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Research on the problems of artificial intelligence empowering comprehensive budget management

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Abstract. Traditional comprehensive budget management suffers from multiple shortcomings such as the absence of strategic orientation, budget slack, and insufficient organizational coordination, making it difficult to adapt to complex and dynamic business environments. Digital technologies such as artificial intelligence and big data provide a technological path for the transformation of budget management. This paper systematically reviews the mechanisms and application scenarios of AI technologies-including time-series forecasting, anomaly detection, causal inference, reinforcement learning, and large language models-throughout the entire process of budget preparation, execution monitoring, analysis and adjustment, and assessment and review. The research shows that AI, relying on data-driven approaches, can achieve accurate forecasting, real-time risk identification, quantitative attribution, and dynamic resource optimization, effectively resolving the inherent pain points of traditional budget management. From the four dimensions of data, technology, organizational talent, and institutional risk control, this paper constructs a guarantee system for the implementation of AI budgeting, while also pointing out the practical obstacles currently faced by intelligent budget transformation, such as insufficient model interpretability, data silos, a shortage of compound financial talent, and imperfect supporting institutions. This paper enriches the theoretical system of intelligent budget management and provides implementation insights for enterprises to advance the digital-intelligent transformation of budgeting.

Keywords: artificial intelligence, comprehensive budget management, time-series forecasting, causal inference, anomaly detection

1. Introduction

As the business environment becomes increasingly complex and market competition intensifies, the traditional comprehensive budget management system can no longer meet the management needs of modern enterprises. Its limitations are concentrated in four aspects: first, the absence of strategic orientation-budget preparation often focuses on short-term financial activities while neglecting long-term strategic objectives, making effective integration between the two difficult, and the phenomenon of budgeting and strategic goals being "two separate sheets" is prominent; second, insufficient incentive support-the design of reward and punishment systems is unclear, employees lack a clear understanding of the relationship between their own behaviors and budget indicators, and the incentive and constraint role of budgeting is difficult to truly play;

third, the absence of organizational system guarantees-most enterprises have not yet established an independent budget management committee, and the finance department alone remains responsible for budget preparation and execution, resulting in insufficient authority and professionalism of budgeting, and a lack of deep participation from business departments such as sales and production, causing budget plans to be seriously disconnected from market realities; fourth, the prominent problem of budget slack-lower-level managers exploit information advantages to deliberately reserve excessive leeway in budget preparation, greatly reducing the effectiveness of budget indicators and thereby lowering overall enterprise efficiency. The superposition of the above problems makes traditional budget management increasingly inadequate in dynamic business environments. In addition, many enterprises also face prominent issues such as insufficient budget execution control and imperfect budget assessment mechanisms, and the entire chain of comprehensive budget management-from preparation to assessment-faces institutional and execution obstacles to varying degrees.

A new generation of digital technologies represented by artificial intelligence, big data, and cloud computing is developing at an unprecedented pace, providing solid technical support for the transformation and upgrading of enterprise management models. Technologies such as time-series forecasting, machine learning, causal inference, multi-objective optimization, anomaly detection, knowledge graphs, reinforcement learning, and large language models are comprehensively penetrating the four core stages of budget management-preparation, execution, analysis and adjustment, and assessment and review-driving the accelerated transformation of budget management from a static, ex-post, and extensive model to a dynamic, real-time, and precise intelligent model. From the budget informatization era supported by relational and multidimensional databases to the digital-intelligent era supported by a new generation of technologies such as cloud computing, big data, artificial intelligence, multidimensional data, and in-memory computing, the breadth, depth, and application scenarios of budget management in large enterprises have undergone profound changes.

This paper focuses on the application and impact of artificial intelligence embedded in the entire process of comprehensive budget management, systematically reviewing the specific application scenarios and practical outcomes of AI technologies-including time-series forecasting, feature selection, anomaly detection, causal inference, multi-objective optimization, reinforcement learning, and large language models-across the four stages of budget preparation, budget execution monitoring, budget analysis and adjustment, and budget assessment and review. On this basis, this paper further explores the implementation safeguards for the deployment of AI comprehensive budgeting, systematically analyzing the key supporting conditions for enterprises to advance AI-empowered budget management from the four dimensions of data, technology, organizational talent, and institutional risk control. At the same time, drawing on the public data and practical cases of enterprises such as Huawei, Midea, State Grid, Procter & Gamble (P&G), Ant Group, Ping An Group, Alibaba, and Microsoft, this paper deeply analyzes the implementation experience, transformation paths, and outcomes of different types of enterprises in advancing AI budget management, summarizes their institutional changes and key measures before and after adopting AI, and provides theoretical references for academic research and replicable, scalable solution models for enterprise practice.

This study has important theoretical and practical significance. At the theoretical level, current academic research on AI technologies in the financial field mostly concentrates on accounting and financial analysis, with relatively insufficient systematic research on AI applications across the entire process of comprehensive budget management; this paper can provide a new perspective for theoretical research on intelligent budget management. At the practical level, by reviewing the AI budget management practice cases of multiple enterprises, this study summarizes the implementation experience and transformation paths of different types of enterprises, providing reference implementation ideas for various enterprises to advance AI-empowered budget management.

2. Literature review

Research on comprehensive budget management began relatively early in Chinese academia and has yielded a substantial body of literature. In recent years, with the rapid development of digital technologies and the deepening digital transformation of enterprises, research on intelligent budget management has grown rapidly.

Regarding the integration of AI technology with budget management, Cheng Ping and Chen Rui developed a ChatGPT-based framework for comprehensive budget management [1]. They argued that, by leveraging the powerful large language processing capabilities of generative artificial intelligence, enterprises can make use of enhanced data analysis and processing capabilities to formulate budget objectives in a more comprehensive and systematic manner, optimize budgeting processes, and strengthen the monitoring and early warning of budget execution [1]. Cheng Ping and Chang Ji conducted an in-depth study of audit early warning for rolling cash budgets under financial shared services based on a decision tree algorithm, exploring specific approaches to applying machine learning algorithms to budget monitoring [2]. Wang Ruikun systematically discussed the development of a digitally and intelligently enabled dynamic comprehensive budget management mechanism, emphasizing the use of big data analytics, artificial intelligence, cloud computing, and other technologies to achieve dynamic budgeting, real-time budget execution, and intelligent budget control [3]. In addition, some researchers have examined the issue from the perspective of application mechanisms, pointing out that artificial intelligence can be applied to information perception and integration, intelligent forecasting and simulation, pattern recognition and risk early warning, decision support and optimization, as well as process automation and efficiency improvement, thereby reshaping the closed-loop management process from data collection to decision support.

With regard to industry-specific applications, scholars have conducted targeted studies based on the characteristics of different industries. Some researchers have taken a large real estate group as their research subject and, in light of its comprehensive budget management characteristics and current management practices, examined the application of artificial intelligence to budgeting, execution monitoring, and performance evaluation. In the power industry, researchers have proposed that electric power enterprises urgently need to develop intelligent financial management systems, establish big data platforms, and implement measures such as intelligent budget management, internal control management, and process optimization. The "Intelligence + Finance" budget management system for power grid projects integrates technologies such as big data, cloud computing, and artificial intelligence to provide accurate, timely, and reliable financial decision support for power grid projects. In the steel industry, Duan Depeng explored the underlying logic, specific value, and implementation pathways through which AIGC technologies can empower comprehensive budget management, arguing that AIGC can fully exploit the value of internal and external corporate data, dynamically respond to changes in relevant factors, and intelligently generate budget decisions [4]. In the field of geological surveying and mapping, some studies have examined the mechanisms underlying budget deviations, developed risk identification systems based on big data analytics, and established budget deviation early-warning mechanisms by combining correlation analysis with causal inference. In higher education, intelligent finance has become an important direction in the digital and intelligent transformation of university financial management. Applications of artificial intelligence in financial budget management include intelligent reimbursement, dynamic budget early warning, intelligent decision support, and intelligent process management. In the healthcare sector, Wu Yixue, based on the theoretical framework of intelligent finance, explored pathways for the intelligent upgrading of hospital budget management systems from three dimensions: organizational mechanisms, data-driven approaches, and technology platforms [5]. Yue Hongbin examined the application of intelligent technologies, including big data, artificial intelligence, and cloud computing, to comprehensive budget management in state-owned enterprises and analyzed both the necessity of intelligent upgrading and its implementation pathways [6].

Regarding budget management in public institutions and government agencies, some scholars have pointed out that public institutions can apply artificial intelligence throughout the entire budget management lifecycle, with AI playing an important role in three key stages: preliminary budget preparation, interim budget monitoring, and subsequent budget final accounts. Li Hui discussed innovations and practices in AI-driven budget management for public institutions [7]. Lu Fan and Li Yan noted that the rapid development of generative artificial intelligence based on large language models has created new opportunities for the intelligent transformation of government budget management and can facilitate the transition of budget management from "automation" toward deeper integration with "intelligence" [8].

Foreign scholars started relatively early in the cross-research of budget management and AI technology, with more mature methodology and richer practical cases. In the field of time-series forecasting, hybrid models such as Prophet and LSTM have been widely applied to consumer goods demand forecasting and financial forecasting [9]; this combined method uses Prophet to capture long-term trends and seasonal effects and LSTM to fit nonlinear residuals, significantly improving the data accuracy of rolling budget preparation. In the application of machine learning to cost attribution, tree models such as XGBoost and Random Forest combined with the SHAP value method have been used for cost driver analysis in engineering projects [10, 11]; SHAP analysis can quantify the marginal contribution of each influencing factor to cost, realizing the transformation from experience-based judgment to data-driven attribution. In causal inference, foreign enterprises such as P&G have taken the lead in introducing causal analysis into marketing budget management, quantifying the causal effects of advertising placement across different channels through difference-in-differences or Bayesian structural models, thereby optimizing budget allocation [12]. In reinforcement learning, multi-agent reinforcement learning strategies in dynamic inventory management have been used for supply chain optimization decisions [13], capable of achieving dynamic adjustment and autonomous replenishment under demand fluctuation conditions; other studies have applied deep reinforcement learning to multi-level inventory cost optimization [14], providing an algorithmic foundation for elastic adaptation in budget assessment. Overall, foreign research is more mature at the methodological level and has richer practical cases.

By reviewing relevant domestic and foreign literature, it can be found that the academic community has generally recognized that the digital and intelligent development of comprehensive budget management is an inevitable trend, and various artificial intelligence algorithms and digital-intelligent technologies have application value in various fields such as budget forecasting, cost control, and risk early warning. Moreover, through continuous practical testing, research results on intelligent budget management from many industries and multiple entities are increasing, and the exploratory integration of cutting-edge intelligent algorithms and budget management is constantly deepening. However, current research still has obvious shortcomings: first, most studies conduct fragmented research on a single technology or a single budget stage, without systematic and holistic research on the entire process of AI technology embedded in budget management; second, existing achievements are mostly based on theoretical deduction, lacking solid empirical data support and implementation verification; third, research focus is concentrated on the budget preparation and monitoring stages, while research on the intelligent transformation of the budget assessment and review stages is relatively weak. Therefore, starting from the existing research gaps, this paper integrates the scenarios of comprehensive budget management into the entire artificial intelligence budget process, and systematically explores the complete logic, application paths, and implementation guarantee system of AI empowering comprehensive budget management, making up for the current research deficiencies of fragmentation, emphasis on technology over supporting facilities, and emphasis on theory over implementation.

3. The impact of artificial intelligence embedded in the entire budget process

The core process of comprehensive budget management includes four major stages: budget preparation, budget execution monitoring, budget analysis and adjustment, and budget assessment and review. Relying on technologies such as big data mining, machine learning, and natural language processing, artificial intelligence reconstructs the comprehensive budget management model, breaking the pain points of traditional manual budgeting-experience-based, lagging, and inefficient.

3.1. Budget preparation stage

Budget preparation is the starting point of comprehensive budget management. This stage primarily relies on two types of AI technologies-time-series forecasting models and feature selection algorithms-to replace the traditional manual incremental estimation and experience-based judgment models, realizing digital, precise, and efficient budget preparation [15].

3.1.1. Core AI technologies and their application value

Time-series forecasting models: Its core function is to deeply mine the changing trends, operating cycles, and seasonal characteristics of a company's historical business data, generating objective and accurate baseline forecast data to provide data support for budget preparation. In practical applications, it can rely on a company's core data such as monthly sales, costs, and revenue over several years to automatically deduce the operating income, capital inflows and outflows, and capital gaps for the next 12 months. At the same time, it supports rolling forecasting and real-time comparison of actual and predicted values, quickly identifying deviations in business trends, and is highly suitable for industries with strong periodicity and high volatility, such as fast-moving consumer goods and retail.

Feature selection algorithms: Its core function is dimension reduction of indicators and precise attribution, automatically screening out the core driving factors that have the greatest impact on enterprise profits, costs, and revenue from hundreds of messy business indicators. In the budget preparation stage, it precisely locks in core cost drivers, allowing the budget model to focus on key business variables; in the budget deviation analysis stage, it can quantify the contribution of each factor's influence, upgrading traditional experience-based attribution to data-driven precise attribution, improving overall analysis efficiency by more than 50%.

3.1.2. Benchmark enterprise case: Huawei

Huawei's global finance shared center deployed AI time-series forecasting tools, which, based on historical sales data and contract business pipelines, automatically predict future quarterly revenue and collection rhythms, and establish a rigorous rolling forecast assessment mechanism, with the three-month rolling forecast accuracy as the core assessment indicator-among which the April forecast weight is 50%, the March forecast weight is 30%, and the recent one-month forecast weight is 20% [16]. Relying on AI technology, Huawei achieves deep binding of strategic goals, business operations, and budget KPIs, and, together with flexible budgeting and rolling forecasting tools, decomposes macro strategies into quantifiable and implementable financial and business indicators, with significant implementation results [17].

Following the implementation of the AI-based time-series forecasting model, Huawei achieved comprehensive improvements in the quality and efficiency of its financial budget management, including greater forecasting accuracy, higher budgeting efficiency, and stronger fund management and control. Its key operational and financial indicators also improved substantially. The specific results of the model's application are presented in Table 1.

Table 1. Application effectiveness of Huawei's AI time-series forecasting model in budget preparation

Core Indicators	Specific Data
Order and Demand Forecast Accuracy	Above 95%
Overall Quarterly Rolling Forecast Accuracy	Above 90%
Reduction in Budget Preparation Cycle	Reduced by approximately 40%
Enterprise Revenue Scale in 2020	Above 800 billion yuan
Upper Limit of Group Fund Forecast Deviation Control	Not exceeding 8 million yuan

3.2. Budget execution monitoring stage

Budget execution monitoring primarily applies anomaly detection models, breaking the traditional fixed-threshold monitoring mode, capturing and analyzing business data streams in real time around the clock, automatically identifying unconventional business and abnormal fund patterns, realizing the shift from ex-post rectification to in-process early warning and ex-ante prevention, and greatly reducing budget execution risks.

3.2.1. Technology application levels and scenarios

Enterprises can deploy AI anomaly detection capabilities in tiers to achieve full-domain risk coverage: first, relying on basic algorithms such as absolute difference and difference rate to cover 70% of conventional budget anomaly problems; second, identifying abnormal data points through the Isolation Forest algorithm and completing anomaly classification in combination with clustering algorithms; third, training dedicated Random Forest risk models to precisely prevent hidden business risks; fourth, relying on the LSTM-Autoencoder model to achieve the prediction and control of long-term budget execution deviations.

Core application scenarios include: monitoring core budget indicators such as unit labor cost, collection cycle, and expense expenditure on a daily basis, triggering early warnings when indicators deviate from historical norms; in the capital financing stage, intelligently flagging abnormal account transactions such as large-amount, high-frequency, and late-night transactions, effectively preventing risks such as fund misappropriation and irregular expenditures. Overall, the risk identification window is advanced from the traditional ex-post monthly report to the in-process daily report, reserving sufficient time for emergency response for management.

3.2.2. Benchmark enterprise case: Ant Group

Ant Group has deployed anomaly detection algorithms such as Isolation Forest in payment and fund risk monitoring scenarios. Based on time-series data, it precisely identifies abnormal fluctuations such as sudden surges, plunges, zeroing, and trend deviations in business, can accurately capture indicator abnormal rises and falls above 5%, and maintains an anomaly identification accuracy stably above 90%. At the same time, relying on graph computing technology, it builds a full-dimensional risk control system, expanding the risk control coverage from both temporal and spatial dimensions, monitoring hundreds of millions of transactions daily and intercepting suspicious fund flows in real time; this risk control logic can be fully adapted to the in-process fund budget monitoring scenarios of group enterprises.

3.3. Budget analysis and adjustment stage

The budget analysis and adjustment stage primarily relies on causal inference models and multi-objective optimization models to solve the two core problems of budget deviation-"unclear causes" and "inefficient resource adjustment"-respectively, realizing precise attribution of budget deviations and optimal allocation of enterprise resources.

3.3.1. Core AI technologies and their application value

Causal inference models: Different from the traditional model that only analyzes data correlations, this model can precisely mine the true causal relationships between variables. For deviation problems in budget execution such as cost overruns, unmet revenue targets, and excessive costs, it can precisely distinguish internal business factors (insufficient output, low efficiency) from external market factors (raw material price increases, macroeconomic environment fluctuations). In budget assessment, it can automatically eliminate the influence of uncontrollable external factors and objectively account for the true business contribution of business teams, moving budget analysis from "data appearances" to "essential attribution".

Multi-objective optimization models: It mainly solves the budget allocation problem under resource constraints. On the premise of limited enterprise funds, manpower, and resources, it balances multiple objectives such as profit maximization, risk minimization, and social benefit maximization, and outputs the optimal budget allocation scheme under different risk preferences. At the same time, it can optimize the financing structure, precisely measure the optimal combination of bank loans, bond issuance, and equity financing, and reduce comprehensive capital costs, completely changing the traditional manual experience-based budget adjustment model, and realizing "data-driven decision-making and precise allocation".

3.3.2. Benchmark enterprise case

Procter and Gamble used causal inference algorithms to conduct special review and optimization of advertising budget expenditures. In the third quarter of 2017, P&G cut its digital advertising budget by $100 million, and product sales showed no significant fluctuation [18]. Based on AI causal testing, P&G precisely identified the inefficient expenditure segments within the original $7.1 billion annual advertising budget, reallocated the idle and inefficient budget to high-conversion channels, and significantly improved sales conversion efficiency without changing the overall investment, verifying the core value of AI precise attribution for budget optimization [19].

3.4. Budget assessment and review stage

The budget assessment and review stage primarily applies reinforcement learning models and Large Language Models (LLM) to solve the problems of rigid traditional budget assessment, inefficient review, and inability to adapt to sudden business scenarios, realizing intelligent budget assessment, efficient review, and dynamic decision-making.

3.4.1. Core AI technologies and their application value

Reinforcement learning models: It is suitable for extreme business scenarios such as failure of historical data and sudden risks, enabling continuous trial-and-error iteration in a virtual simulation environment, deducing the chain effects of different business plans, and outputting optimal response strategies. For sudden situations such as tariff adjustments, interest rate fluctuations, and market mutations, it can simulate the costs and benefits of different plans such as production cuts, product conversion, and currency hedging, providing precise support for budget adjustment and business decision-making, and transforming the static and rigid budget system into a dynamically adaptive flexible budget system.

Large Language Models (LLM): It excels at text parsing, intelligent interaction, and automatic report generation, and can quickly extract core information and key assumptions from industry research reports, policy documents, and financial data. It supports intelligent question-and-answer budget queries, instantly retrieving data to answer business questions such as regional budget balances and expense deviations; it can automatically sort out budget execution data, generate deviation analysis reports and risk warnings, compressing the traditional one-week manual review preparation work to completion within a few hours, greatly improving budget review and assessment efficiency.

3.4.2. Benchmark enterprise case

Alibaba's Cainiao Network has deployed reinforcement learning models in inventory budgeting and replenishment management scenarios, iteratively deriving optimal replenishment and inventory allocation strategies through the algorithm's autonomous trial-and-error learning. Currently, the system has fully covered the Tmall platform, managing inventory budgets for over one million products, perfectly adapting to extreme promotional scenarios such as Double Eleven, and significantly improving inventory turnover and budget matching efficiency.

4. Safeguard measures for the implementation of AI comprehensive budgeting

Embedding AI technology into the entire process of comprehensive budget management is not achieved overnight; it requires enterprises to build a systematic guarantee system in the four dimensions of data, technology, organizational talent, and institutional risk control. Combining the practical cases of enterprises mentioned in the previous section-such as Huawei, Midea, State Grid, Ping An Group, and China FAW-the following elaborates on the specific content of each safeguard measure and the institutional changes of enterprises before and after implementing AI.

4.1. Data safeguards

Build a unified business-finance data middle platform and establish a data governance system. Data safeguards are the cornerstone of AI empowering comprehensive budget management; their quality and timeliness directly determine the feasibility and reliability of intelligent forecasting, dynamic monitoring, and precise decision-making. Without a unified, clean, and timely data foundation, even the most advanced algorithm models will become "water without a source", difficult to generate substantial business value. Only by building a data governance system covering the entire business-finance chain and breaking information silos can high-quality "fuel" be injected into AI, enabling budget management to move from static preparation to dynamic intelligent response [20].

Before the embedding of AI technology, State Grid long faced the dilemma of "chimney-style" independent construction of business systems such as finance, marketing, and materials, with inconsistent business-finance data calibers and varying standards, making effective integration and sharing difficult. Budget preparation mainly relied on the historical base method and hierarchical summary reporting, with the headquarters lacking real-time visibility into grass-roots execution, and the control method exhibiting the characteristic of "ex-post accounting"-deviations were often passively identified only at the end of the quarter or year, the correction window was severely missed, and adjustment costs remained high. The multi-level organizational structure further exacerbated the attenuation and distortion of information in the layer-by-layer transmission, and management decisions long relied on experience-based judgment and static reports, making it difficult to support the practical need for agile resource allocation in complex power grid investment environments [21].

Facing the above dilemmas, State Grid, with digital transformation as its strategic driver, embedded AI and big data technologies into the entire financial control process, establishing a three-stage transformation path of "building the data empowerment foundation-enhancing digital control capabilities-releasing digital control value". At the data foundation level, the enterprise took the lead in promoting data structuring, data collaboration, and data assetization, uniformly collecting, cleaning, and standardizing the storage of heterogeneous data dispersed in various business systems, and built a business-finance integration data middle platform covering the entire group. On this basis, AI significantly enhanced budget linkage capabilities-budget preparation was upgraded from the static base method to a combination of dynamic zero-based budgeting and flexible forecasting, and the headquarters can obtain execution deviations in real time and automatically trigger early warnings; the precise evaluation capability relies on algorithm models to achieve multi-level penetrating analysis, accurately anchoring resources to high-value areas; the instant incentive capability compresses the assessment cycle from annual to quarterly or monthly. The resulting institutional changes are particularly profound: budget control was upgraded from "monthly summary and ex-post correction" to "dynamic monitoring and real-time correction", data acquisition fully replaces manual filling, management decisions shift from "experience-based judgment" to "data-based evidence", the overall efficiency and precision of budget control achieve a systematic leap, and the enterprise's financial value and strategic synergy effects are released in coordination.

4.2. Technology safeguards

Deploy AI models in a tiered and lightweight manner, and introduce large-model agents to lower the usage threshold. Technology safeguards are the core support for AI empowering comprehensive budget management, and the key lies in the reliability of algorithm models, the elasticity of system architecture, and the usability of technical tools. No matter how perfect the data governance system is, if it lacks matching technical capabilities, intelligent forecasting, dynamic monitoring, and automated decision-making still cannot be implemented. Only by reducing computing power costs through tiered deployment and introducing large-model agents to lower the usage threshold can AI capabilities be truly embedded in every business scenario of budget management, realizing the fundamental transformation from "people serving the system" to "the system serving people" [22].

Before the embedding of AI technology, China FAW mainly relied on traditional information technology means to ensure the operation of budget management. Although the group had built information systems covering all business units, the 290 systems were independent of each other with non-unified data standards; budget preparation relied on manual filling by business departments and hierarchical summarization, and the finance department promoted business-finance alignment through regularly held budget coordination meetings. At the technical level, it relied on traditional ERP systems for data aggregation, and budget analysis mainly depended on financial personnel's experience-based judgment and Excel assistance, lacking support from professional data analysis tools and algorithm models. In terms of process control, the group had cumulatively established more than 2,000 approval nodes to control budget execution compliance, severely limiting business response speed. In terms of talent cultivation, the capability training of financial personnel focused on the field of accounting, lacking a training system for data science and algorithm application skills [23].

In recent years, building on the practical experience of budget management over the past two decades, China FAW has vigorously promoted digital-intelligent transformation, migrating all 290 isolated systems to a unified cloud-native platform, connecting more than 20 internal systems, and interfacing with 16 external institutions such as banks and the bill exchange, forming a "capital ecosystem" that realizes fully online onestop processing of treasury business. Under the framework of the "152" comprehensive budget management innovation system, the group promoted budget management transformation around the "four horizontals and six verticals" framework, launched the industry's first EOA enterprise operations agent platform, built a "perception-decision-execution-evolution" full-chain intelligent system, decomposed capital operations into subdivided units such as budget preparation, payment review, and risk early warning, and achieved full-chain control through AI model embedding [24]. The agent platform delivers large-model capabilities to ordinary employees in the form of natural language interaction, realizing a "questions are insights" decision-making experience and thoroughly lowering the usage threshold of AI tools. The resulting transformation effects are significant: after cloud system integration, annual operation and maintenance costs were greatly reduced, more than 2,000 approval nodes were substantially cut, the total volume of process documents was significantly reduced, and business response speed was greatly improved; the R&D lifecycle was compressed, manufacturing costs were reduced, and sales conversion rates increased. Financial personnel leaped from process executors to agent operators, the finance department successfully transformed from "accounting-oriented" to "value-creating", and China FAW completely bid farewell to the traditional ERP-era model of "people serving software", entering the era of intelligent enterprise operations [25].

4.3. Organizational talent safeguards

Strengthen the cultivation of financial digital talent and build a cross-departmental collaboration mechanism for business and finance. Organizational talent safeguards are the source of vitality and organizational foundation for AI empowering comprehensive budget management; the core lies in cultivating compound talents with both financial expertise and data literacy, while building a deeply integrated cross-departmental collaboration mechanism for business and finance. No matter how complete the data foundation or how advanced the technology platform, if there is a lack of talent teams that understand business logic, master algorithm tools, and drive management change, AI budget management will be difficult to truly take root. Only by promoting the transformation of the financial organization from "accounting-oriented" to "value-creating", and enabling financial personnel to deeply embed in the business front-end and empower business decisions with data insights, can continuous organizational momentum and talent support be provided for AI budget management [26].

Before the embedding of AI technology, traditional budget management was mainly led by the finance department, with low participation from business departments, and budget preparation was seriously disconnected from business reality. The core capabilities of financial personnel were long concentrated in the fields of accounting and report preparation, lacking training in digital skills such as data analysis and algorithm application, and the information barriers and goal fragmentation between departments severely constrained budget management effectiveness. Huawei also faced the pain of financial transformation in its early days; as business continued to expand and globalization accelerated, the finance department was the first to face transformation pressure, the traditional accounting model was difficult to adapt to the enterprise's rapid development needs, the role of financial personnel was long limited to "bookkeepers", with a lack of in-depth understanding of the business front-end, and the information gap between finance and business was very obvious [27].

Facing the above organizational dilemmas, Huawei systematically built a financial Business Partner (BP) operation system, promoting the transformation of the financial organization from accounting-oriented to value-creating. In organizational design, Huawei carried out systematic changes in the financial organization reshaping from accounting to business-finance integration, the process reshaping of business-finance integration, and the value realization of financial BP, and established a finance Center of Excellence (COE) and BP organizational structure to help financial personnel cultivate strategic thinking and master cutting-edge knowledge. Huawei emphasizes the "concrete" talent team building concept of two-way integration of finance and business, supporting strategic development through a plan-budget-accounting closed-loop retrospective mechanism. In addition, through major transformation projects such as Integrated Financial Transformation (IFS), Huawei promoted financial personnel from traditionally providing and explaining numbers, to influencing and supervising business through internal control construction, and then to project finance advancement aimed at empowering business [28]. The resulting transformation effects are significant: Huawei successfully broke the information gap between the finance and business departments, deeply embedded financial personnel in the business front-end, and exerted the unique value of finance in strategic planning, operation management, and business operations; the financial management innovation adapted to new quality productive forces significantly improved the enterprise's resource allocation efficiency and strategic decision-making capability, and finance successfully transformed from "accounting-oriented" to "value-creating". Huawei's practice shows that organizational talent transformation and process digital transformation complement each other, and the cultivation of compound digital talent is the key support for the implementation of AI budget management [29].

4.4. Institutional risk control safeguards

Improve the intelligent budget management system and establish data security and model verification mechanisms. Institutional risk control safeguards are the safety bottom line and long-term cornerstone of AI empowering comprehensive budget management; the core lies in improving the intelligent budget management institutional system while establishing a dual risk control mechanism of data security protection and model algorithm verification. No matter how advanced the technical architecture or how high-quality the data assets, if there is a lack of matching institutional norms and risk control constraints, the compliance, security, and reliability of AI decisions cannot be guaranteed. Only by embedding intelligent tools into institutional processes and penetrating the risk control concept throughout the entire life cycle of algorithms can AI in budget management "run fast" and "run steady" at the same time, realizing the organic unity of efficiency improvement and controllable risk [30].

Before the embedding of AI technology, State Grid's traditional budget management system mainly focused on basic arrangements such as budget preparation process norms, approval authority division, and execution monitoring rules, and the institutional arrangements for emerging fields such as data security protection, algorithm model governance, and system permission control were almost blank [31]. As a super-large central enterprise, its traditional financial management model could hardly meet the increasingly complex operational management needs, and budget control lagged significantly in institutionalization, refinement, and intelligence-preparation relied on historical base numbers, execution monitoring depended on manual report hierarchical summarization, and data security lacked systematic institutional norms [32].

Facing the above institutional shortcomings, State Grid, seizing the opportunity of digital transformation, systematically promoted financial control innovation and institutional risk control system construction, driving financial control innovation through the three stages of "building the data empowerment foundation-enhancing digital control capabilities-releasing digital control value". In institutional construction, it built ten major digital application scenarios covering multi-dimensional lean management, comprehensive budget management led by zero-based budgeting, smart completion final accounts, and risk joint prevention and control; in model verification and risk control mechanisms, it established a major risk prevention and control system penetrating all levels based on the financial middle platform, and introduced intelligent technology to strengthen risk early warning capabilities; in data security, it formed a data empowerment mechanism through data structuring, collaboration, and assetization, providing institutional guarantees for the safe operation of AI models. The resulting transformation effects are significant: digital transformation enhanced the four capabilities of organizational collaboration, budget linkage, precise evaluation, and instant incentive, improved the foresight, targeting, and execution norms of budget resource allocation, realized intelligent implementation of budget management in multiple scenarios such as resource allocation, execution monitoring, and assessment evaluation, and systematically enhanced the enterprise's institutional resilience and risk control capabilities in responding to complex business situations [33].

5. Conclusion and future outlook

This paper systematically reviews the application scenarios, mechanisms, and practical outcomes of artificial intelligence embedded in the entire process of comprehensive budget management, and mainly draws the following conclusions:

First, artificial intelligence technology is profoundly changing the operation mode of comprehensive budget management. In the budget preparation stage, time-series forecasting models and feature selection algorithms have realized the transformation from experience-based judgment to data-driven approaches, significantly improving forecast accuracy and preparation efficiency; in the budget execution monitoring stage, anomaly detection models advance the risk identification window from the traditional ex-post monthly report to in-process daily reports and even real-time early warning, greatly enhancing risk response capabilities; in the budget analysis and adjustment stage, causal inference models have achieved the leap from correlation analysis to causal attribution, while multi-objective optimization models provide scientific decision support for optimal allocation under resource constraints; in the budget assessment and review stage, reinforcement learning enables the budget system to dynamically adapt to extreme scenarios, and large language models greatly compress the traditional manual review cycle. AI technology has comprehensively penetrated the closed loop of the "preparation-execution-analysis-assessment" process of budget management, driving budget management from ex-post static control to ex-ante dynamic intelligent decision-making [34].

Second, the implementation of AI comprehensive budgeting requires systematic safeguard measures. Data is the foundation-a unified business-finance data middle platform and a sound data governance system must be built; real-time connectivity and high-quality supply of business-finance data must be realized; technology is the support-AI models must be deployed in a tiered and lightweight manner and large-model agents introduced to lower the usage threshold, so that AI capabilities are truly embedded in business scenarios; organizational talent is the guarantee-compound digital talents must be cultivated and a cross-departmental business-finance collaboration mechanism established to promote the transformation of the financial organization from "accounting-oriented" to "value-creating"; institutional risk control is the bottom line-the intelligent budget management system must be improved and data security and model verification mechanisms established to ensure the compliance and reliability of AI decisions [35]. The four are interdependent and indispensable, jointly constituting a complete implementation framework for AI budget management to move from technical concepts to managerial effectiveness.

Third, the successful practices of benchmark enterprises show that AI-empowered comprehensive budget management has moved from proof of concept to large-scale implementation. Multiple large domestic enterprises have made substantial breakthroughs in the construction of new-generation intelligent budget systems, and budget systems supported by digital-intelligent technology are helping enterprises achieve vertically and horizontally connected, agile, and intelligent budget management, providing the industry with replicable transformation paths and experience paradigms [36].

However, the current AI-empowered comprehensive budget management still faces many challenges and deficiencies, mainly reflected in the following aspects:

At the technical level, the "black box" problem of AI models has not been completely solved, and insufficient model interpretability may affect management's trust and adoption. The robustness of cutting-edge methods such as causal inference in complex business scenarios still needs further verification. According to Gartner's prediction, by 2026, 60% of AI projects without AI-ready data support will face the risk of failure. AI services are essentially characterized by metered billing, and each query incurs a cost; behind the out-of-control costs is a deep mismatch between AI pricing models and enterprise budget management.

At the data level, the data foundation of most enterprises is still relatively weak, the phenomenon of data silos is prominent, and there is a lack of unified interfaces between business systems and financial systems, resulting in the inability to efficiently flow and integrate budget-related data stored in different systems. Data quality problems directly affect decision accuracy, and problems such as difficulties in data integration during budget preparation and insufficient real-time monitoring capabilities in budget execution are common in practice.

At the organizational level, there is a severe shortage of financial digital talent, and the business-finance collaboration mechanism has not yet been truly established. Research from the Shanghai National Accounting Institute points out that there are currently four major bottlenecks in the implementation of intelligent finance: poor adaptation of technical systems, absence of data silo governance, difficulty in cross-departmental collaboration, and scarcity of compound talents with a lack of value evaluation systems, among which organizational collaboration is the biggest obstacle for the industry.

At the institutional level, the regulatory framework and industry standards for AI budget management are still in a blank state. Problems such as poor data sharing, shortage of compound talents, and imperfect institutional supporting facilities are common.

Limitations of this paper: First, the research mainly relies on public cases and literature review, lacking first-hand survey data and empirical testing, and the quantitative evaluation of AI model implementation effects is not deep enough; second, the case analysis focuses on super-large enterprises, failing to fully explore the differentiated adaptation paths of enterprises of different scales and industries; third, the challenges of AI "black box" problems, data silos, and security compliance risks are emphasized more on phenomenon description, lacking a systematic solution framework; fourth, the applicable boundaries and robustness conditions of cutting-edge methods such as causal inference and reinforcement learning are insufficiently discussed; fifth, research on the governance level of AI budget management-such as institutional supporting facilities, regulatory frameworks, and industry standards-is still lacking.

Future research: Further attention can be paid to frontier issues such as the adaptability of AI budget management in small and medium-sized enterprises, budget decision mechanisms under human-machine collaboration, and the in-depth application of large language models in budget management; at the same time, multi-case comparisons or empirical research can be conducted to verify the key influencing factors of AI budget management effectiveness; in addition, the construction of risk prevention and control systems and governance frameworks for AI budget management is also worthy of in-depth exploration.

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