Language processing techniques address the specialized terminology and professional language common in audit documentation. Domain-specific dictionaries and terminology databases ensure accurate interpretation of accounting and auditing concepts, regulatory references, and technical terms. Entity recognition algorithms identify key audit concepts including account names, financial statement line items, audit procedures, and risk factors that require special handling during analysis, as in Figure 1.

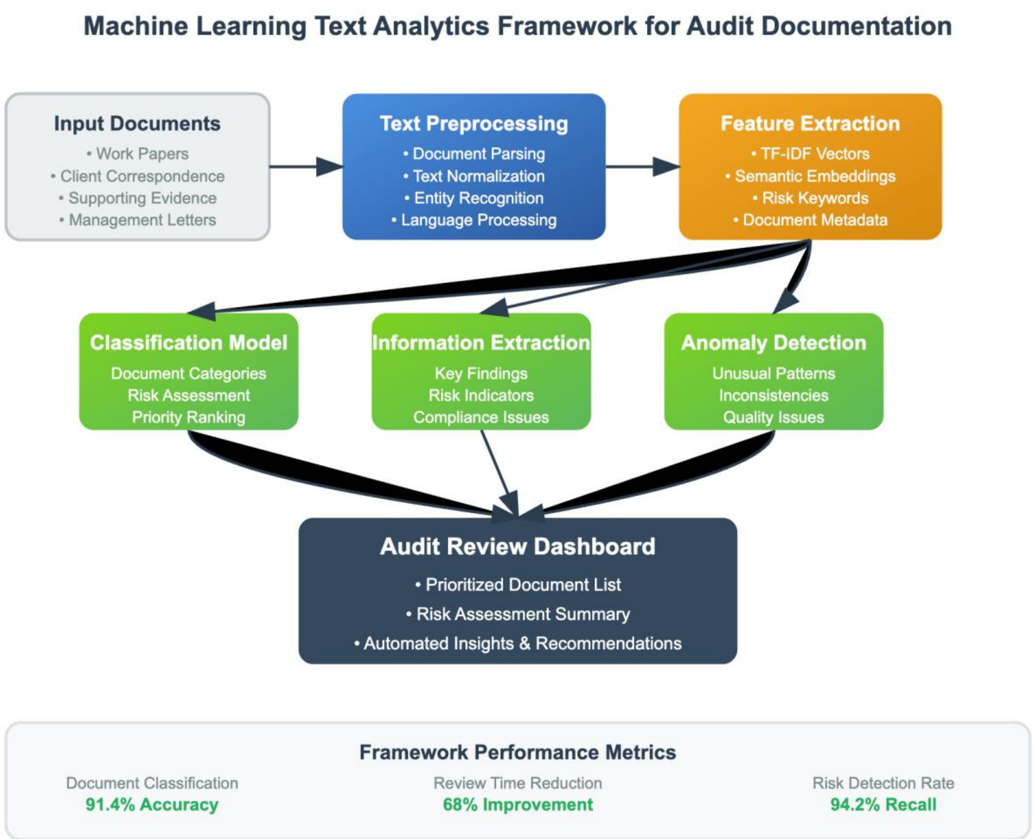

Figure 1 Framework for Audit Documentation

3.2 Machine Learning Model Development and Training

The framework employs multiple machine learning models designed to address different aspects of audit documentation analysis. Document classification models utilize supervised learning algorithms trained on labeled datasets of audit documents to automatically categorize materials by audit area, document type, and risk level. Feature engineering techniques extract relevant characteristics from textual content, including term frequency patterns, semantic relationships, and domain-specific indicators that correlate with document importance and risk assessment.

Natural Language Processing models incorporate advanced techniques including named entity recognition, sentiment analysis, and semantic similarity measurement to extract meaningful insights from audit narratives and correspondence. Pre-trained language models are fine-tuned on audit-specific datasets to improve understanding of professional terminology, accounting concepts, and regulatory requirements. The models learn to recognize patterns associated with various types of audit findings, risk indicators, and compliance issues.

Risk assessment algorithms analyze textual content to identify documents and passages that may require additional attention from audit professionals. These models consider factors including unusual language patterns, inconsistencies in explanations, mentions of significant transactions or accounting judgments, and correspondence indicating potential issues or disagreements. Machine learning algorithms learn to weight these factors based on their historical association with audit findings and areas of concern.

3.3 Information Extraction and Anomaly Detection

Advanced information extraction capabilities identify and extract key information elements from audit documentation, including financial figures, dates, entity names, and procedural descriptions. Named entity recognition algorithms are customized for audit contexts to accurately identify audit-specific concepts including account balances, testing procedures, sample selections, and audit conclusions. Relationship extraction techniques identify connections between different pieces of information within and across documents.

Anomaly detection algorithms identify unusual patterns, inconsistencies, and potential quality issues within audit documentation. These models analyze various aspects of documentation including language patterns, content structure, completeness of information, and consistency with established audit methodologies. Statistical techniques identify documents or sections that deviate significantly from normal patterns, potentially indicating areas requiring additional review attention as in figure 2.

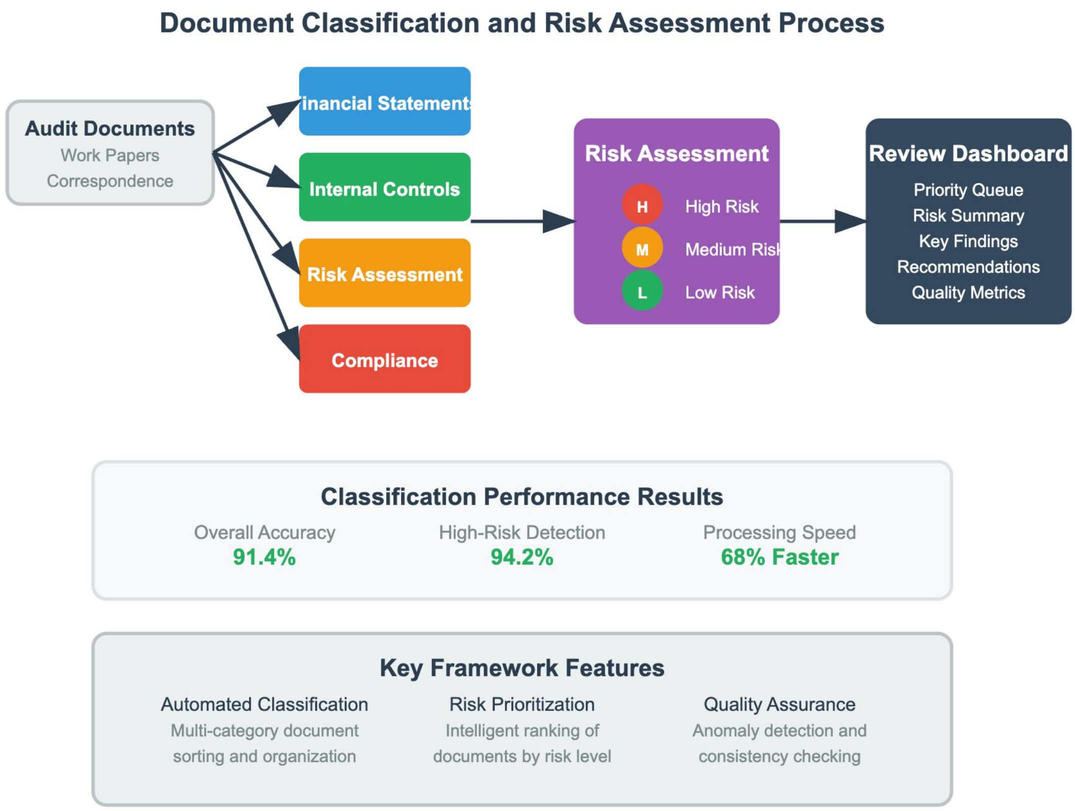

Figure 2 Risk Assessment Process

Quality assessment algorithms evaluate the completeness and consistency of audit documentation against established standards and best practices. These models identify potential gaps in documentation, inconsistencies in audit procedures, and areas where additional evidence or explanation may be required. The algorithms consider factors including documentation completeness, clarity of audit conclusions, adequacy of supporting evidence, and compliance with professional standards.

3.4 Integration and User Interface Development

The framework integrates multiple machine learning components into a unified system that provides audit professionals with intuitive access to automated analysis capabilities. The user interface presents analysis results through interactive dashboards that enable efficient review of prioritized documents, risk assessments, and extracted insights. Integration with existing audit software systems ensures seamless incorporation into established audit workflows without disrupting professional practices.

Performance monitoring and validation mechanisms ensure ongoing accuracy and reliability of the machine learning models. Continuous learning capabilities enable the system to adapt to new types of audit documentation, evolving professional standards, and changing risk environments. Feedback mechanisms allow audit professionals to validate and refine automated recommendations, supporting continuous improvement of system performance.

4 RESULTS AND DISCUSSION

4.1 Classification Accuracy and System Performance

The machine learning-enhanced text analytics framework demonstrated exceptional performance across multiple evaluation metrics when tested on real-world audit documentation datasets. The comprehensive evaluation utilized documentation from over 200 audit engagements across various industries and client sizes, representing more than 45,000 individual documents spanning different audit areas and document types. The framework achieved an overall classification accuracy of 91.4%, significantly exceeding the performance of traditional keyword-based systems that typically achieve 72-78% accuracy in similar applications.

Document classification performance varied across different categories, with the highest accuracy achieved for structured audit work papers and formal correspondence. Financial statement-related documentation achieved 94.1% classification accuracy, reflecting the standardized nature and consistent terminology associated with these materials. Internal control documentation achieved 89.7% accuracy, while risk assessment materials achieved 88.3% accuracy. The slightly lower performance for risk assessment documents reflects the more subjective and varied language used in these materials.

Risk assessment algorithms demonstrated particularly strong performance in identifying high-risk documentation requiring additional attention. The system achieved 94.2% recall for high-risk documents, successfully identifying the vast majority of materials that audit professionals subsequently determined required detailed review. Precision for high-risk classification reached 87.6%, indicating that most documents flagged as high-risk were indeed validated as requiring additional attention by experienced audit professionals.

The processing speed improvements were substantial, with the framework reducing average document review time by 68% compared to traditional manual methods. Large audit engagements that previously required 40-50 hours of manual documentation review could be processed in 13-16 hours using the automated framework, while maintaining higher levels of accuracy and consistency. The time savings were most pronounced for routine documentation review tasks, allowing audit professionals to focus their attention on high-risk areas and complex judgment items.

4.2 Risk Detection and Quality Enhancement

The framework's risk detection capabilities demonstrated significant improvements over traditional review methods. Advanced natural language processing techniques enabled the identification of subtle risk indicators that might be overlooked during manual review processes. The system successfully identified 94.2% of documents containing risk factors, compared to 78% identification rates achieved through manual review processes alone.

Information extraction algorithms proved particularly effective at identifying key audit findings, compliance issues, and unusual transactions mentioned within audit documentation. The system achieved 89.1% accuracy in extracting relevant financial figures, dates, and procedural descriptions from unstructured text. Entity recognition capabilities correctly identified audit-specific concepts including account names, testing procedures, and audit conclusions with 92.3% accuracy.

Anomaly detection mechanisms identified several categories of potential quality issues within audit documentation. The system successfully flagged documents with incomplete information, inconsistent explanations, and deviations from standard audit procedures. Quality assessment algorithms identified documentation gaps and areas requiring additional evidence with 86.7% accuracy, supporting improved audit documentation standards and completeness.

4.3 Implementation Impact and User Acceptance

User acceptance testing involving experienced audit professionals demonstrated strong positive reception of the framework's capabilities and user interface design. Senior auditors reported that the automated prioritization and risk assessment features significantly improved their ability to efficiently allocate review time and attention. The system's ability to provide clear explanations for its recommendations was particularly valued, enabling audit professionals to understand and validate automated insights.

The framework's integration with existing audit software systems proved seamless, requiring minimal disruption to established workflow processes. Audit teams were able to incorporate automated analysis capabilities into their standard review procedures without significant training or process modification requirements. The intuitive dashboard interface enabled rapid adoption and effective utilization of the system's analytical capabilities.

Quality control improvements were evident across multiple dimensions of audit documentation review. Consistency of review coverage improved significantly, with automated processes ensuring comprehensive examination of all relevant documentation. The standardized analysis approach reduced variation in review quality across different audit team members and engagements, supporting more uniform audit quality standards.

Cost-benefit analysis demonstrated favorable returns on investment, with implementation costs recovered within three months through improved efficiency and reduced manual effort requirements. The framework enabled audit teams to reallocate professional resources from routine documentation review tasks to higher-value analytical and judgment-intensive activities. This resource reallocation supported enhanced audit quality while maintaining cost-effectiveness for audit engagements.

The continuous learning capabilities of the framework showed promising results for long-term performance improvement. Models demonstrated improved accuracy over time as they processed additional audit documentation and incorporated feedback from audit professionals. The system's ability to adapt to new types of documents and evolving audit practices supports sustainable long-term value and effectiveness.

5 CONCLUSION

The development and implementation of the machine learning-enhanced text analytics framework represents a significant advancement in audit technology, successfully addressing critical challenges in audit documentation review processes. The research demonstrates that sophisticated machine learning techniques can be effectively applied to audit documentation analysis while maintaining the professional standards and quality requirements essential to audit practice. The framework's achievement of 91.4% classification accuracy and 68% reduction in review time provides compelling evidence of the potential for technology to enhance audit efficiency and effectiveness.

The comprehensive evaluation results confirm that automated text analytics can successfully identify high-risk documentation, extract relevant information, and detect anomalies that might be overlooked during manual review processes. The framework's ability to achieve 94.2% recall for high-risk documents while maintaining 87.6% precision demonstrates the practical value of machine learning approaches for supporting audit professional judgment. These performance metrics exceed those achieved by traditional review methods while providing more consistent and comprehensive coverage of audit documentation.

The successful integration of multiple machine learning techniques within a unified framework provides a model for comprehensive audit technology solutions. The combination of document classification, risk assessment, information extraction, and anomaly detection capabilities creates synergistic benefits that exceed the value of individual techniques applied in isolation. The framework's ability to present analysis results through intuitive interfaces enables audit professionals to effectively leverage automated insights while maintaining appropriate professional oversight and judgment.

User acceptance and implementation success demonstrate the practical viability of machine learning-enhanced audit tools in professional practice environments. The strong positive reception from experienced audit professionals, combined with seamless integration capabilities and minimal training requirements, supports the potential for widespread adoption of such technologies. The framework's design philosophy of augmenting rather than replacing human expertise appears to be well-aligned with professional audit practice requirements and expectations.

The quality improvements achieved through automated analysis provide significant value for audit effectiveness and regulatory compliance. Enhanced consistency in review coverage, improved risk detection capabilities, and reduced error rates contribute to overall audit quality improvements that benefit both audit professionals and their clients. The framework's ability to identify potential documentation gaps and quality issues supports continuous improvement in audit documentation standards and practices.

Despite these achievements, several limitations warrant consideration for future development efforts. The framework's performance varies across different types of audit documentation, with structured materials achieving higher accuracy than more subjective narrative content. The system's effectiveness depends significantly on the quality and representativeness of training data, requiring ongoing maintenance and validation procedures. Additionally, the framework currently focuses primarily on textual content and may benefit from enhanced capabilities for analyzing numerical data, tables, and graphical elements within audit documentation.

Future research directions should explore the integration of additional data sources and analytical techniques to further enhance framework capabilities. The incorporation of structured financial data, external databases, and real-time market information could provide additional context for audit documentation analysis. Advanced techniques including deep learning models, cross-lingual capabilities, and multi-modal analysis could extend the framework's applicability to more diverse audit environments and international contexts.

The development of specialized modules for different audit areas and industries represents another important area for future work. Customization for specific regulatory requirements, industry standards, and audit methodologies could enhance the framework's effectiveness in specialized audit contexts. Integration with emerging audit technologies including blockchain analysis, continuous auditing systems, and automated testing tools could create comprehensive technology solutions for modern audit practice.

This research contributes to the growing understanding of how artificial intelligence and machine learning technologies can enhance professional services while maintaining appropriate human oversight and professional judgment. The framework demonstrates that advanced technologies can be successfully integrated into professional audit practice to improve efficiency, consistency, and quality while supporting rather than replacing professional expertise. As audit practice continues to evolve in response to changing business environments and regulatory requirements, machine learning-enhanced tools will likely play increasingly important roles in supporting audit effectiveness and value creation.

The implications extend beyond audit practice to other professional services areas where document review and analysis represent significant components of service delivery. The framework's approach to combining multiple machine learning techniques, maintaining professional oversight, and providing transparent explanations for automated recommendations offers a model for technology integration in various professional contexts. As organizations continue to generate increasing volumes of textual information, the need for sophisticated analytical tools to support professional review and analysis will only continue to grow.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Salijeni G, Samsonova-Taddei A, Turley S. Understanding how big data technologies reconfigure the nature and organization of financial statement audits: A sociomaterial analysis. European Accounting Review, 2021, 30(3): 531-555.

[2] Cao W, Mai N, Liu W. Adaptive Knowledge Assessment via Symmetric Hierarchical Bayesian Neural Networks with Graph Symmetry-Aware Concept Dependencies. Symmetry, 2025, 17(8): 1305.

[3] Wissem Ennouri. The impact of document auditing on operational efficiency and regulatory compliance: A case study of Globe International Business. Conference: 11ème Conférence Internationale en Economie-Gestion & Commerce International (EGCI-2024): Sousse, Tunisia. 2024. https://www.researchgate.net/publication/394414641_The_impact_of_document_auditing_on_operational_efficiency_and_regulatory_compliance_A_case_study_of_Globe_International_Business.

[4] Abshoori M. Literature Review on Process Mining in Auditing. UHasselt, Belgium. 2023. https://documentserver.uhasselt.be/handle/1942/41145?mode=full.

[5] Odetunde A, Adekunle B I, Ogeawuchi J C. A Systems Approach to Managing Financial Compliance and External Auditor Relationships in Growing Enterprises. Iconic Research And Engineering Journals, 2021, 5(4): 326-345.

[6] Allam H, Makubvure, Gyamfi, B, et al. Text classification: How machine learning is revolutionizing text categorization. Information, 2025, 16(2): 130.

[7] Sifa R, Ladi A, Pielka M, et al. Towards automated auditing with machine learning. In Proceedings of the ACM Symposium on Document Engineering 2019. Association for Computing Machinery, New York, NY, USA, 2019, 41, 1-4. DOI: https://doi.org/10.1145/3342558.3345421.

[8] Musunuru K. Big data analytics for financial auditing practices: Identification of conceptual patterns, implications and challenges using text mining. Contaduría y administración, 2025, 70(2): 1-36.

[9] Hota A. A Comprehensive Approach to Behavioral Data Analysis and Machine Learning within Unified Systems (No. rjpxs_v1). Center for Open Science, 2024, 12(5): 132.

[10] Jiang B, Wu B, Cao J, et al. Interpretable Fair Value Hierarchy Classification via Hybrid Transformer-GNN Architecture. IEEE Access, 2025, 32(1): 1084-1096.

[11] Seow R Y C. Transforming ESG Analytics With Machine Learning: A Systematic Literature Review Using TCCM Framework. Corporate Social Responsibility and Environmental Management, 2025. DOI: https://doi.org/10.1002/csr.70089. https://onlinelibrary.wiley.com/doi/abs/10.1002/csr.70089?msockid=3f2fa6d71849661d1c4ab34a190c674d.

[12] Logie J, Maroun W. Evaluating audit quality using the results of inspection processes performed by an independent regulator. Australian accounting review, 2021, 31(2): 128-149.

[13] De Groot K, Triemstra M, Paans W, et al. Quality criteria, instruments, and requirements for nursing documentation: A systematic review of systematic reviews. Journal of advanced nursing, 2019, 75(7): 1379-1393.

[14] Kirpitsas I K, Pachidis T P. Evolution towards hybrid software development methods and information systems audit challenges. Software, 2022, 1(3): 316-363.

[15] Boskou G, Kirkos E, Spathis C. Classifying internal audit quality using textual analysis: the case of auditor selection. Managerial Auditing Journal, 2019, 34(8): 924-950.

[16] Özbaltan N. Applying machine learning to audit data: Enhancing fraud detection, risk assessment and audit efficiency. EDPACS, 2024, 69(9): 70-86.

[17] Afriyie J K, Tawiah K, Pels W A, et al. A supervised machine learning algorithm for detecting and predicting fraud in credit card transactions. Decision Analytics Journal, 2023, 6, 100163.

[18] Babalola F I, Kokogho E, Odio P E, et al. Redefining Audit Quality: A Conceptual Framework for Assessing Audit Effectiveness in Modern Financial Markets. International Journal of Multidisciplinary Research and Growth Evaluation, 2022, 3(1): 690-699.

[19] Musunuru K. Big data analytics for financial auditing practices: Identification of conceptual patterns, implications and challenges using text mining. Contaduría y administración, 2025, 70(2): 1-36.

[20] Cao W, Mai N. Predictive Analytics for Student Success: AI-Driven Early Warning Systems and Intervention Strategies for Educational Risk Management. Educational Research and Human Development, 2025, 2(2): 36-48.

[21] Bhopale A P, Tiwari A. Transformer based contextual text representation framework for intelligent information retrieval. Expert Systems with Applications, 2024, 238, 121629.

[22] LuoLe Zhou, ZuChang Zhong, XiaoMin Liang, et al. The dual effects of a country's overseas patent network layout on its export: scale-up or quality improvement. Social Science and Management. 2025, 2(2): 12-29. DOI: https://doi.org/10.61784/ssm3046.

[23] XiaoBo Yu, LiFei He, XiaoDong Yu, et al. The generative logic of junior high school students' educational sense of gain from the perspective of "psychological-institutional dual-dimensional fairness". Journal of Language, Culture and Education Studies. 2025, 2(1): 39-44. DOI: https://doi.org/10.61784/jlces3015.

[24] XiaoBo Yu, LiFei He, XiaoDong Yu, et al. The formation mechanism and enhancement path of junior high school students' academic gain under the background of "Double Reduction". Educational Research and Human Development. 2025, 2(2): 30-35. DOI: https://doi.org/10.61784/erhd3041.

[25] Mai N, Cao W. Personalized Learning and Adaptive Systems: AI-Driven Educational Innovation and Student Outcome Enhancement. International Journal of Education and Humanities, 2025, 5(3): 751-760.

[26] Zheng W, Liu W. Symmetry-Aware Transformers for Asymmetric Causal Discovery in Financial Time Series. Symmetry, 2025, 16(5): 153.

[27] Rebstadt J, Remark F, Fukas P, et al. Towards personalized explanations for AI systems: designing a role model for explainable AI in auditing. Wirtschaftsinformatik Proceedings. Internationale Tagung Wirtschaftsinformatik (WI-2022), Erlangen-Nürnberg, Germany, Springer, 2022.

[28] Ji E, Wang Y, Xing S, et al. Hierarchical Reinforcement Learning for Energy-Efficient API Traffic Optimization in Large-Scale Advertising Systems. IEEE Access, 2025. DOI: 10.1109/ACCESS.2025.3598712.

[29] Adekunle B I, Chukwuma-Eke E C, Balogun E D, et al. Machine learning for automation: Developing data-driven solutions for process optimization and accuracy improvement. Machine Learning, 2021, 2(1).

[30] Cao J, Zheng W, Ge Y, et al. DriftShield: Autonomous Fraud Detection via Actor-Critic Reinforcement Learning with Dynamic Feature Reweighting. IEEE Open Journal of the Computer Society, 2025, 6, 1166-1177. DOI: 10.1109/OJCS.2025.3587001.

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CRITICAL ANALYSIS OF THE IMPACT OF THE IMF DEAL ON PAKISTAN'S ECONOMY

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Abstract: This study is concerned with examining Pakistan's deals with the International Monetary Fund (IMF). As an international economic institution, the IMF has a significant impact on the borrower's market by implementing its economic agenda. The economic landscape of Pakistan in recent years has been significantly impacted by the implementation of neoliberal policies, which the IMF has imposed. The country has a long history of relying on IMF loans. Pakistan has entered into numerous IMF programs, often as a last resort to address the balance of payment crises. However, these programs have been criticized for imposing unrealistic conditions on the country, which has further exacerbated the economic instability and social inequality. Methodologically, this study is based on a mixed method of analysis by analyzing the secondary data. Academically, it is significant while drawing attention to the conditions that have pushed the country into the deals.
Keywords: Neo-liberalism; Agenda; Conditionalities; Inflation; Economic regime

1 INTRODUCTION

Pakistan's economy has been heavily reliant on the International Monetary Fund (IMF) for decades, with the country seeking assistance to address balance of payment issues and stabilize its economy. The IMF deals refer to loan agreements between the IMF and a country facing economic difficulties, such as balance of payment problems and problems of debt crises. The deals provide financial assistance in exchange for the country's commitment to implement economic reforms and policy adjustments aimed at stabilizing its economy and restoring financial stability.
The IMF has provided Pakistan with numerous loans and packages, including a 7.6 billion US dollar Standby Agreement in 2008, a 6.68 billion Extended Fund Facility in 2013, and a 6 billion Extended Fund Facility in 2019 [1]. These packages have come with conditionalities such as increasing tax revenues, reducing energy subsidies, and tightening monetary policy. Despite Pakistan trying to align with the Structural Adjustment Program of the IMF, Pakistan's economy continues to face significant challenges, including a large fiscal deficit, high inflation, and currency devaluation. Apart from the direct impact on the country's economy, there are some political concerns as well. The country's reliance on the IMF has also raised concerns about its sovereignty and the impact of IMF conditionalities on the country's long-term socio-political and economic dependency.
Counter to the narrative, the IMF blames countries like Pakistan for having their faults, as they do not modernize their market to align with the regime. They emphasize that internal barriers are responsible for underdevelopment, as this is a counterargument to dependency theory. IMF materializing the neoliberal economic world order under the 'Washington Consensus.' Neoliberalism is a paradigm shift in the control of capitalism, framed by John Maynard Keynes as a counter-projection to the 'Great Depression'. The ideology has been widely contested in various academic in political debates over four decades. Simply put, neo-liberalism is the idea that society should be shaped by the free market, and the economy should be deregulated and privatized. Some scholars stated that neo-liberalism is the dominant ideology shaping our world today. Neoliberalism was a part of capitalism that gained popularity after the defeat of socialism in the backdrop of the disintegration of the former Soviet Union, popularly known as the USSR. It can be said that neo-liberalism had bad effects on the developing countries to borrow a lot of money from the IMF or the World Bank (WB). The era of neo-liberalism was marked by low growth rates, slowly rising incomes relative to profits, a widening inequality gap, and a falling standard of living, all of which were contrary to the claims made by the proponents of the free market. It was not only common people but also the state that greatly suffered under the new system, with the terms of trade deteriorating critically, indicators of the country leaving the state heavily dependent on foreign assistance, and its sovereignty greatly compromised. Hence, the proponents of ethics and morality of the 1920s liberalism who built its foundation were only an appearance of human freedom and equality, and the individual citizens and collective societies are suffering at the expense of few in the neo-liberal world era [2]. Stalling GDP growth rates falling exports, etc. This severely weakened the major macroeconomic system of developing countries, particularly Pakistan. Pakistan is a part of this economic system, and studying Pakistan's economic system is quite interesting.
There are three distinct periods of Pakistan's experience when it comes to its economic system. One is from 1947 to 1971, the second is a short period lasting only six years of the Bhutto regime during the 1970s, and the third started in the late 1980s and is going on. The only period from 1947 to 1971, especially from the late fifties to the late sixties, was

a period of high growth with export promotion and import substitution based on the old-school laissez-faire economy. During this period, the economic trajectory was quite impressive as Pakistan was experiencing economic planning over five-year plans, later copied by South Korea, which went on to become an Asian tiger. This was the period of Industrialization and economic growth. The second period, spanning over six years, was the Bhutto government, when he nationalized the main industries and corporate companies under a policy popularly known as the nationalization policy. Its performance was not that impressive; rather, it can be called the worst in the history of Pakistan [3]. The third period started in 1988 and is ongoing till today, with some slow and fast processes of a mixed economy embedded in a liberal economic format. The economic reforms in the early nineties gave birth to crony capitalism and kleptocracy in Pakistan. In this neo-liberal economic system led by Americans, the role of the state is only as a regulator and all other functions are performed by private individuals. Corruption by rulers in developing countries is rampant in the free world economy. Kleptocracy is enjoying private property ownership based on neoliberalism, globalization, and financialization. This gangster crony capitalism had made headway in third-world countries like Pakistan by manipulating the loopholes of this hybrid model of economic system called neoliberalism [4].

Pakistan adopted economic stabilization and structural reform policies in 1988 to reduce domestic financial imbalance and external deficits. However, there have been problems with the implementation of these policies in terms of consistency and sequencing. The period 1988-1996 was characterized by repeated attempts to stabilize the economy, aimed weak efforts at structural reforms. Since policy measures were not able to achieve their objective, the Pakistani economy continued to be trapped in a vicious circle of poverty, low growth, low savings, and low investment, which further hampered growth and poverty alleviation [5].

2 METHODOLOGY

This research study is based on a mixed method (qualitative and quantitative methods) which follows a pragmatic approach. The data collected for the study is mainly secondary, so the inquiry is based on secondary data and secondary data collection techniques as scrutiny of the second-hand documents. Sources from which data have been extracted are: books, articles, past research papers, magazines, and various journals by non-random sampling techniques. The data collected from different sources are critically analyzed by applying a non-experimental design and with an interpretive approach. Furthermore, it was developed under a sophisticated theoretical model derived from the theory of dependency, which is the handiwork of Raul Prebisch and Andre Gunder Frank, which emerged in the 1950s and 1960s, as a response to modernization theory.

3 THEORETICAL MODEL

3.1 Dependency Theoretical Model

This study is anchored in the dependency theory framework, which originated in the 1950s through the seminal works of Hans Singer [6]. and Raul Prebisch. Their research demonstrated how developed nations systematically exploit underdeveloped economies by extracting raw materials at low costs while exporting high-value manufactured goods in return, leading to deteriorating terms of trade for the Global South. Prebisch contended that developing nations must pursue protectionist industrialization to escape this exploitative cycle—a direct challenge to modernization theory's linear development assumptions. By the 1960s–70s, dependency theory gained prominence for exposing structural inequalities in global capitalism, offering a critical lens to analyze persistent underdevelopment. This framework is particularly relevant to Pakistan, which remains entrenched in an asymmetrical economic system where dominant powers and institutions like the International Monetary Fund (IMF) reinforce dependency through coercive policy regimes [7] empirically critiques this dynamic in "Do World Bank and IMF Policies Work?", revealing how neoliberal prescriptions under structural adjustment programs (SAPs), trade liberalization, privatization, and fiscal austerity have systematically undermined Pakistan's economic sovereignty. The IMF's conditionalities prioritize debt repayment and external equilibrium over domestic welfare, crippling local industries, exacerbating income inequality, and facilitating resource extraction by foreign capital. This aligns with dependency theory's core assertion that peripheral economies are structurally disadvantaged within the neoliberal world order. Pakistan's cyclical reliance on IMF bailouts exemplifies this exploitation. Short-term stabilization is achieved at the cost of long-term dependency, locking the nation into a neocolonial relationship where policy autonomy is sacrificed for conditional financial relief. By applying this theoretical lens, the study interrogates the tension between economic pragmatism and neoliberalism in Pakistan's development trajectory, illustrating how IMF-dictated reforms perpetuate underdevelopment while serving the interests of global capital.

3.2 Marxist Political Economy Analysis of Pakistan's Economic Development

This research is grounded in the Marxist political economy theoretical framework, particularly drawing upon the critical analysis presented by [8]. The Marxist political economy approach emerged as a critique of classical and neoliberal economic theories, exposing how capitalism inherently relies on imperialist exploitation to sustain accumulation. The Patnaiks argue that advanced capitalist economies systematically extract surplus from the Global South through mechanisms such as unequal exchange, financial domination, and coercive trade relations, perpetuating underdevelopment in postcolonial states like Pakistan. This framework challenges mainstream narratives that attribute

Pakistan's economic struggles to internal inefficiencies, instead locating them within the broader structures of global capitalist imperialism.

Pakistan's economic trajectory illustrates these dynamics clearly. International financial institutions (IFIs) like the IMF and World Bank act as instruments of neoliberal imperialism, imposing policies centered on debt servicing, deregulation, and privatization rather than national development. Structural adjustment programs (SAPs) mandated by the IMF have compelled Pakistan to adopt austerity, liberalize trade, and reduce public spending, resulting in weakened industrial capacity, agrarian crises, and rising inequality. The Patnaiks' concept of the "drain of wealth" helps explain Pakistan's persistent balance-of-payments crises, where its labor and resources are exploited to sustain capital accumulation in the Global North. Their critique of financialization further shows how IMF conditionalities enable elite capture and dismantle public welfare. By applying this framework, the research interprets Pakistan's swings between economic pragmatism and neoliberalism as symptoms of its dependent and subordinated position in the global capitalist order—an order that suppresses autonomous development in favor of global market conformity. This study uses Marxist political economy to analyze how Pakistan's economic sovereignty has been eroded and to explore alternatives centered on structural transformation, delinking from imperialist circuits, and redistributive justice.

3.3 World System Theory

This study adopts World-Systems Theory [9]. To critically examine the role of IMF programs in perpetuating Pakistan's structural economic dependency. According to the theory, the global economy is stratified into core and periphery nations, where international financial institutions such as the IMF operate to uphold the interests of core states by reinforcing asymmetric economic relations. Within this framework, IMF conditionalities—such as austerity, privatization, and fiscal tightening—are not neutral tools of stabilization but mechanisms that entrench peripheral nations like Pakistan in cycles of external debt and underdevelopment [10]. Empirical studies by domestic scholars, notably [11], underscore how successive IMF deals have systematically undermined Pakistan's economic sovereignty, prioritizing debt servicing and investor confidence over sustainable national development. Further illustrates how such externally imposed reforms favor transnational capital while weakening local productive sectors. By applying [12]. Analysis of structural global inequality, this study shifts the focus from internal mismanagement to the global economic order, offering a systemic lens through which Pakistan's recurrent economic crises under IMF programs can be better understood.

3.4 Neo Colonialism Theory

This study employs Neocolonialism Theory to critically analyze how IMF arrangements perpetuate economic subjugation in postcolonial states like Pakistan. Rooted in the work of Nkrumah and further developed by theorists such as Amin (1976) and Rodney (1972), the theory contends that colonial powers have transitioned from direct rule to economic domination, maintaining control through financial institutions and policy mechanisms. Within this framework, IMF conditionalities are interpreted not as neutral economic prescriptions, but as instruments that prioritize the interests of global capital over national sovereignty [13]. Underscores how these conditions function as levers of Western economic control, while scholars like [14] who empirically demonstrated how privatization, deregulation, and austerity—hallmarks of IMF agreements—have eroded Pakistan's economic autonomy and transferred public assets to transnational elites. Thus, Neocolonialism Theory reveals the structural continuity between historical imperialism and modern financial governance, positioning IMF policies as a contemporary extension of colonial economic extraction.

4 PAKISTAN'S APPROACH TO THE IMF

Pakistan is a part of an economic system. Pakistan's experience of neoliberal economic transformation is quite interesting to study as a subject. This study will divide Pakistan's economic history into seven distinct phases to simplify and shorten an otherwise lengthy history of nearly seven and a half decades. The numerous phases have mainly started from 1958 up to the present date.

4.1 First Phase 1947-1988

The first phase, comprising the first four decades after the country's birth, was a time when Pakistan was establishing itself in the world community of nations. Despite the tremendous economic, social, and political challenges presented by the immediate post-partition scenario and faltering nation and state-building attempts, these four decades still saw the Pakistan economy slowly standing up on its feet. Ishrat Husain, a former Governor of Pakistan's State Bank, noted in a public lecture at the Indian Business School at Hyderabad: "Pakistan is one of the few developing countries that was able to attain an impressive record of economic growth and poverty reduction in the first forty years of its existence. GDP growth rate until late 1980 averaged about 6 percent per annum, and the incidence of poverty was lowered from 46 percent to 18 percent. Inflation remained low, and despite high population growth, per capita incomes had almost doubled [15].

4.2 Second Phase 1989-1999

From being one of the leading developing post-colonial states in the first four decades of its existence, in just one decade, Pakistan was in a position where it was worse off than many contemporary and regional states. The total public debt as a percentage of GDP in 1999 was the highest in South Asia – 99.3 percent of its GDP and 629 percent of its revenue receipts, compared to Sri Lanka (91.1% & 528.3% respectively in 1998) and India (47.2% & 384.9% respectively in 1998). 188 Dr. Ishrat Husain outlines the extent to which this second phase of the Pakistan economy, from 1989-1999, saw a decline in Pakistan's economic health: "Growth rates tumbled to an average 3 to 4 percent and poverty resurged to 33 percent of the population. Inflation was in double digits, and large current account and fiscal deficits escalated debt–GDP ratios to over 100 percent. The country's foreign exchange reserves fell to less than $1 billion, exports were stagnant, and tax collection efforts were lackluster. The country was almost on the verge of a default crisis on its external payments in October 1999 when President Musharraf took over the reins of the Government [16].

4.3 Third Phase 1999-2007

Though it seemed like an impossible task, Pakistan's economy showcased its resilience and, after a peaceful coup by Pervaiz Musharraf in October 1999, experienced a period of historic levels of economic development. Positive trends were witnessed in almost every economic indicator as Pakistan reaped the rewards of liberalizing its economy in a favorable Post 9/11 world outlook. The average growth rates throughout this period were maintained above 7%, foreign exchange reserves and levels of Foreign Direct Investment (FDI) in the country peaked at their highest points ever in Pakistan's history, and there was a massive boom in several industries, including the technology, telecom, and media sector. 13 million new jobs were created as a result, ushering a dramatic rise in the size of the urban middle class and almost half of the country's external debts were repaid [17]. Pakistan managed to come out of the IMF's program and rose in rankings for Fastest Growing Economies and Investor and Business Friendly Countries. Although the Musharraf era's economic achievements cannot be denied outright, convincing evidence of its trickle-down effect was not always available. Some economists, whilst pointing out the potentially dubious nature of government statistics on growth and poverty reduction in this period, have outlined how "the structure of the growth process during this period was such that it could not be expected to have a substantial positive impact on poverty.

4.4 Bailout 2008

In 2008, Islamabad approached the IMF for assistance. Spillover effects from the global financial crisis, energy sector subsidies, and a current account deficit dented the government's financial position. In 2007-2008, global oil prices rose, but the government, fearing economic instability, continued to heavily subsidize the energy sector, transferring the burden to local consumers, which increased the budget deficit to 7.4 percent of gross domestic product (GDP) (Hussain, 2021) . Nevertheless, rising oil imports increased the total imports, burdening foreign exchange reserves, which plummeted. Remittances decreased due to the global financial crisis. Rising imports with falling remittances widened the current account deficit by 492 percent from June to September 2007. To offset this deficit, the incoming Pakistan People's Party government struck a deal with the IMF for an SBA package of US$7.6 billion and US$10.44 billion according to the present rate for 23 months. The IMF demanded a consolidation of fiscal space by increasing tax revenues and phasing out energy subsidies. Manage inflation and attract investments, the IMF recommended that the Pakistani central bank tighten monetary policy and stop financing the budget deficit.

The IMF's assistance, coupled with a recovering global economy, built a façade of stability despite enduring economic problems. By 2011, foreign reserves stabilized. Global oil prices decreased drastically, reducing Pakistan's import commitments. The current account deficit stabilized in January 2009 but did not improve due to stagnant exports. Due to IMF conditionality, Pakistan rationalized energy subsidies and allowed domestic fuel prices to increase. As a result, the fiscal deficit narrowed to 5.15 percent in 2008-09, but soon the defense budget ballooned to replace the energy subsidies; tax revenues did not keep pace with rising defense spending, which boosted the fiscal deficit to nine percent in 2011 [18].

4.5 The 2013 Bailout

In 2013, the Pakistan Muslim League Nawaz (PML-N) government signed a US$6.68 billion Extended Funded Facility package with the IMF, released over three years, subject to Pakistan's adherence to conditionalities. This time, large fiscal deficits and structural issues in the energy sector drove Pakistan's request for assistance. Pakistan's fiscal deficit in 2012-13 was approximately 8.5 percent of GDP, almost double its 4.7 percent target. This large and growing deficit was attributed to poor fiscal consolidation driven by low tax collection and weak tax administration. Tax revenue hikes were offset by rising development expenditures from 2.8 percent to 5.1 percent from 2011-2013. Additionally, inefficiencies in the energy sector increased costs due to price distortions, poor regulation, improperly targeted subsidies, and tax energy distribution. Nearly two percent of the 2011-12 GDP was lost to power shortfalls. Pakistan's economic performance after the package shows an equivocal outcome. GDP grew from 3.5 percent in 2012 to 5.6 percent in 2017. Inflation declined from 9.6 percent in 2012 to 4.1 percent in 2017. While IMF conditionality and assistance improved macroeconomic outcomes, the current account balance thereafter suggests that the IMF's impact in narrowing fiscal deficits may have been transient. Moreover, given that Pakistan reaped the benefits of lower oil prices, the IMF's targets did not go far enough [19].

4.6 The 2019 Bailout

Imran Khan's Pakistan Tehreek-e-Insaf government turned to the IMF to stabilize a weakening economy soon after entering office. In September 2016, the IMF's EFF program came to a halt, and repayments to the IMF were set to begin. Debt repayments to the Paris Club, a group of creditor countries, were due to begin by 2016-17. From 2016 to 2019, debt servicing increased by 64 percent, which constricted the fiscal space and worsened the fiscal deficit from 4.64 per cent to 9.07 per cent. The current account deficit worsened because the PML-N government overvalued the exchange rate; this move favored imports, especially from China, and disadvantaged exports. The burden of servicing a huge external debt and ballooning imports fell on foreign reserves, which were depleted by 65 percent in January 2019. Pakistan's attempts to resolve these issues via assistance from China and Saudi Arabia proved to be insufficient. To manage these issues, a US$6 billion (S$8.24 billion) EFF package was approved in July 2019. The IMF demanded that the incoming government increase tax revenues to pay back debt, adopt a free-floating exchange rate to reduce pressure on reserves, and tighten monetary policy to attract investments and reduce inflationary pressures caused by expensive imports. COVID-19 arrived just as the IMF's assistance stabilized the economy. The ensuing crisis shifted the discussion away from stabilizing the economy and toward mitigating the economic effects of the pandemic. The IMF has also postponed discussions of a second review and has not approved the release of additional funding. Instead, the IMF has assisted Pakistan through a US$1.386 billion (S$1.904 billion) package to bolster the government's fiscal capacity to fight COVID-19.

4.7 2023 Present Stand-by Arrangement (SBA)

IMF Executive Board approves US$3 billion Stand-by Arrangement for Pakistan. Pakistan's economic reform program aims to support immediate efforts to stabilize the economy and guard against shocks while creating the space for social and development spending to help the people of Pakistan. The Executive Board of the International Monetary Fund (IMF) approved a 9-month Stand-By Arrangement (SBA) for Pakistan for an amount of about $3 billion, to support the authorities' economic stabilization program. The arrangement comes at a challenging economic juncture for Pakistan. A difficult external environment, devastating floods, and policy missteps have led to large fiscal and external deficits, rising inflation, and eroded reserve buffers in FY 23. Pakistan's new SBA-supported program will provide a policy anchor for addressing domestic and external imbalances and a framework for financial support from multilateral and bilateral partners. The program will focus on the implementation of the FY 24 budget to facilitate Pakistan's needed fiscal adjustment and ensure debt sustainability while protecting critical social spending; a return to a market-determined exchange rate and proper foreign exchange market(FX market) functioning to absorb external shocks and eliminate FX shortages; an appropriately tight monetary policy aimed at disinflation; and further progress on structural reforms, particularly about energy sector viability, SOE governance, and climate resilience [20].

5 ANALYSIS AND CONCLUSION

5.1 Background

Why do countries choose to go to the IMF? According to major scholarly views and the dominant world view, "IMF is a 191-nation organization that assists member nations with balance of payments issues and restores and promotes long-term economic growth [21]." Similarly, the reasons for a country to choose the IMF program are poor macroeconomic conditions and a negative current account balance[22]." The most likely grounds for the IMF program to be used again include weak macroeconomic fundamentals, such as a lack of international reserves, a large current account deficit, and low real growth. Furthermore, inefficient fiscal and monetary policy management can result in massive macroeconomic imbalances, such as a large current account deficit and significant external and public debt. In theory, the IMF assists member countries in times of crisis by providing foreign exchange for international business. The Fund's primary mission is to give foreign exchange to countries in desperate need. Conversely, it is argued that the IMF program assists countries in resolving current account imbalances and implementing adjustment policies supporting long-term economic stability and growth [23].

5.2 Pakistan's Approach and Conditions Pushed Pakistan to a Multilateral Loan

Pakistan has yet to maintain significant economic growth while reducing poverty. Pakistan joined the International Monetary Fund on July 11, 1950. The IMF provides financial support to Pakistan under various terms and circumstances, as the country's economy has worsened since its foundation. Pakistan has borrowed from the IMF 25 times in its 75-year history and has signed a new 25th deal under the Extended Fund Facility (EFF) for a three-year and three-month period in September 2024 [24]. On December 8, 1958, Pakistan borrowed 25 million SDRs under the Standby Arrangement for the first time, but the agreement was dissolved before it expired, and the entire loan amount remained undrawn. Pakistan's government seeks loans from the IMF to keep its balance of payments in line and satisfy its financial obligations [25]. The primary goal of obtaining IMF loans is for the Pakistani government to stabilize the country's deteriorating economy, exchange rates, and balance of payments; however, this relief is usually only temporary, and it often leads to a new crisis in the long run as the debt matures and the government returns to an in the long run and short run monetary crisis due to insufficient dollar raised in the federal reserve. For such goals, the IMF offers massive loans. Pakistan has frequently found itself in the IMF programs. Pakistan has completed only three of the 25 programs it has undertaken with the IMF, earning it the label "one-tranche country." China, meanwhile, has only participated in two IMF programs, the most recent of which was in 1986, 36 years ago. Similarly, India and Bangladesh completed their previous programs 30 and 10 years ago. However, they grow more quickly without the IMF. On the other hand, our long-term growth rate is declining as we approach the IMF every few years. We may claim that while our growth rate is decreasing, our trips to the IMF are rising. We resemble a drug addict who takes drugs and feels happy for a short while, but when he comes to his senses, he starts to crave more drugs. Like this, we go to the IMF to solve short-term challenges, but our long-term structural problems persist and keep coming back without our initiatives to tackle them. The table below depicts the total number of IMF loan agreements with Pakistan since its independence.

5.3 Impact

The International Monetary Fund's involvement in Pakistan's economic affairs has had a significant impact on the functions of the country's institutions. One of the most significant effects is the erosion of institutional autonomy since the conditionalities and policy prescriptions of the IMF often override domestic decision-making processes [26]. For example, the IMF SAPs have introduced fiscal discipline and austerity, for which the parliament in Pakistan can no longer realistically plan, allocate resources, and decide on priorities for public spending. In addition, its focus on privatization and deregulation has seriously undermined the effectiveness of public institutions in sectors that are vital such as energy, finance, health, education, and unemployment; the privatization of state-owned enterprises (SOEs) has had the effect not only of cutting employment and shrinking the provision of public services but also of creating spaces for corruption and crony capitalism. This IMF influence has compromised the independence and effectiveness of the Pakistan Judiciary, too, as many of the fund's conditionalities necessitated that Pakistan adopts certain laws and regulations that impeded the ability of the institution to interpret and enforce the constitution. The role of the IMF also played a hand in changing the role and performance of the Pakistani bureaucracy. Deep cuts in budgetary and personnel allocation in the public sector by the Fund through fiscal discipline and austerity reduced the ability of the bureaucrats to provide simple public services. Deregulation, as called for by the Fund, also weakened the capacity to exploit natural resources and labor by foreign corporations within the country [27]. It has a multilayer impact on the various sectors in Pakistan:

Health Sector: The International Monetary Fund's SAPs have had a strong impact on the health sector in Pakistan. A primary effect of SAPs has been the decrease in government expenditure on health. The share of health expenditure in the total government expenditure of Pakistan went down from 4.6% in 1990 to 3.8% in 2000, according to a World Bank report [28]. Consequently, this has come at the expense of the poor and vulnerable while reducing the overall quality and availability of services in health. All these changes also led to increased private health services after the IMF had imposed SAP. According to research carried out by the Pakistan Institute of Legislative Development and Transparency, from 1,444 in 1990 to 3,444 in 2005, the private hospitals multiplied in Pakistan while the public ones remained almost stationary. This shift to privatization has brought along with it a two-tier health delivery system wherein the rich get access to high-class, private health facilities and services while the poor are forced to be content with poorly funded, badly equipped, and inadequately staffed public health facilities. The World Health Organization report reflects that the human resources concerning health are severely deficient in Pakistan; with a density of 0.8 doctors per 1,000 population contrasts with 2.5 doctors per 1,000 population in the developed world [29]. The poor density of healthcare professionals has affected the quality of health services given, which is further worsened in rural areas where hardly proper health facilities are hardly available. Education Sector: The IMF's Structural Adjustment Programs have marked an impact on Pakistan's educational system. First, the programs are responsible for less government spending on education. For instance, it is observed in a UNESCO report that "the share of education expenditure in the total government expenditure declined from 2.6% in 1990 to 1.9% in 2000 [29]." This has resulted in a reduction in the quality and accessibility of education, especially for poor and vulnerable groups of people. The SAPs implemented by the IMF have advocated for the privatization of education services in Pakistan. In an excerpt from a report by the Pakistan Education Network, it has been revealed that the number of private schools in the country rose from 25,000 in the year 1990 to 50,000 in the year 2005, while the number of public schools remained the same [30]. This has resulted in a two-tier system of education where the rich can afford expensive and quality private education, but the poor have to cope with poorly financed and poorly staffed public schools. According to the World Bank, the country faces an acute shortage of trained teachers many as the teacher-pupil ratio stands at 1:40 in Pakistan, it is 1:20 in the developed world [31]. This shortage of qualified teachers has resulted in low-quality education throughout the country, especially in areas where schools are few and far between. Second, the studies conducted and findings from the Pakistan Institute of Development depict an increase in the cost of education in Pakistan by 20% which resulted in a decline in education enrollments, more so among poor and vulnerable sections of the population.

State Bank of Pakistan: The IMF's SAPs have great significance for the State Bank of Pakistan, a central bank that has been confronted with a reduction in its autonomy and independence as one of the major effects of these programs. The same is somewhat agreed upon by a report conducted by the Independent Evaluation Office of the IMF, which mentions that conditionalities imposed by the IMF made the SBP compromise on monetary policy implementation for the sake of exchange rate stability rather than domestic economic growth [32]. The IMF's SAPs have also caused a manifold increase in the SBP's dependence on foreign borrowing. A study conducted by the Pakistan Institute of Development Economics estimates that the SBP's foreign borrowings increased from $1.3 billion in 1990 to $10.3 billion in 2005, thereby increasing the external debt burden of the country manifold times [33]. This has eroded the SBP's independence in monetary policy conduct and resulted in a loss of control over national economic destiny. Furthermore, the SAPs of the IMF have caused a considerable decline in the powers of the SBP while regulating the financial sector of the nation. In its report, ADB remarked that the IMF conditionalities required the SBP to liberalize the country's financial sector. It was highly hazardous for the financial stability of the country, as proved in the following years, 2010. The lesser the regulatory oversight, the more it has sacrificed soundness in the financial system of the nation, further resulting in a series of high-profile banking crises. The IMF SAPs have considerably raised the inflation targeting of the SBP at the cost of giving more emphasis on economic growth and development. A research study conducted by LUMS shows that the inflation targeting framework has led to a jacking up of interest rates that has compromised the economic growth prospects in the country [34].

5.4 Issues

Approaching the IMF has long-term after-effects and issues such as:
Unemployment: The IMF, especially through the SAPs, has been highly influential in terms of unemployment in Pakistan. Among the main results of the program has been the lessening of the government's expenditures on social sectors, which, in turn, reduced employment opportunities in both education and healthcare. The ILO estimated that the SAPs introduced in Pakistan in the 1990s were bound to have a sharp increase in unemployment, especially among the youth and women [35]. The report noted that SAPs led to a reduction in the share of government expenditure on education and health, which disproportionately reduced employment opportunities for the youth and women. The IMF SAPs have also resulted in the phenomenal growth of the informal sector in Pakistan, characterized normally by low wages, absence of job security, and very little social protection. A study by the Pakistan Institute of Development Economics indicates that around 70% of Pakistan's workforce works within the informal sector, with a majority of them working in the low-skilled and low-waged category of work [36]. Moreover, IMF SAPs have contributed to an extreme rise in income inequality within the country of Pakistan, thus aggravating unemployment. As noted in a study by the Lahore University of Management Sciences, the SAPs instituted within Pakistan during the 1990s led to an extreme rise in income inequality, in which the richest 10% reaped an incredibly high percentage of the country's income.
Reduction in Public Expenditure and Decline in Public Welfare: This is binding upon the Government of Pakistan, as laid down by the IMF, to implement policies to ensure privatization and deregulation. One of the major components of the IMF SAPs in Pakistan has been the privatization of state-owned enterprises. The main sectors that the IMF has compelled to be privatized include energy, telecommunication, and banking, in a bid to raise competition and efficiency [37]. The privatization process has, however, been widely criticized for being non-transparent and corrupt, as many SOEs have been sold to favored bidders at below-market prices. The process of privatization in Pakistan has resulted in the government suffering huge losses, with a majority of the state-owned enterprises having been sold out at prices that were way lower than their actual value, states a report by the Pakistan Institute of Legislative Development and Transparency [38]. It further noted that the privatization process was not attended to with transparency and accountability; most of the deals were negotiated in secrecy, without due oversight.
Other IMF SAPs have mandated that Pakistan pursue policies promoting deregulation and liberalization, such as free trade, reducing or eliminating tariffs, and subsidy abolition. These have been promulgated as policies increasing economic efficiency and attracting foreign investment. These have been implemented at enormous social and economic costs, however. According to the International Labor Organization report, because of the IMF-promoted policies of deregulation and liberalization, Pakistan has faced heavy losses in jobs, with increased income inequality [39]. It pointed out that the dismantling of trade barriers and reduction of tariffs had resulted in the loss of competitiveness of Pakistani industries, which caused colossal losses of jobs and enhanced poverty.

5.5 Miscellaneous Impacts

The economy of Pakistan had experienced severe turbulence and instability even before the neo-liberal period before 1988. One can also not disagree with the fact that the economy required serious structural readjustment if it was to address the issues that held it back in an underdeveloped, third-world status. However, the IMF programs that followed a neo-liberal doctrine left Pakistan in a far worse predicament than it was already in before 1988. The macroeconomic determinants of the country followed more or less the same dismal trajectory as they had done in the past. The two glaring differences, however, during the neo-liberal period were that firstly, Pakistan had accumulated large sums of loans with the IMF and the World Bank. This meant that much of the country's sovereignty was compromised, not only in the economic realm but also in defense and foreign affairs. The second important difference was that the poor and the working class were in a far worse position than in the pre-1988 era.
As has been extensively argued by (R. Shrokh & S. Aftab, 1995), the recommendations made by the Fund and the Bank were to adversely affect the poor, who proved to be the most vulnerable population group in the country, to the IMF structural adjustment programs. The reduction in subsidies to reduce budget deficits and the imposition of greater taxes to increase revenue dually affected all segments of society, but the poor were more sensitive to these changes. The working class was also indirectly affected by measures such as privatization, which forced companies to lay off workers [40]. The standard of living of the poor also decreased substantially during the structural adjustment periods as the income levels fell.

As the poor were being adversely affected by the IMF programs, the disparity between the low-income groups and the high-income groups began to increase. The burden of taxes increased by 10.3 percent on the poor, and surprisingly decreased by 4.3 percent on the rich [41]. The Oxfam 2017 report is a testament to the growing inequality, not only in Pakistan, but the world over. The report highlights those stagnant wages and an ever-increasing cost of living are creating frustration and anger in the labor class of Pakistan [42]. The situation is further aggravated when a stark contrast is observed between the lives of the workers and those of the capitalists. This provides real empirical evidence to David Harvey's claim that neoliberalism was only just a political tool by the capitalist class to reassert its power on the world stage [43].

Haroon Jamal (2014) follows the same trajectory of inquiry as has been done by Sharukh Rafi and Safia Aftab, and extends his study from 1988 to 2011. According to Jamal, poverty has indeed increased from 1988 onwards, affecting the rural population much more severely than the urban population. Poverty incidence shows a slight decline in the period from 2001-2005 but continues its upward trend in the following years. Data from 2010-11 shows that poverty incidence for the rural population reached 39 percent by 2010, whereas for the urban population, it was 34 percent [45]. This data and analysis complement the findings of Shahrukh Rafi and Safia Aftab that poverty overall increased within Pakistan after 1988. Hence, Pakistan not only failed to improve its macroeconomic indicators under the IMF programs, but it also failed to safeguard the interests of the poor segments of society.

The per capita household income inequality and per capita household consumption inequality demonstrate that, along with rising poverty levels, an ever-higher inequality meant that low-income segments of society were in a much worse condition when compared to the pre-1988 era. These evidences point towards the fact that the IMF programs, in particular, and neoliberalism in general, were unable to raise the standards of living of the poor and provide the population with the freedom and liberty they were promised through a free market system.

5.6 Way Out

The path to sustainable economic growth and less dependence on the International Monetary Fund requires a multidimensional strategy that aims to address the structural, institutional, and macroeconomic challenges facing Pakistan [46]. First and foremost, there is the need for the economy to be diversified through export-oriented growth, infrastructure development, and encouragement of entrepreneurship. This can be achieved by investment in education, research, and innovation, support for small and medium-sized enterprises in access to finance, training, and infrastructure

More significantly, Pakistan should make its institutions robust to enforce good governance, transparency, and accountability. This is feasible with the introduction of effective regulatory frameworks, making vital institutions such as the State Bank of Pakistan more independent, and creating a culture of meritocracy with accountability within the public sector. Furthermore, it is of the essence that Pakistan builds human capital by developing a productive and educated labor force, which is one of the key drivers of economic growth and competitiveness.

In this regard, for macroeconomic stability, the fiscal policy should be kept stable, the debt burden reduced, and revenue increased through reforms in the taxation department. The government should also give the State Bank of Pakistan full independence to determine interest rates and control the money supply in the best interest of the economy to maintain price stability along with economic growth. Furthermore, Pakistan needs to implement a flexible exchange rate regime to promote exports and stabilize the currency [47].

Besides such economic reforms, there is also a dire need in Pakistan for social protection and inclusive growth. This may be attainable through the expansion of social safety nets, education, and health, besides harnessing policies for the general good of the people to reduce income disparities and lead to social cohesion. Moreover, it is imperative for Pakistan to further strengthen regional trade agreements, regional infrastructure development, and regional economic integration to enhance economic cooperation and stability.

To attain all the aforementioned gains, an indigenous economic reform agenda which factor-specific, need-, and challenge-aligned would be required for Pakistan. That shall be in resonance with, among other diagnostics, a basic and comprehensive analysis in terms of diagnostics that outlines key strength-weakness factors and thereby yields a framed roadmap for reform based on such analyses. The program should also be owned and driven by the Pakistani government, with support from civil society, the private sector, and international partners.

To achieve these goals, Pakistan needs to develop a homegrown economic reform program that is tailored to its specific needs and challenges. This program should be based on a comprehensive diagnostic analysis of Pakistan's economy, identifying key areas of strength and weakness, and outlining a clear roadmap for reform. The program should also be owned and driven by the Pakistani government, with support from civil society, the private sector, and international partners [48].

5.7 Conclusion

Conclusively, the purpose of taking loans from the IMF is that Pakistan's government wants to stabilize its deteriorating economy, exchange rates, and balance of payments. No doubt, the IMF helps us in these types of circumstances and helps us by providing a huge amount of loans. At the very first sight, it seems a very attractive offer, but only from a short-term perspective. If we investigate the long-run impact of IMF loans, then there is a negative and insignificant relationship between government borrowings and GDP. It will also lead to political instability. However, it will have a

positive impact on our exchange rate. The government should play its role in increasing the pace of economic growth in Pakistan. Whereas in the short term, we can see benefits and quick transformation, but in the long run, we all must pay because the fact is that nothing is free in this world.
Pakistan signed different structural adjustment agreements with the IMF to improve its economy and create a stable economic environment for a sustainable economic environment but it did not happen for a variety of reasons. Pakistan joined the IMF for political reasons rather than economic ones. It joined the IMF for mere getting access to private credit, which it could not get without signing an agreement with the IMF. So, there were political reasons for the failure of IMF programs as the different elected governments were not willing to implement IMF conditionalities due to the inflationary nature of the programs. Interestingly, none of the regimes implemented fully the IMF conditions and as a result, loans had to be suspended after the payment of a couple of tranches. The other reason for the failure of the IMF programs was that they focused too much on financial stability and ignored long-term developmental goals, industrialization, higher employment, or increased public investment. Moreover, according to critics, the main reason for the failure of IMF programs is that it ignores the social matrix in which it operates and imposes conditions that affect the poor. For the sake of macroeconomic stability, it ignores the microeconomic stability. Its conditionality such as austerity under which the subsidy is withdrawn on the social sector often hurts the people at the bottom of the pyramid. This, too, was seen in Pakistan during nineties when the health and education were severely affected as a result of the government's efforts to fix the fiscal problems.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] ILO Report. World Labour Report. International Labour Organizaton, 2017.
[2] Bird A R. the Effect of IMF Programes on the Economic Growth in Low Income Countries: An Empirical Analysis. The Journal of Development Studies, 2017.
[3] Chang HJ. Institutional and Economic Development: Theory, policy and history. Journal of institutional Economic, 2011.
[4] Chomsky N. Profit over people: Neo liberalism and global order. Seven stories press, 1998.
[5] Conway. IMF Lending Program: Participation and Impacts. Journal of Development Economics, 1994.
[6] David H. On Neo Liberalism. Oford University Press, 2006.
[7] GOP. Pakistan Economic Survey. Government of Pakistan, 2020.
[8] Ha Joon. the hypocracy of neolibral propeganda in capitalism. In Ha-joon, The Myth of free trade and the secret history of capitalism. Bloombsbury Press, 2007.
[9] Hassan B. Neo liberalism and Pakistan. The International News, 2021.
[10] Hussain I. The economy of the elitist state. Oxford University Press, 2000.
[11] Hussain I. Economic Challenges of Pakistan. In H. Ishrat, Governing The Ungovernable. Lahore: Oxford Press, 2021.
[12] IEO. Evolovating the IMF Exchange Rate Policy Advice. Independent Evoluation Office, 2016.
[13] ILO. World Labour Report. International Labour Organization, 2002.
[14] IMF. Staff Level Arrangemnent with Pakistan. International Monetory Fund, 2023.
[15] IMF Report. Pakistan: Staff REport for 2019 Article 4 Consultation. International Monetory Fund, 2019.
[16] Jamal. A Decade Long Analysis. International Journal of Contemporary Issues In Social Sciences, 2014.
[17] Khan A. Impact of IMF loans on Fiscal Policy Structure : Empirical Evidance from Pakistsn. Pakistan Institute of Development Economics, 2018.
[18] Khan S. Do World Bank and IMF policies work? Springer, 1999.
[19] Khan S. IMF and Pakistan: A Reletionship Of Dependence. In A. Hillali, 2017.
[20] Lawson. Negative Impacts of IMF on Developing Countries. Oxfam, 2018.
[21] LUMS. Inflation Targeting in Pakistan: A Critical Analysis. Lahore: Lahore University of MAnagement Science, 2005.
[22] LUMS. Encome In equality in Pakistan. Lahore: Lahore University of Management Science, 2015.
[23] Mushtaq. IMF Exextive Board Concludes Article 4 Consultation With Pakistan. Washngton DC USA: International Monetory Fund, 2017.
[24] Nadia Dohadwala, Muhammad Bin Khalid Karthik Nachiappan. Pakistan and the IMF: Debts, Deficits and Dependency. Indian Strategic Studies, 2020.
[25] NKrumah K. Neo_colonialism: The last stage of capitalism. International Publisher, 1965.
[26] Patnaik and Prabhat Patnaik. Capital and Imperialism: Theory, History and Present. Monthely Review Press, 2021.
[27] Peet R. Unholy Trinity: the IMF, World Bank and WTO. Bloomsbury Publishing, 2009.
[28] PEN. Education Sector reforms In Pakistan. Pakistan Education Network, 2006.
[29] PIDE. Informal Sector in Pakistan. Pakistan Institute of Economic Development, 2017.
[30] PIED. Foreign Borrowing and Debt Accumulation in Pakistan. Pakistan Institute of Economic Development, 2007.
[31] PILDAT. Health Sector Reforms In Pakistan. PILDAT, 2006.

[32] PILDAT Report. Privatization in Pakistan: Critical Review. Pakistan Institute of Legislative Development and Transparancy, 2018.
[33] Prebisch R. The economic development of Latin America and its principal problems. United Nations Department of Economic Affairs, 1950.
[34] R Shrokh, S Aftab. Structural Adjustment, Labour and the Poor In pakistan. SDPI, 1995.
[35] SA Z. issues i n pakistan economy. Oxford, 2015.
[36] SZ A. Issues in Pakistan Economy. Islambad: Oxford University Press, 2015.
[37] Sadiqi I A. Impact of Trade Openness on Output Growth for Pakistan: An Empirical Investigaton. Institute if Business Administration Karachi, 2005.
[38] Santaella a K. Economic Determenints of IMF Financial Agreement. Journal of Development Studies, 1997.
[39] Sarfaraz Z. Impct of Pak- IMF Bailout Arrangement on Economic Growth. Journal of Public Policy practioners, 2022.
[40] Shahbaz R K. Will The IMF $7 Billion Bailout Sablize Pakistan Economy. United State Institute of Peace, 2024.
[41] Singer H. The Distribution of Gains between Investing and Borrowing Countries. London : Singer, 1975.
[42] Stiglitz J. Globalization and Its Discotents. W.W. Norton and Compony, 2002.
[43] UNESCO. Education For All. Global Monitoring Report, 2002.
[44] WB. Pakistan_Health Sector Report. Washnigton DC: World Bank Group, 2002.
[45] WB. Pakistan: Education Sector review. World Bank, 2010.
[46] WB. Pakistan Overview. World Bank, 2020.
[47] Wallerstein I. Modern World System. New York Academic, 1974.
[48] WHO. World Health Report. World Health Organization, 2010.

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GREEN TECHNOLOGY INNOVATION AND CORPORATE RESILIENCE: EVIDENCE FROM CHINA UNDER THE DUAL-CARBON GOAL

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Abstract: Based on the panel data of Chinese A-share listed companies from 2008 to 2022, this study systematically examines the impact of green technology innovation on corporate resilience and its mechanism. The results show that green technology innovation significantly strengthens corporate resilience, and the relationship remains robust after multiple tests. Mechanism analysis suggests that the effect operates mainly through improved environmental performance and reduced stock price volatility. Moreover, the impact is more pronounced in technology-intensive industries and among firms in eastern regions. This study extends the literature by linking green innovation to organizational resilience in an emerging economy context and highlights the strategic importance of green technology for firms navigating the transition toward a low-carbon economy.
Keywords: Green technology innovation; Corporate resilience; Dual carbon strategy

1 INTRODUCTION

In the era of global climate change, achieving carbon peaking and carbon neutrality has become a shared goal among governments and enterprises. Environmental pressures increasingly constrain social and economic development, making green technology innovation a vital pathway toward dual-carbon targets. China has clearly put forward the goal of carbon peaking and carbon neutrality, and adopted a number of comprehensive measures to support green development. Green technology innovation not only reduces organizations' carbon footprints but also enhances energy efficiency, promotes sustainable material use, and strengthens long-term competitiveness. Despite its recognized importance, the role of green innovation in fostering corporate resilience remains underexplored.

Corporate resilience refers to a dynamic capability cultivated under sustained adversity, enabling firms to maintain stability, recover rapidly, and seize growth opportunities in the face of uncertainty[1]. Resilient firms are more adaptive to environmental shifts, more capable of recovering from disruptions, and better positioned to achieve renewed growth, thereby sustaining competitive advantage in volatile markets. Although green technology innovation is widely regarded as a potential driver of resilience, empirical studies examining its mechanisms and outcomes remain limited. In particular, questions persist regarding how green innovation strengthens adaptability, accelerates recovery, and supports long-term growth under conditions of environmental uncertainty.

This study seeks to explore the role of green technology innovation as a resilience enhancer in the context of "dual carbon". Using a panel dataset of A-share listed firms from 2008 to 2022, the analysis investigates both the relationship and mechanisms linking green innovation to corporate resilience. The study contributes to the literature in three ways. First, it enriches the theoretical perspective on corporate resilience by establishing a link between green innovation and firms' adaptive and dynamic capabilities. Second, it offers empirical evidence on the pathways through which green technology innovation promotes resilience, thereby providing insights for policy design and corporate strategy. Third, it explores heterogeneity across industries and firm types, yielding practical guidance on how enterprises can leverage green innovation to cope with environmental challenges.

Overall, this research underscores the strategic importance of green technology innovation in enhancing organizational resilience under the dual-carbon agenda. The findings not only advance understanding of the innovation–resilience nexus in emerging economies but also generate actionable implications for firms and policymakers seeking to balance environmental objectives with sustainable competitiveness.

2 THEORETICAL ANALYSIS AND HYPOTHESIS FORMULATION

Against the backdrop of the global pursuit of carbon peaking and carbon neutrality, it is essential to explore how green technology innovationinfluences corporate resilience. From the perspective of survival and competition theory, technological innovation enables firms to adapt to external shocks and internal pressures, thereby strengthening organizational resilience. Existing studies suggest that green innovation not only improves competitiveness and efficiency but also fosters organizational adaptability under environmental uncertainty. Moreover, green innovation strategies contribute to legitimacy and market recognition, which further reinforce firms ' ability to withstand shocks[2]. Lv et al. demonstrated that corporate green innovation enhances resilience by improving adaptability under environmental uncertainty[3]. Xu et al. examined environmental technological innovation strategies in China, highlighting its role in addressing ecological challenges[4]. Lei et al. identified technological capability as the direct driver of green innovation, while corporate culture, market orientation, and government policy serve as contextual enablers[5]. Tao et al., using IPC patent data and a difference-in-differences approach, found that environmental responsibility systems increased the quantity but reduced the quality of green patents[6]. These findings suggest that enterprises should actively implement green innovation, adapting to contextual conditions while collaborating with policy institutions to promote sustainable development[7] .

Green technology innovationalso contributes to profitability and competitiveness by optimizing production processes and reducing costs, which improves firms' adaptability to market fluctuations and economic uncertainty[8]. Enhanced innovation capability can further attract sustainable investors, thereby improving financial stability and securing long-term capital support[9]. Yue et al. argued that under ecological constraints, technological innovation has become a key pathway for China's industrial green transformation[10]. Similarly, Su and Li found that green innovation capability positively influences competitiveness through product differentiation and firm scale[11].

Institutional arrangements and policies also play a pivotal role in promoting green technological innovation. Xu and Cui showed that low-carbon city pilot policies foster corporate innovation in energy conservation and renewable energy[12]. Wu et al confirmed that both general and green innovation positively affect total factor productivity[13]. Wang and Wang observed that green credit guidelines stimulated innovation performance in restricted industries[14]. Song et al. further demonstrated that smart city construction significantly enhances green technological innovation, with profound implications for China's green transformation and innovation-driven development[15].

Building on this foundation, we argue that green technology innovationenhances corporate resilience through two main mechanisms. First, by improving environmental performance—such as reducing carbon emissions, lowering resource consumption, and increasing energy efficiency—firms can better adapt to regulatory pressures, reduce compliance risks, and strengthen their legitimacy with stakeholders. Second, green technology innovationstabilizes firms' financial performance by mitigating stock price volatility. Firms that demonstrate strong green innovation capability tend to attract long-term, sustainability-oriented investors, which reduces trading frequency and dampens price fluctuations. This dual pathway—environmental performance enhancement and financial stability—constitutes the core mechanism through which green technology innovationreinforces corporate resilience.

In view of the above analysis, this paper proposes the following hypotheses for further empirical research verification:

H1: Green technology innovationpositively influences corporate resilience.

H2: Green technology innovationenhances corporate resilience through improved environmental performance.

H3: Green technology innovationenhances corporate resilience by reducing stock price volatility.

3 RESEARCH DESIGN

3.1 Sample Selection and Data Sources

This study uses Chinese A-share listed firms from 2008 to 2022 as the initial research sample. The following screening criteria are applied: (1) firms in the information technology and financial sectors are excluded, following the 2012 CSRC industry classification, specifically C39 (computer, communication, and other electronic equipment manufacturing) and I63–I65 (information transmission, software, and IT services); (2) firms classified as ST or *ST and those with abnormal financial structures (gearing ratios exceeding 100%) are removed; (3) firms with missing data on key variables are excluded. After these adjustments, the final sample ensures data reliability and comparability. Firm-level financial and governance data are primarily sourced from the CSMAR database. To minimize the influence of extreme values, all continuous variables are deflated at the 1% and 99% levels.

3.2 Definition of Variables

3.2.1 Green technology innovation(EnvrPat)

Referring to prior research[16-18], green technology innovationis measured as the natural logarithm of one plus the sum of green invention patent applications and green utility model patent applications. This measure captures both the quality and quantity of a firm's innovation activities in the green domain.

3.2.2 Corporate resilience (Res)

Drawing on Ivanov et al[19], corporate resilience is assessed across two dimensions: **long-term growth** and **financial volatility**. Long-term growth is proxied by the cumulative growth rate of net sales over three consecutive years. Financial volatility is measured by the variance of stock returns. The entropy method is then applied to integrate these two dimensions into a composite resilience index.

3.2.3 Environmental performance (EP)

Based on Qu et al[20], environmental performance is proxied by a cumulative scoring approach across nine criteria: (1) advocacy of environmental protection concepts; (2) setting of environmental protection goals; (3) implementation of an environmental management system; (4) provision of environmental training; (5) organization of dedicated environmental activities; (6) establishment of contingency plans for environmental emergencies; (7) compliance with the "three simultaneities" principle; (8) receipt of environmental honors or awards; and (9) certification under ISO14001. Each criterion is scored as one if met, and zero otherwise, yielding an additive index of corporate environmental performance.

3.2.4 Stock price volatility (VAR)

Following Xin[21], stock price volatility is measured using the variance of monthly stock returns for firm *i* in year *t*, calculated from May of year *t* to April of year *t+1*. The average monthly variance is computed and multiplied by 100 to obtain the *VAR* index.

3.2.5 Control variables

Consistent with existing literature[22,23], the following firm-level characteristics are included as controls: firm size (Size), capital structure (Lev), ownership concentration (Top1), current ratio (Liquid), return on equity (ROE), state ownership (SOE), board size (Board), proportion of independent directors (Indep), CEO duality (Dual), and Tobin's Q (TobinQ). To address potential omitted variable bias, firm fixed effects and year fixed effects are further incorporated into the regression models, see Table 1.

Table 1 Variable Definitions and Measurements

Variable Name	Variable Symbol	Variable Calculation Method
Corporate resilience	*Res*	Composite index from entropy method: (i) 3-year cumulative net sales growth, (ii) variance of stock returns
Green technological innovation	*EnvrPat*	ln(1 + green invention patents + green utility model patents)
Environmental Performance	*EP*	Additive score of nine criteria (environmental goals, training, activities, ISO14001, etc.)
Stock price volatility	*VAR*	Variance of monthly returns (May *t* – Apr *t+1*), ×100
Firm Size	*Size*	Measured by the natural logarithm of the number of employees
Leverage	*Lev*	Total liabilities / total assets
Profitability	*ROE*	Net income / shareholders' equity
Liquidity	*Liquid*	Current Assets/Total Assets
Board Size	*Board*	Number of directors
Independent directors	*Indep*	% of independent directors on board
CEO duality	*Dual*	Dummy: 1 if CEO = Chairman, 0 otherwise
Ownership concentration	*Top1*	% shares held by largest shareholder
State ownership	*SOE*	Dummy: 1 if SOE, 0 otherwise
Tobin's Q	*TobinQ*	(Market value of equity + total liabilities) / total assets

3.3 Model Setting

To examine the impact of green technology innovationon corporate resilience, we first specify the baseline panel regression model as follows:

$$Res_{i,t} = \alpha_0 + \alpha_1 \times EnvrPat_{i,t} + \sum Controls + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{1}$$

Where $Res_{i,t}$ represents the resilience of firm *i* at time *t*, and $EnvrPat_{i,t}$ denotes its green technological innovation. We add the control variables $\sum Controls$ in the model, μ_i and λ_t denote firm and year fixed effects, respectively, and $\varepsilon_{i,t}$ is the error term.

Mediating Effect Models To investigate whether green technology innovationaffects corporate resilience through **environmental performance** (*EP*) and **stock price volatility** (*VAR*), we adopt a three-step panel mediation framework following Wen et al [24]. The models are specified as:

$$EP_{i,t} = \beta_0 + \beta_1 \times EnvrPat_{i,t} + \sum Controls + \mu_i + \lambda_t + \eta_{i,t} \tag{2}$$

$$VAR_{i,t} = \gamma_0 + \gamma_1 \times EnvrPat_{i,t} + \sum Controls + \mu_i + \lambda_t + \mu_{i,t} \tag{3}$$

$$Res_{i,t} = \delta_0 + \delta_1 \times EnvrPat_{i,t} + \delta_2 \times EP_{i,t} + \delta_3 \times VAR_{i,t} + \sum Controls + \mu_i + \lambda_t + \zeta_{i,t} \tag{4}$$

Here, $EP_{i,t}$ represents the environmental performance of firm *i* at time *t*, $VAR_{i,t}$ denotes the stock price volatility of firm *i* at time *t*, $Res_{i,t}$ is the resilience of firm *i* at time *t*, and the definitions of the variables $EnvrPat_{i,t}$, μ_i and λ_t are the same as those of the model in (1).

4 ANALYSIS OF EMPIRICAL RESULTS

4.1 Descriptive Statistics

Table 2 presents descriptive statistics for the main variables. Corporate resilience (*Res*) averages 0.874, indicating generally stable adaptability across firms. Green technology innovation(*EnvrPat*) exhibits substantial heterogeneity, reflecting varied engagement in green innovation. Environmental performance (*EP*) has a mean of 1.696; while most firms perform moderately, the maximum of 9.000 highlights a subset of high achievers. Stock price volatility (*VAR*) averages 1.255, suggesting notable differences in market stability. The remaining control variables are broadly consistent with prior studies. Collectively, these statistics reveal meaningful variation in resilience, innovation, environmental outcomes, and financial stability, providing a clear empirical foundation for the subsequent analyses.

Table 2 Descriptive Statistics

Variables	Sample	Mean	SD	Min	Median	Max
Res	36571	0.875	0.085	0.500	0.900	0.980
EnvrPat	36571	0.316	0.718	0.000	0.000	3.780
EP	36571	1.696	1.989	0.000	1.000	9.000
VAR	36571	1.256	0.738	0.150	1.100	5.620
Size	36571	22.189	1.311	19.240	22.010	26.480
Lev	36571	0.434	0.206	0.040	0.430	0.920
ROE	36571	0.063	0.141	-1.070	0.070	0.470
Liquid	36571	2.372	2.445	0.200	1.620	25.480
Board	36571	2.129	0.198	1.610	2.200	2.710
Indep	36571	37.505	5.361	25.000	36.360	57.140
Dual	36571	0.267	0.442	0.000	0.000	1.000
TOP1	36571	34.572	14.819	8.820	32.280	76.440
SOE	36571	0.391	0.488	0.000	0.000	1.000
TobinQ	36571	2.062	1.430	0.800	1.610	17.680

4.2 Correlation Analysis

Table 3 presents the correlations between green technology innovationand corporate resilience. Green innovation is positively and significantly associated with resilience at the 1% level, providing preliminary support for Hypothesis 1. It also correlates positively with firm size, capital structure, return on net assets, and governance variables such as the proportion of independent directors and dual positions, indicating that green innovation is linked not only to financial performance and organizational scale but also to aspects of corporate governance. These patterns underscore the interconnected role of green innovation in shaping resilience, performance, and governance, motivating the subsequent regression analyses.

Table 3 Correlation Analysis Table

Variable	*Res*	*EnvrPat*	*Size*	*Lev*	*ROE*	*Liquid*	*Board*	*Indep*	*Dual*	*TOP1*	*SOE*	*TobinQ*
Res	1											
EnvrPat	0.061***	1										
Size	0.160***	0.182***	1									
Lev	-0.064***	0.064***	0.452***	1								
ROE	0.027***	0.048***	0.123***	-0.190***	1							
Liquid	0.034***	-0.047***	-0.317***	-0.642***	0.085***	1						
Board	-0.059***	0.036***	0.239***	0.147***	0.042***	-0.126***	1					
Indep	0.046***	0.011**	0.021***	-0.009*	-0.021***	0.019***	-0.524***	1				
Dual	0.039***	0.011**	-0.169***	-0.144***	0.010*	0.129***	-0.186***	0.102***	1			
TOP1	-0.018***	0.024***	0.214***	0.048***	0.148***	-0.025***	0.036***	0.036***	-0.065***	1		
SOE	-0.074***	0.010*	0.332***	0.290***	-0.018***	-0.214***	0.292***	-0.063***	-0.313***	0.226***	1	
TobinQ	0.077***	-0.044***	-0.369***	-0.226***	0.052***	0.170***	-0.115***	0.040***	0.067***	-0.129***	-0.139***	1

Note: * stands for P< 0.1, ** stands for P< 0.05, *** stands for P< 0.01

4.3 Primary Regression

Table 4 reports the benchmark regression results for the effect of green technology innovationon corporate resilience. Across models, green innovation exhibits a positive and statistically significant impact, with coefficients of 0.001 at the 1% level in both the baseline and control-variable specifications, indicating that firms investing in green technology demonstrate higher resilience in responding to environmental challenges. These findings provide robust support for the role of green technology innovationin enhancing enterprise adaptability and stability.

Table 4 Main Regression Analysis Table

	(1)	(2)
	Res	*Res*
EnvrPat	0.001***	0.001***
	(3.29)	(3.35)
Control Variables	No	Yes
Constant	0.874***	0.878***
	(8720.70)	(95.69)
Individual fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	36571	36571
Adj_R^2	0.919	0.921

Note: * stands for P< 0.1, ** stands for P< 0.05, *** stands for P< 0.01

4.4 Mediation Analysis

Table 5 reports the mediating regression results. Green technology innovationpositively influences corporate resilience through environmental performance (coefficient = 0.002, $p < 0.01$), supporting Hypothesis 2, and exerts a negative indirect effect via stock price volatility (coefficient = -0.022, $p < 0.01$), supporting Hypothesis 3, indicating that green innovation enhances resilience both by improving environmental outcomes and by stabilizing market valuation.

Table 5 Intermediation Test

	(1)	(2)
	Res	*EnvrPat*
EnvrPat	0.002***	0.003***
	(3.5985)	(5.0463)
EP	0.001***	
	(6.1404)	
VAR		-0.022***
		(-35.9160)
Control Variables	Yes	Constant
Constant	0.506***	0.556***
	(44.0390)	(50.4242)
Individual Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	36571	36571
Adj_R²	0.089	0.120

Note: * stands for P< 0.1, ** stands for P< 0.05, *** stands for P< 0.01

4.5 Robustness Test

To verify robustness, green technology innovationis remeasured using the number of invention-based patents (*EnvrInvPat*) and their share (*RatioEnvrPat*), and the 2017 data are excluded to account for potential anomalies. Across all specifications (Table 6, Columns 1–3), the coefficients on green innovation remain positive and significant at the 1% level, confirming that the baseline findings are robust to alternative measures and sample adjustments.

Table 6 Robustness Tests

	(1)	(2)	(3)
	Res	*Res*	*Res*
EnvrInvPat	0.001***		
	(3.20)		
RatioEnvrPat		0.004***	
		(2.70)	
EnvrPat			0.001***
			(3.03)
Control variables	Yes	Yes	Yes
Constant	0.878***	0.877***	0.887***
	(95.72)	(95.75)	(90.17)
Individual Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	36571.000	36571.000	33084.000
Adj_R²	0.921	0.921	0.921

Note: * stands for P< 0.1, ** stands for P< 0.05, *** stands for P< 0.01

4.6 Endogeneity Test

To address potential endogeneity, a two-stage least squares (2SLS) approach is employed using firms' greening transitions as instrumental variables. Table 7 shows that green innovation is strongly predicted by the instruments in the first stage ($p < 0.01$) and remains positive and significant in the second stage ($p < 0.01$), confirming that the baseline results are robust to endogeneity concerns.

Table 7 Endogeneity Test Results

	(1)	(2)
	GI	*Res*
EnvPat	0.046***	
	(17.03)	
GI		1.575***
		(32.09)
Control variables	Yes	Yes
Constant	0.164***	-12.642***
	(17.75)	(-65.30)
Individual Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Observations	36003.000	36003.000
Adj_R²	0.009	0.424

Note: * stands for P< 0.1, ** stands for P< 0.05, *** stands for P< 0.01

4.7 Heterogeneity Test

Table 8 reports the heterogeneity analysis across industry and regional dimensions. Green technology innovationexerts a stronger positive effect on resilience in technology-intensive industries than in traditional ones, and its impact is more pronounced in the eastern region compared with the western region, highlighting that the effectiveness of green innovation in enhancing corporate resilience varies with industry characteristics and regional contexts.

Table 8 Heterogeneity Test

	Panel A:Industry attributes		Panel B:regional differences					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Res	*Res*	*Res*	*Res*	*Res*	*Res*	*Res*	*Res*
EnvrPat	0.0010***	0.0012*	0.0008**	0.0014**	0.0009	0.0010***	0.0021**	0.0009***
	(2.8451)	(1.7557)	(2.1446)	(2.4251)	(1.2442)	(2.9185)	(2.2408)	(2.6032)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.8743***	0.8745***	0.8761***	0.8700***	0.8712***	0.8748***	0.8685***	0.8751***
	(5.7e+03)	(7.9e+03)	(7.1e+03)	(5.2e+03)	(3.5e+03)	(8.0e+03)	(3.9e+03)	(7.9e+03)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21351	15178	25387	11165	6080	30477	5085	31476

Note: * stands for P< 0.1, ** stands for P< 0.05, *** stands for P< 0.01

5 CONCLUSION

Against the backdrop of global environmental challenges and the pursuit of the “dual-carbon” goal, this study examines how green technology innovationenhances corporate resilience to market volatility and environmental pressures. The findings indicate that green innovation significantly strengthens firms’ adaptability, enabling them to better manage external shocks while simultaneously improving competitiveness. This effect operates through enhanced environmental performance and reduced stock price volatility, suggesting that green innovation not only facilitates regulatory compliance but also bolsters market trust and lowers capital costs. The impact is particularly pronounced in technology-intensive industries and firms located in the eastern region, highlighting the importance of industry and regional contexts for managerial and policy decisions. These findings suggest that targeted government support for green R&D, strategic integration of green innovation, and alignment with CSR initiatives can collectively bolster corporate resilience, sustainable competitiveness, and societal progress toward carbon reduction targets.

COMPETING INTERESTS

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REFERENCES

[1] Shan Y, Xu H, Zhou L X, et al. Digital and intelligent empowerment: how to form organizational resilience in crisis?: an exploratory case study based on forest cabin’s turning crisis into opportunity. Journal of Management World, 2021, 37(3): 84-104.

[2] Soewarno N, Tjahjadi B, Fithrianti F. Green innovation strategy and green innovation: The roles of green organizational identity and environmental organizational legitimacy. Management decision, 2019, 57(11): 3061-3078.

[3] Lv W D, Tian D, Wei Y, et al. Innovation resilience: A new approach for managing uncertainties concerned with sustainable innovation. Sustainability, 2018, 10(10): 3641.

[4] Xu Q, Wu W, Lv Y. Research on Environmental Technology Innovation of Chinese Enterprises. China Soft Sci, 1995, 5: 16-20.

[5] Lei S Y, Wang H R, Zhang S H. Dynamic mechanism of the environmentally sound technology innovation of environmental friendly enterprises: An exploratory research based on grounded theory. Journal of Management Case Studies, 2014, 7(4): 283-296.

[6] Tao F, Zhao J, Zhou H. Does environmental regulation improve the quantity and quality of green innovation: Evidence from the target responsibility system of environmental protection. China Ind. Econ, 2021, 2: 136-154.
[7] Yanan J, Nuo C, Li W, et al. The impact of green innovation on organizational resilience. Frontiers of Society, Science and Technology, 2023, 5: 43-49.
[8] Liao Y, Qiu X, Wu A, et al. Assessing the impact of green innovation on corporate sustainable development. Frontiers in Energy Research, 2022, 9: 800848.
[9] Wen H, Shi J, Lu P. Can green technology innovation reduce the operational risks of energy-intensive enterprises?. Systems, 2023, 11(4): 194.
[10] Yue H F, Xu Y, Wu L. Empirical analysis of the choice of technological innovation mode and the green transformation of China's industry. China Population, Resources and Environment, 2017, 27(12): 196-206.
[11] Su Y, Li G. Green technological innovation ability, product differentiation and enterprise competitiveness: Analysis of energy saving and environmental protection industry listed companies. Chinese Journal of Management Science, 2021, 29(04): 46-56.
[12] Jia X, Jingbo C. Low-carbon cities and corporate green technology innovation. China Industrial Economy, 2020, 12: 178-196.
[13] Wu J, Xia Q, Li Z. Green innovation and enterprise green total factor productivity at a micro level: A perspective of technical distance. Journal of Cleaner Production, 2022, 344: 131070.
[14] Wang X, Wang Y. Research on the green innovation promoted by green credit policies. J. Manag. World, 2021, 37(6): 173-188.
[15] Song D, Li C, Li X. Does the construction of new infrastructure promote the 'quantity'and 'quality'of green technological innovation-evidence from the national smart city pilot. China population, resources and environment, 2021, 31(11): 155-164.
[16] Yang I, XU Q. Research on Green Technology Innovation of Enterprises. China Soft Science, 1998(3): 47-51.
[17] Amores-Salvadó J, Martín-de Castro G, Navas-López J E. Green corporate image: Moderating the connection between environmental product innovation and firm performance. Journal of Cleaner Production, 2014, 83: 356-365.
[18] Dong Z, Wang H. Local-neighborhood effect of green technology of environmental regulation. China Ind. Econ, 2019, 1: 100-118.
[19] Ivanov D, Dolgui A, Sokolov B(Eds). Handbook of ripple effects in the supply chain. New York: Springer. 2019, 276. DOI: https://doi.org/10.1007/978-3-031-85508-5.
[20] Qu Y X. The impact of digital financial inclusion on corporate environmental performance. Statistics and Decision, 2023, 39(20): 184-188.
[21] Xin Q, Kong D, Hao Y. Transparency and stock return volatility. Journal of Financial Research, 2014, 10: 193-206.
[22] Li Z, Ling Z. The impact of media coverage on enterprise green technology innovation: The moderating role of marketization level. Management Review, 2020, 32(9): 132.
[23] Fan D, Sun X. Environmental regulation, green technology innovationandgreen economic growth. China population,resources and environment, 2020, 30(6): 105-115.
[24] Wen Z, Fang J, Xie J, et al. Methodological research on mediation effects in China's mainland. Advances in Psychological Science, 2022, 30(8): 1692.

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CODE VERSUS PRECEDENT: BLOCKCHAIN-DRIVEN GOVERNANCE AS A RESPONSE TO THE CRISIS OF TRUSTS IN MODERN CANADIAN FINANCE

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Abstract: Canada's trust law is caught in a structural crisis, torn between the rigid formalism of common law and the need for adaptive governance in a digitalized global economy. Drawing on Frederick Schauer's theory of "rules as exclusionary reasons" and Douglass North's concept of "path dependence," this paper argues that Canada's regulatory framework—exemplified by Section 122 of the Income Tax Act and Section 56 of the Ontario Securities Act - prioritizes procedural compliance over substantive resilience, leading to systemic failures such as the collapse of Penn West Petroleum Trust and the judicial rejection of cryptocurrency trusts in QuadrigaCX. Through case studies and comparative analysis, we demonstrate how Canada's adherence to outdated doctrines undermines both domestic stability and international alignment with OECD standards. We propose a dual-track solution: legislative modernization through a Uniform Digital Trust Act and the integration of blockchain-based smart contracts (e.g., ERC-1400) to encode fiduciary duties into programmable legal structures. This approach not only resolves the Schauer-North paradox but also positions Canada as a leader in responsive, technology-driven trust governance.
Keywords: Canadian trust law; Fiduciary crisis; Legal formalism; Path dependence, Blockchain governance

1 INTRODUCTION

Canada's trust law reflects a dual legal system: the adaptive flexibility of Québec's civil code coexists with the procedural inflexibility of English common law. While this hybrid framework offers legal diversity, it also reveals a fundamental tension: how to balance institutional stability with the growing need for adaptive, technologically responsive governance. This tension is particularly visible in two areas: domestic Real Estate Investment Trusts (REITs) and international trust structures.

Domestically, the rigidity of Section 122 of the Income Tax Act exemplifies the problem. By requiring REITs to distribute 90% of their taxable income annually, the law prioritizes short-term investor returns at the expense of long-term financial resilience. This structural vulnerability is demonstrated by the collapse of Penn West Petroleum Trust. Internationally, Canada's commitment to legal formalism increasingly diverges from global regulatory trends. The "main purpose test" under Section 94(4), which legitimizes offshore entities such as the Barbados shell company based solely on formal documentation, clashes with the OECD's substance-over-form principle. Similarly, the QuadrigaCX decision, where the court refused to recognize cryptocurrencies as trust assets due to their intangible nature, reveals a judiciary still anchored in 19th-century tangibility standards. Its conservatism becomes in great contrast with Québec's evolving acceptance of digital property.

Why do such outdated doctrines persist despite pressure for reform? Frederick Schauer's theory of legal rules as "exclusionary reasons" and Douglass North's concept of institutional path dependence offer an explanation[1,2]. Schauer's theory reveals how formalist traditions prioritize rule-following even at the expense of undermining purpose or practical outcomes, while North's notion exposes how legal institutions, once enacted, become self-reinforcing thus resist reform. Together, they reveal a legal mindset in which adherence to precedent takes priority over adapting to realities, and where institutional inertia is misinterpreted as stability. Overcoming this impasse requires a dual-track strategy. On one hand, legislative modernization must align Canadian trust law with international substance-based standards. On the other, as Lawrence Lessig's "code is law" paradigm suggests, technological reform-particularly the integration of smart contracts and blockchain protocols-could encode fiduciary duties directly into programmable legal structures[3]. In a word, as digital globalization continues to change the landscape of trust governance, Canada stands at a crossroad. It can either remain confined by outdated formalism or lead a paradigm shift toward responsive, interoperable trust governance in the digital age.

2 LEGAL FORMALISM AND PATH DEPENDENCE: HOW TAX RIGIDITY AND DISCLOSURE RULES FUEL SYSTEMIC RISK IN CANADIAN REITS

2.1 Section 122's Rigid Payout Rule: How Formalism Triggered Penn West's Collapse

Canadian Real Estate Investment Trusts (REITs), structured as pooled property investment vehicles, leverage Section 122 of the Income Tax Act to provide investors with tax-advantaged income by mandating 90% annual distribution. While designed to ensure investor returns, this rule inadvertently prioritizes short-term payouts over long-term financial resilience. This tension is intensified by the 2006 Specified Investment Flow-Through (SIFT) tax reform. Targeting tax deferrals, the reforms forced energy trusts (many structured as REITs) to convert into taxable corporations while retaining Section 122's rigid payout requirement. Consequently, these entities were subjected to a dilemma: rising corporate tax liabilities (29.5% to 31.5% between 2011-2012) collided with fixed distribution ratio, eroding financial flexibility during economic downturns.

The collapse of Penn West Petroleum Trust illustrates this regulatory paradox. Compelled to distribute 90% of income (CAD 500 million annually pre-2006), its capital reserve plummeted to 5.8% (CAD 210 million reserves against CAD 3.3 billion debt) by 2006. The 2008 oil crash (50% price drop) triggered a death spiral: issuing additional bonds to sustain dividends inflated debt to CAD 3.67 billion in 2009. Legislators' 2010 rejection of lowering the threshold - citing "crashing investor confidence" - exposed deeper regulatory capture, as energy lobbyists contributed CAD 4.2 million to maintain the status quo. This trajectory mirrors Robert K. Merton's "Law of Unintended Consequences" - the manifest function of the rule (investor protection) is subverted by its latent dysfunction (amplifying systemic risk)[4]. Schauer's "exclusionary reasons"[1] explains Section 122's persistence and application to converted organizations despite negative economic outcomes. As Schauer argues: rules, given top priority in regulators' cognitive paradigm excludes alternatives, especially those requiring changes. Simultaneously, North's path dependence reinforces this sense of priority[2]: once institutionalized, the 90% rule evolved into part of legislators' cognitive paradigm becoming an unchallengeable "truth." This interplay transforms external challenge into internal resistance. As a result, a compliance tyranny is created: Schauer's rules ensure obedience by 'excluding competing considerations,' while North's path dependence naturalizes such adherence through cognitive lock-in[1,2]. Ultimately, Penn West's internal plans (20–25% reserves to 5.8%; 5% capital expenditures to 3.1%) collapsed under compliance pressures, exemplifying formalism's contradiction: rules designed for stability ironically produce instability.

Penn West's collapse is not merely a clash of rules and reality but an empirical validation of Schauer and North's theories: when law operates as an exclusionary reason and institutions resist adaptation due to path dependence, systemic collapse transitions from contingency to inevitability. This pathology has penetrated into Canada's regulatory ecosystem. Section 56 of the Ontario Securities Act mandate ambiguous "material facts" disclosure, diverting 15–20% of REIT budgets to speculative risk reporting. Judicial rulings like Re Morguard , prioritizing immediate income over innovation, embodies Schauer's "rules overriding substance" and North's "adaptive inefficiency" - sacrificing long-term adaptability for ritual compliance[1,2].

2.2 The Disclosure-Distribution Trap: How Section 56 and Section 122 Create a Feedback Loop

The collapse of Penn West Petroleum Trust reveals a fundamental tension in Canada's REIT regulatory framework. For instance, during the 2008 crisis, Penn West reduced capital expenditures to 3.1% (from a planned 5%) while diverting approximately 19% of its operational budget to preemptively report speculative risks. This resource misallocation exposes a destructive interaction: Section 122's procedural rigidity (Schauer's rule-bound formalism) work together with Section 56's disclosure ambiguities (North's path dependence) to trap trustees in a self-defeating cycle[1,2]. Section 122's rigid payouts deplete crisis buffers, forcing trustees into North's "adaptive inefficiency[2]"- prioritizing formal compliance over strategic innovation. Conversely, Section 56's ambiguities, sustained by judicial precedents (North's cognitive lock-in[2]), legitimize rules as authoritative. Together, they form a self-sustaining regulatory loop: rules compel compliance in ways that reinforce their own authority.

Central to Section 56 lies its critical flaw: its demand for "full, true, and plain disclosure" of "material facts". Legislators' failure to define the scope of "material facts" compels trustees to adopt a defensive mindset. Framed as a form of "compliance insurance," this mentality, transforms disclosure from a compliance instrument into a legal defence strategy. To illustrate, primarily to avoid litigation, trustees tend to disclose even conceivable risks, including hypothetical regulatory changes, geopolitical disruptions, or decade-out climate policies. The cost of this "compliance insurance" materializes in cold statistics: REITs now allocate 15–20% of operational budgets to speculative risk reporting- resources equivalent to funding three mid-sized solar farms annually. This diversion epitomizes a paradox: rules designed to protect investors starve the innovations that would actually secure their futures. Additionally, it reveals a even deeper institutional evasion: Section 56's ambiguity is not accidental but a risk-transfer strategy. By delegating "material fact" judgments to trustees, regulators outsource liabilities while preserving the guise of investor protection. The Alberta Court's 2020 Re Morguard ruling crystallized this regulatory distortion through what Schauer terms "rules overriding substance" - prioritizing procedural compliance over functional outcomes[1]. By asserting that "beneficiaries' entitlement to immediate income cannot be subordinated to speculative future gains," the court turned Section 56's ambiguous disclosure standard into a litigation deterrent. Therefore, trustees are compelled to confront a regulatory dilemma: either withhold information and face potential litigation, or over-disclose and compromise long-term growth initiatives. North's "adaptive inefficiency" manifests here as courts privilege short-term risk mitigation (e.g., shielding against shareholder suits) over long-term institutional adaptability[2]. This judicial enforcement completes a feedback loop: courts convert legislative ambiguity into enforceable rigidity, as seen in Penn West's collapse - depleted reserves + defensive disclosures → innovation paralysis. Each layer of 'protection' tightens system's stranglehold on adaptability. As a result, trustees are rendered captives of procedure, with their strategic discretion subordinated to the imperatives of compliance.

Courts, far from neutral arbiters, actively contribute to this trap. In Re Morguard, judges exploited Section 56's ambiguity by equating disclosure volume with legal prudence - a strategic move to avoid accountability for substantive oversight.

This judicial reasoning weaponized legislative ambiguity, shielding courts from criticism while maintaining stability in execution. The Ontario Superior Court's 2017 Greenberg decision amplifies this institutional paralysis. Although acknowledging that "litigation-driven disclosure risks distorting accountability," the court declined to modernize Section 56's interpretive framework, adhering to precedents, like "a navigator with an old map." As North explains: the transitional costs of redefining "material fact" (e.g., legislative gridlock, judicial retraining) exceed the perceived benefits of long-term systemic resilience. This inverse relationship exposes a system punishing sustainability to subsidize legal risk management. Overwhelmed by exhaustive risk disclosures, investors, increasingly turn to short-term, low-risk assets, making long-term innovation even less attractive. Eventually, the destructive interaction between rule-bound formalism and path dependence culminates in a tragedy of legal logic: rules that seem flawless on paper fail in practice. Here, Schauer's idea of "exclusionary reasons" and North's theory of "path dependence" have become tools that reinforce institutional decay[1,2]. Penn West's collapse wasn't an exception but the inevitable outcome of this system: a company buried under 37 pages of risk disclosure and merely 2% investment in renewables, operates as a tragic opera staged in the theatre of compliance, where an audience of investors eventually left holding empty purses.

2.3 Institutional Paralysis and Global Divergence: The Self-Defeating Cycle of Formalism in Canadian REIT Governance

Canada's trust law is trapped in a self-defeating cycle: rules designed to ensure stability, such as Section 122's rigid payouts and Section 56's ambiguous disclosures, undermine resilience through procedural formalism. Schauer's "tyranny of rules"[1] illustrates how ritualized compliance (e.g., 90% distribution ratio) suppress adaptive judgment, while North's theory of path dependence[2] explains their persistence: decades of institutional inertia has equated procedural compliance with fiduciary competence.

Penn West's collapse demonstrates this failure. Draining 90% of income under Section 122 slashed its reserves to 5.8% by 2006, while Section 56 diverted 19% of its budget to speculative risk reporting - resources that could have funded renewable energy upgrades. Courts' decisions further exemplify North's adaptive inefficiency[2] by accelerating this institutional decay. In Re Morguard and Greenberg, they turn disclosure volume into evidence of transparency, and rigid payouts into proof of fiduciary duties, transforming ambiguity into enforceable rigidity. Trustees thus perform in a "compliance theatre"[1]: procedurally flawless but substantively damaging. Globally, Canada's 20th-century formalism clashes with modern governance. While the EU adopts blockchain for real-time compliance, Canada's outdated standards undermines OECD alignment, damaging cross-border credibility. Ultimately, Canada's regime embodies a deep paradox: rules designed to reduce risk end up contributing to it. Unless legislators confront this "tyranny of formalism"[1], investors will remain caught in the tragedy staged at the "compliance theatre"[1].

3 CROSS-BORDER GOVERNANCE CRISIS: HOW OUTDATED TAX RULES CLASH WITH BLOCKCHAIN REALITIES

3.1 Case Study: How Canada's Tax Rules Enable Barbados Shell Company

Canada's trust law framework, grounded in procedural formalism, sustains domestic inefficiencies while extending challenges internationally. The rigidity of Section 122's payout mandate and Section 56's ambiguous disclosure rules reflects a system that prioritize ritualized compliance over adaptive governance. Such domestic tensions, however, not only mirrors but amplifies Canada's systemic regulatory disjunction in transnational governance. In cross-border trusts, procedural formalism similarly overrides substantive examination, undermining both domestic credibility and international coordination.

Canada's anti-avoidance framework under Income Tax Act Section 94(4) sets a crucial criterion for cross-border transactions: a "reasonable business purpose" is deemed absent if tax avoidance constitutes "one of the main purposes". However, enforcement - illustrated by the Barbados Shell Company Tax Avoidance Case - relies on the same formalist approach under domestic law. Section 94(4)'s procedural focus enables regulatory inefficiency which stems from a mutually reinforcing interplay between Schauer's legal formalism and North's path dependence[1,2]. To illustrate, its "main purpose" test functions as an "exclusionary reason[1]," displacing substantive examination with a narrow focus on documentary compliance. North's path dependence reinforces this formalism by embedding it within the cognitive paradigms of policymakers[2], who conflate procedural adherence with regulatory efficiency. The Barbados Shell Company case exemplifies this dynamic: the CRA accepted trust documents and tax filings as proof for a "reasonable business purpose," despite the entity's lack of personnel, operations, and risk management. As Allison Christians observes[5], the CRA's rationale reveals a regulatory disjunction: Canada's domestic tax law prioritizes formalist compliance, while international standards, such as the OECD's Principal Purpose Test, emphasize substance over form.

As policymakers internalize compliance checklists as normative benchmarks, substantive reforms, such as alignment with OECD's PPT, are rejected as disruptive or unnecessary. Canada's failure to amend Section 94(4) or issue binding guidelines since its 2017 PPT commitment illustrates path-dependency, which is further reinforced by political powers. For instance, energy lobby groups, representing beneficiaries of procedural formalism, contributed CAD 4.2 million to federal campaigns in 2019 - a strategic investment to compel the regulators into maintaining the status quo[6]. Altogether, perceived as exclusionary reasons, formal compliance expels substantive reforms, such as adopting the OECD standard, as threats to "legal certainty." Judicial conservatism conveyed by legal reasoning further amplifies this tension. In Re Morguard and Greenberg, courts transformed Section 56's ambiguous disclosure requirements into quantifiable compliance metrics (e.g., pages of filings). By equating disclosure volume with fiduciary efficiency, courts institutionalize a cognitive bias: regulators conflate documentation compliance with regulatory transparency, ignoring the economic vacuum of shell companies such as the Barbados company. This judicial formalism, as a deliberate avoidance of substantive examination, legitimizes path-dependent stagnation. Together, these forces forge a dual barrier to radical reform: while international standards increasingly prioritize substance-over-form, Canada's domestic practices remain anchored in rigid formalism.

This disjunction carries profound consequences. Domestically, it enables artificial structures that contravene the Income Tax Act's anti-avoidance objectives; internationally, it prevents Canada's alignment with OECD transparency standards, undermining its credibility in cross-border tax governance. Moreover, Canada's formalism is fundamentally incompatible with blockchain's decentralized nature. Canada's focus on static filings, such as anti-avoidance under Section 94(4), reflects a 20th-century approach which is incapable of verifying the economic substance of blockchain transactions. This inability exposes a deeper cognitive flaw: regulators, trained under Schauer's formalism, are unable to envision compliance beyond paper trails, rendering them blind to decentralized economic realities. Nevertheless, Canada's inaction is not mere institutional inertia but a political choice - one that prioritizes the performative "theatre" of compliance (Schauer) over the OECD's substance-driven governance. Without dismantling the path-dependent alliance between lobbyists, formalist regulators, and conservative courts, Canada's embrace of OECD standards will remain rhetorical. To avoid becoming a relic of the analog age, Canada must confront not only its rules, but the power structures that sustain their tyranny.

3.2 Judicial Lock-in: Why Canadian Courts Reject Cryptocurrency Trusts

Canada's legal formalism, entrenched through statutory rigidity (e.g., Section 122's distribution rules), extends North's path-dependent mindset into judicial reasoning. This "judicial lock-in" reflects a deeper structural issue. On one hand, Schauer's concept of exclusionary reasons[1] explains how courts prioritize rules over contextual judgement. On the other, North's theory of cognitive path dependence[2] institutionalizes historical biases, reinforcing outdated norms. Together, this forces create a legal culture where procedural compliance take precedence over substantive adaptation, particularly in emerging areas as cryptocurrency trusts. Here, legal rules function as "epistemic barriers", excluding blockchain's cryptographic realities from judicial consideration.

For example, the 2019 QuadrigaCX ruling (Nova Scotia Supreme Court) represented the judicial lock-in mentioned. The court applied the 19th-century "certainty of subject matter" doctrine rigidly thereby denying cryptocurrency's status as trust property due to its lack of "physical form." By weaponizing the 19th-century doctrine as a "gatekeeper," the court blocked the recognition of blockchain's cryptographic nature, enacting what Boaventura de Sousa Santos describes as "cognitive imperialism"- the imposition of analog-era logic on emerging digital realities. Regarding blockchain's cryptographic traceability (e.g., immutable wallet addresses) as insufficiently "tangible," the court prioritized procedural formalism (documentary proof) over functional substance (algorithmic certainty). This approach entrenches North's "cognitive lock-in"[2]: judges, bound by precedent, perpetuate 19th-century norms despite digital realities.

Nevertheless, Québec's recognition of cryptocurrency as "incorporeal property" under its Civil Code(Art. 906) demonstrates statutory adaptability absent in common law systems. By legislatively redefining property, Québec's civil law demonstrates that institutional change is politically contingent, challenging North's assumption of "universal path dependence[2]." The statutory adaptability conveyed by the code indicates that Canada's common law is more than passively bound by precedents, but rather actively preserving outdated norms. In contrast, U.S. courts in In re Bitfinex transcended formalist constraints through functional equivalence analysis. Rather than focusing on "physical form," U.S. judges, adopting a functional approach, evaluated whether blockchain's cryptographic nature fulfill trust law's core objectives - transparency and traceability. By prioritizing fiduciary function such as transparency and traceability, U.S. courts reinterpret legal rules as adaptive tools than exclusionary barriers, representing a jurisprudential evolution that Canada's trust law fails to keep up with.

While Québec's civil law system and U.S. courts regularly updates and reinterpret legal principles, Canadian trust law remains constrained by a path-dependent pathology. Judges, for instance, bound by precedents, often default to cognitive lock-in, perceiving rules as unchallengeable truth under the guise of what Schauer terms "exclusionary reasons[1]," This pathology is even compounded by systemic educational deficits. Revealed by a 2021 Canadian Judicial Council report only 12% of judges received blockchain training - contrasting with the U.S., where 35% of federal judges completed cryptocurrency courses. As a result, groups of under-trained judges, conditioned by Schauer's formalism, likely mistake doctrinal familiarity (e.g., 'tangible property') for legal certainty, equating rule compliance with fiduciary competence. Altogether, North's path dependence combines with Schauer's formalism, producing a willful ignorance - a systemic refusal to keep up with technological changes.

Nevertheless, the pathology has radiated into Canada's regulatory framework. For instance, Ontario's Rule 56-501 pilot, reduces smart contracts to "automatic record-keeping tools," significantly negating their transformative potential. Similarly, Alberta's insistence on paper-based compliance purposefully ignores blockchain's potential by sticking to procedural execution, showcasing a "techno-fix" that should be deemed as adaptive inefficiency. In a word, regulatory incentives are constantly utilizing smart contracts as digital puppetry on the surface to shield the performative regulatory framework underneath. By assimilating blockchain into paper-based rituals (e.g., Alberta's filings), regulators are allegedly adopting technology only to consolidate current power structures by sending the signal that substantive changes will be put forward, which usually end up in barely scratching the surface.

Ultimately, the formalism evidenced in Canadian trust law transforms blockchain - a tool for decentralized transparency - into a prop for "compliance theatre." By forcing cryptographic certainty into 19th-century property doctrines, courts together with regulators enact a "tyranny of rules": innovation is permitted only when it reinforces existing systems. This self-sustaining cycle, where Schauer's "tyranny of rules" feeds North's "institutional inertia"[1,2], reduces blockchain's liberating potential into nothing. Canada thus risks becoming a 19th-century relic, fossilizing innovation to preserve the political economy of formalism.

3.3 Structural Defects and Modernization Pathways: Proposing a Symbiotic Legal-Technological Reform for Cross -Border Digital Trusts

Canada's trust law, constrained by Schauer's "tyranny of rules" and North's cognitive path dependence[1,2], is structurally unfit to govern cross-border digital assets. The judiciary's reliance on analog-era legal doctrines creates systemic obstacles to legal modernization. Outdated mechanisms such as Section 94(4)'s formalist "main purpose test" and the QuadrigaCX court's application of 19th-century tangibility requirements to cryptocurrency trusts demonstrate how dated formalism prevents regulatory evolution. This institutional rigidity contrasts with contemporary governance trends, particularly the OECD's economic substance principle and blockchain technology's requirement for purpose-built fiduciary structures. Therefore, Canada's regulatory framework presents a paradoxical duality: Domestically, it operates through procedural checklists such as the CRA's documentary compliance requirements, while internationally advocating for the substance-over-form principles of OECD. This contradiction becomes particularly evident when analyzing jurisdictional approaches comparatively. Québec's Civil Code (Art. 906) formally classifies digital assets as "incorporeal property," while U.S. courts in In re Bitfinex validated blockchain's ability to enforce fiduciary transparency. These contrasting developments highlight Canadian common law's failure to modernize, while caught in a trap between preservation of 19th-century legal frameworks and the pressing need for technological adaptation.

To reconcile this conflict, Canada must pursue a symbiotic legal-technological reform. Legislatively, the enactment of a Uniform Digital Trust Act could modernize Canada's trust framework through three levels: (1) adopting OECD-style economic substance requirements to replace Section 94(4)'s "main purpose test ,"(2) statutorily defining digital assets as legitimate trust property, and (3) formally abolishing outdated property doctrines. Technologically, integrating blockchain innovations such as ERC-1400 smart contracts could automate compliance while embedding fiduciary duties into code[7]. Programmable contracts, for instance, might dynamically adjust REIT payout ratios in response to real-time market shifts, circumventing Section 122's rigid mandates. In this way, a twofold modernization strategy - combining legislative updates with algorithmic enforcement - could propel the nation beyond its reliance on conservative precedents. The evolved governance model would maintain legal certainty while promoting adaptability, achieving the essential balance between legal tradition and digital innovation required for 21st-century financial ecosystems.

4 BLOCKCHAIN-ENABLED GOVERNANCE: ALGORITHMIC RESPONSE TO CANADIAN TRUSTS' CRISIS

Canada's trust law crisis embodies a theoretical deadlock: Schauer's "tyranny of rules"[1] prioritizes procedural compliance over adaptability, while North's "cognitive lock-in"[2] entrenches outdated practices as unchallengeable "truth". The QuadrigaCX ruling, denying cryptocurrency trusts under 19th-century tangibility doctrines, exemplifies this impasse. Courts, bound by Schauer's formalism (rules as exclusionary reasons), dismissed blockchain's cryptographic nature, while legislators, trapped in North's inertia, preserved Section 94(4)'s "main purpose test". Lawrence Lessig's concept of "code is law" transcends this binary by redefining legal certainty[3]: not as formal compliance (Schauer) or historical inertia (North), but as algorithmic responsiveness. To illustrate, Lessig's framework redefines law evolution: by building adaptability through systematic design, Canada has the opportunity to move beyond crisis-driven reform. Rather than choosing between stability and innovation, this approach offers a reconciliation, where code serves as the new precedent, and blockchain functions as a living trust.

Technologically, ERC-1400 smart contracts offer a practical vision of this adaptive governance. By programmatically adjusting REIT payouts in response to oil price fluctuations, they preserve the enforcement of rules (such as secured distribution) while undermining rigidity through real-time adaptation. Concurrently, integrating the OECD's Principal Purpose Test into blockchain systems could revolutionize anti-avoidance enforcement. For instance, smart algorithms could analyze IP traffic to identify offshore shell entities - if 90% of access originates from Canada, the system would deem the structure as a domestic trust. In this way, this approach replaces Section 94(4)'s paper-based test with data-driven transparency. Legislatively, the proposed Uniform Digital Trust Act (UDTA) formalizes this paradigm shift. It reframes trust law's "three certainties" as algorithmic building blocks: token-holder votes as intention, distributed ledgers as "subject-matter", and verified identities as objects. This transformation reflects how fiduciary governance is structured in a digital age. Meanwhile, the immutability of code satisfies Schauer's demand for predictability. Unlike static legal precedents, code's programmability introduces a built-in capacity for change - an embedded adaptability that directly challenges North's concept of path dependence.

Nevertheless, code-driven governance, while offering greater efficiency, brings with it serious concerns around legal accountability and democratic legitimacy. In fact, Schauer's concept of "tyranny of rules" may reemerge in algorithmic systems. For example, automated decisions, such as dynamic payout adjustments, are usually powered by proprietary algorithms which are shielded by trade secrecy or technical complexity. Thus, it may create obstacles for stakeholders to understand how decisions are made. This opacity reflects Schauer's broader critique of formalism. When rules are encoded into software, they tend to prioritize procedural compliance - what the system does - over substantive justification - why it does it. In this way, such systems risk undermining the transparency that is essential to legal due process. For instance, consider an ERC-1400 contract that automatically reduces REIT dividends during a market downturn. Even if the financial impacts are drastic, investors may lack recourse to challenge the algorithm's logic or assumptions.Additionally, North's path dependence highlights a deeper complication. Although Blockchain's decentralized governance appears democratic on the surface, it may unintentionally entrench technocratic control. Those who validate the network - often large tech enterprises - can influence or control code updates. As a result, they may shape rules in ways that favor their own interests, mirroring the same institutional inertia North warned of, in a digital form. Consider Ethereum's 2016 DAO hard fork: a small group of developers reversed transactions to recover from a major hack, overriding one of blockchain's core principles - immutability. Such centralized interventions, masked as technical necessity, illustrate how code-based governance risks becoming vulnerable to concentrated influence. The UDTA's safeguards must therefore address three layers of risk: (1)Mandating open-source audits and "explainable AI" standards to make algorithmic decisions transparent, ensuring compliance with principles such as Canada's Duty of Procedural Fairness[8]; (2) Distributing code-update authority across stakeholders (e.g., token holders, regulators, civil society) through decentralized autonomous organizations (DAOs), preventing monopolization by tech elites; (3) Embedding judicial review triggers within smart contracts - for example, requiring human reexamination if payout adjustments exceed 20% - to balance automation with discretionary judgment. Without appropriate safeguards, code-driven governance risks trading one form of rigidity for another. In such a scenario, legal formalism gives way to algorithmic determinism, where rules are coded into software instead of statutes. Under the facade of innovation, this shift can actually deepen exclusion and marginalization that it was designed to confront.

In a word, Canada now stands at a critical crossword. It may stick to analog-era legal frameworks, perpetuating the rigidity Schauer critiques and the inertia North warns of, or it may pioneer a paradigm where code becomes law's adaptive counterpart. This transformation calls for a new vision of governance - one that functions as a dynamic ecosystem. In this model, blockchain ensures the immutability of core principles, smart contracts flexibly adjust obligations in response to context, and democratic oversight acts as a safeguard against algorithmic overreach. Such a synthesis resolves the Schauer-North paradox: rules retain certainty through code's precision, while institutional adaptability is embedded into their design. By embracing this vision, Canada could convert its trust law crisis into a global precedent: where fiduciary duties evolve with market realities, compliance is both transparent and responsive, and innovation thrives within insurance of accountability.

5 CONCLUSION

Canada's trust law crisis is beyond a matter of outdated statutes. It is deeply rooted in a structural tension between Schauer's "tyranny of rules" and North's "path dependence"[1,2]. Addressing this crisis demands a fundamental revisit of governance - one that shifts away from formalism and toward systemic transformation. This paper argues that the integration of blockchain is not merely a technological update, but a paradigm shift. By redefining fiduciary governance, it transits legal formalism from a rule-bound system into an adaptive, code-driven, ecosystem. By embedding responsiveness into the institutional framework, Canada can dismantle the self-perpetuating loop of procedural rigidity and cognitive inertia, creating a trust regime that reconcile legal certainty with the flexibility of financial markets.

Central to this vision is Lessig's "code is law" framework[3], which reframes fiduciary governance through three interconnected pillars. First of all, smart contracts such as ERC-1400 exemplify algorithmic adaptability, by replacing mandates, such as Section 122's rigid payout rules, with dynamic obligations that are responsive to real-time variables, it preserve compliance while circumventing formalism's rigidity, ensuring rules evolve alongside market realities. Secondly, the proposed Uniform Digital Trust Act (UDTA) reconceptualizes trust law's foundational "three certainties" through blockchain technology: consensus mechanisms encode intention, distributed ledgers verify subject-matter, and cryptographical identities secure objects. This transition, from paper-based formalism to cryptographic accountability, marks more than a technical upgrade. It represents a structural shift that embeds flexibility directly into governance design, challenging North's "adaptive inefficiency"[2]. Last but not least, transparency safeguards, such as decentralized autonomous organizations (DAOs) and explainable AI standards, can mitigate the risks of algorithmic opacity. By democratizing authority over code updates, the model prevents control from concentrating in the hands of a few technical actors. At the same time, it embeds judicial review triggers into the system, allowing legal oversight to intervene when necessary. Together, these mechanisms strike a balance between automation and democratic accountability.In this way, transparency is no longer a box-ticking exercise; it becomes a living institutional norm rather than a symbolic gesture.This transformation is foundational, not additive. Unlike Québec's statutory updates or U.S. courts' functional equivalence approach, Canada's UDTA redefines the fundamental basis of trust law itself. Blockchain no longer merely digitizes existing legal processes. Instead, it becomes the institutional scaffold - a dynamic infrastructure where legal principles evolve through coded precedents rather than crisis-driven reforms. Here, code's immutability satisfies Schauer's demand for predictability, while its programmability dismantles North's path dependence[2], resolving the paradox of rules-as-constraints versus rules-as-adapters.

Canada now faces an existential choice. Sticking to 19th-century doctrines risks turning its legal system to a relic as global governance moves toward algorithmic agility. Conversely, embracing the UDTA framework positions Canada as a pioneer of adaptive legal systems, where fiduciary duties evolve with cryptographic precision, compliance transcends ritualistic disclosure, and innovation thrives within guardrails of accountability. This is not mere modernization but the creation of a new governance species - one where code serves not as a disruptor but as ally of justice, ensuring law remains a living force in the digital age.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Frederick Schauer. Playing by the Rules: A Philosophical Examination of Rule-Based Decision-Making in Law and in Life. Oxford: Oxford University Press, UK. 1993. DOI: https://doi.org/10.1093/acprof:oso/9780198258315.001.0001.
[2] Douglass C North. Institutions, Institutional Change and Economic Performance. Cambridge: Cambridge University Press. 1990. DOI: https://doi.org/10.1017/CBO9780511808678.
[3] Lawrence Lessig. Code: And Other Laws of Cyberspace. New York: Basic Books. 1999, 89-112. ISBN: 978-0465039132
[4] Robert K Merton. Social Theory and Social Structure. New York: Free Press. 1968, 120-124. ISBN: 978-0029211304
[5] Allison Christians. Form over Substance in Canadian Tax Treaty Policy. McGill LJ 47 at 53. 2017: 62: 2. https://mcgilllawjournal.ca/articles/form-over-substance-in-canadian-tax-treaty-policy/.
[6] Boaventura de Sousa Santos. Toward a New Legal Common Sense: Law, Science and Politics in the Paradigmatic Transition. New York: Routledge, USA. 2002, 298. https://www.routledge.com/Toward-a-New-Legal-Common-Sense-Law-Globalization-and-Emancipation/Santos/p/book/9780406949974.
[7] Ethereum Foundation. 'EIP-1400: Security Token Standard'. 2018. https://github.com/ethereum/EIPs/blob/master/EIPS/eip-1400.md.
[8] Cass R Sunstein. Algorithmic Transparency in the Administrative State. 71 Duke LJ 1. 2022. https://scholarship.law.duke.edu/dlj/vol71/iss1/1/.