Digital Intelligence Empowers Comprehensive Budget Performance Management in Universities: Construction of the HUPM-Intelligence Model and Case Study

Xin He[1], Ting Ye[2,*], Sihan Yu[3], Zhao Yu[4]
[1]*Nanyang Technological University, Singapore City, Singapore*
[2]*Financial Department, Shanghai Normal University, Shanghai, China*
[3]*Central South University of Forestry and Technology, Changsha, Hunan, China*
[4] *School of art and design, Shanghai Institute of Technology, Shanghai, China*
**Corresponding Author*

Abstract: Under the policy background of comprehensive budget performance management implementation, universities commonly face challenges such as "resource misallocation, lack of process visibility, formalized evaluations, data silos and privacy compliance, and algorithmic explainability and fairness." Adopting the Design Science Research (DSR) paradigm, this paper proposes the HUPM-Intelligence (Holistic University Performance for Budget Management-Intelligence) business model for universities. Its core framework consists of "three-phase closed-loop (ex-ante, interim, ex-post) and six performance dimensions (financial, teaching, research, personnel, infrastructure, and social services) × full-process AI empowerment," supported by a four-layer informatization platform blueprint: "data collection-governance-intelligent analysis-application presentation." A case study using a virtual university's annual budget demonstrates the method. The research established a quantifiable, replicable indicator system and weighting method to integrate budget formulation, execution, and performance feedback. This paper offers a solution that balances academic rigor and practical feasibility for modernizing budget performance governance in resource-constrained universities.

Keywords: Budget Performance Management; University Governance; AI Empowerment; Balanced Scorecard; Design Science Research

1. Introduction

1.1 Research Background

With the continuous advancement of China's fiscal system reform and the modernization of education governance, the "performance-oriented" budget management concept has expanded from pilot programs in specific departments to institutional arrangements. Comprehensive budget performance management has permeated from the macro fiscal framework to various operational lines within the internal governance of universities [1]. As the primary providers of education and research activities, universities' budget management capabilities directly impact resource allocation efficiency, educational quality, and strategic execution. Currently, university budgets face the dual challenges of diversified funding sources, complex expenditure structures, and varied output forms, while also needing to coordinate and optimize multidimensional performance in teaching, research, talent development, infrastructure, and social services within the governance loop of "goal-execution-evaluation-feedback." This tension exposes the limitations of the traditional "incremental base-account control" budget paradigm, such as delayed responsiveness, coarse-grained monitoring, and overly financialized evaluations, when dealing with uncertain environments, multi-objective trade-offs, and cross-departmental collaboration [2].

1.2 Research Significance

First, this study provides a new perspective for the academic research on Comprehensive Budget Performance Management (CBPM) at the theoretical level. Traditional research on university financial management has mostly focused on a single dimension—such as financial budget execution rates or the efficiency of educational fund usage—while lacking a systematic framework that integrates multidimensional performance indicator systems (financial, teaching, research, personnel, infrastructure, and social services) with AI-enabled mechanisms [3]. The HUPM-Intelligence model, building on the Balanced Scorecard (BSC) and PDCA closed-loop management concepts, further embeds AI's multi-level functions—such as prediction, analysis, monitoring, scheduling, analysis, reporting, and optimization—into the entire budget performance process. This interdisciplinary integration not only aligns with the trend of "combining modeling and empirical approaches" in business research but also offers a replicable research paradigm for public administration and educational finance disciplines [4].

Second, this study advances budget performance research from "single-point description" to "systematic explanation" by introducing indicator weight design and causal analysis methods. Unlike previous studies that emphasized static financial analysis, this project highlights the extraction of dynamic data streams and causal drivers through AI methods, thereby explaining the "input-output-performance" relationship. This approach provides new theoretical contributions to university budget performance research, promoting its development toward multi-dimensional, dynamic, and intelligent directions.

2. Literature Review and Theoretical Basis

Scholars at home and abroad have studied the impact of commodity prices on macroeconomic performance from a wide range of perspectives and using diverse methods.

In recent years, Chinese scholars' research on university budget performance management has focused on constructing performance indicator systems, designing performance evaluation methods, and applying information platforms. Domestic studies emphasize that universities should build multidimensional performance indicator systems based on their positioning, tightly linking budget resource allocation to goals like teaching, research, student development, and social services. For example, Qiao Chunhua outlined the basic components of university budget performance management, including strategic orientation, performance goal setting, performance budget formulation, performance contract signing, performance evaluation, and reporting [5]. Some studies propose introducing medium-term budget frameworks to strengthen ex-ante performance planning, while others focus on organizing performance evaluations, such as third-party evaluations and accountability mechanisms. Overall, domestic research is gradually moving toward standardization and refinement, though it remains relatively narrow in perspective and lacks empirical case studies [6].

Internationally, research on university budget performance management is more diverse and multi-layered. In the U.S., many public universities employ Responsibility Center Management (RCM) models, balancing departmental autonomy with performance evaluation and linking budget increments to performance contributions. Studies show that performance-based funding accounts for only about 5% of public university budgets in the U.S. Scholars have also analyzed RCM budgets from organizational behavior and institutional economics perspectives. In Europe, university budget practices vary due to differences in education systems and funding models. Seeber and Lepori found that European universities often mix incremental funding, formula-based allocation, and internal negotiation, making a global consensus unlikely [7]. For example, universities in the Netherlands, Norway, and the U.K. favor low-formula, high-increment models, while Germany and Italy rely heavily on explicit quantitative formulas in public funding allocation [8]. Japan's national universities also introduced performance-oriented funding post-corporatization, aligning with NPM reforms to improve research and teaching efficiency [9]. International research emphasizes analyzing budget performance reforms from institutional perspectives, such as the applicability of government performance budgeting in universities and its coordination with governance structures and academic autonomy. It also explores internal budget decision-making dynamics and power struggles, offering valuable insights for China's reforms [10].

With rapid advancements in information technology and artificial intelligence, AI has emerged as a new tool to enhance efficiency and decision-making in budget formulation and performance management [11]. Studies show that financial AI technologies, leveraging big data, machine learning, and natural language processing, enable deep analysis and intelligent processing of financial data, playing a critical role in budget management. In budget formulation, AI can use predictive models (e.g., time-series analysis and machine learning) to forecast revenue and expenditure trends, generate preliminary budget drafts, and reduce human bias and over-optimism. For instance, corporate practices demonstrate that machine learning significantly improves financial forecasting accuracy, cutting quarterly budget formulation time from weeks to hours [12]. In budget execution, AI can monitor deviations in real time, flag anomalous spending patterns, and alert managers for timely adjustments [13]. Meanwhile, AI-driven data mining and visualization tools (e.g., BI dashboards) enable dynamic presentation of budget execution and performance evaluation results, achieving closed-loop management across the entire "formulation-execution-monitoring-evaluation" process [14].

3. Theoretical Foundations of the HUPM-Intelligence Model

3.1 Theoretical Sources

The Balanced Scorecard (BSC), proposed by Kaplan and Norton in 1992, is a widely used strategic management tool in the field of performance management. Its core idea is to translate organizational strategic objectives into measurable performance indicators through four dimensions—financial, customer, internal processes, and learning and growth—thereby achieving strategic implementation. The BSC has the following characteristics:

Multi-dimensionality: Emphasizes the integration of financial and non-financial indicators to avoid over-reliance on single financial metrics.

Strategic Alignment: Decomposes high-level strategies into departmental and individual goals, ensuring organizational consistency.

Causal Chains: Demonstrates the cause-and-effect relationship of "input-process-output-result" through logical linkages.

The HUPM-Intelligence model draws on the BSC's "multi-dimensionality and causal logic" but expands it into six dimensions—financial, teaching, research, personnel, infrastructure, and social services—to align with the unique characteristics of university budget performance management. Unlike the profit-oriented BSC for enterprises, universities prioritize educational public welfare and social service functions, which is reflected in the dimension selection and indicator design.

The PDCA cycle (Plan-Do-Check-Act), proposed by Deming, is a key tool in quality management. Its core lies in continuous optimization through the iterative cycle of "plan-execute-check-improve":

Plan: Define objectives and develop action plans.

Do: Implement actions according to the plan.

Check: Monitor execution and evaluate goal attainment.

Act: Optimize systems and processes based on feedback.

In the HUPM-Intelligence model, the PDCA cycle is embedded throughout the budget process:

Ex-ante (Plan): Ensures scientific and rational budget formulation through goal-setting, indicator decomposition, and demand forecasting.

Interim (Do & Check): Executes and monitors processes using AI-driven tracking and early-warning algorithms.

Ex-post (Act): Conducts performance evaluation and feedback, integrating results into the next budget cycle for closed-loop optimization.

Public finance theory prioritizes fairness and efficiency in allocating fiscal resources, ensuring government or public-sector budgets strike a balance between social equity and optimal resource use. In university budget management, this translates to:

Fairness: Funds must be distributed equitably, accounting for discipline growth, faculty development, and student needs to prevent resource imbalances.

Efficiency: Every dollar spent should deliver maximum impact, especially in translating research into real-world applications and enhancing social services.

Transparency & Accountability: Budget processes must be open, with clear accountability for how funds are used and their results.

The HUPM-Intelligence model embeds these principles, aligning budget allocation with performance outcomes across teaching, research, staffing, infrastructure, and community engagement.

3.2 Model Framework

See as Table 1, the HUPM-Intelligence model operates on a dynamic "three-phase closed-loop × six performance dimensions × AI-powered workflow" logic, creating a self-sustaining cycle of goal-setting, execution, evaluation, and refinement:

Three-phase closed-loop: Pre-planning, real-time execution, and post-evaluation with iterative improvements.

Six performance pillars: Financial, teaching, research, personnel, infrastructure, and social services—each tracked via a multi-layered metrics system.

AI-driven tools: Leverages robotic process automation (RPA), predictive analytics (ARIMA/LSTM), natural language processing (NLP), anomaly detection (BI+), reinforcement learning, and automated reporting (NLG) for smart decision-making.

By merging management theories (e.g., Balanced Scorecard, PDCA) with public finance standards, the model offers a customized budget-performance framework for Chinese universities.

3.3 Three-Phase Closed-Loop Process

The first phase is Ex-ante (Budget Planning & Goal Setting). Uses ARIMA/LSTM forecasting and NLP-based policy parsing for automated target generation, grounded in the Theory of Planned Behavior.

The second phase is Interim (Execution & Control).Leverages BI dashboards, anomaly detection, and reinforcement learning for dynamic adjustments, aligned with the Internal Control Theory.

The third phase is Ex-post (Evaluation & Optimization). Applies causal analysis, NLG reporting, and simulation for multi-dimensional performance evaluation, rooted in the Organizational Learning Theory.

Table 1. AI Tools and University Budget Performance Applications

AI Tool	Application Scenario	Corresponding Dimension
RPA/ETL	Financial data cleaning	Financial, Personnel
LSTM/ARIMA	Research/teaching fund forecasting	Teaching, Research
NLP	Policy indicator extraction	All six dimensions
BI + Anomaly Detection	Budget monitoring	Financial, Infrastructure
Reinforcement Learning	Dynamic scheduling	Infrastructure, Financial
Causal Analysis	Input-output relationships	Teaching, Research, Personnel
NLG	Automated performance reporting	All dimensions
Simulation	Weight optimization	All dimensions

4. Case Study: S University's Budget Performance Management Experiment

4.1 Case Background

S University is a provincial undergraduate institution with 10 colleges and several teaching and research departments. Its current budget management process largely follows the traditional model: at the beginning of each year, colleges draft annual budget proposals based on university-level tasks and the previous year's expenditure baseline; the finance department consolidates, reviews, and adjusts these to form the overall budget plan; after approval, the budget is allocated to colleges and functional departments; during execution, units must spend funds according to budget purposes and regularly report expenditure details to the finance office; year-end budget settlement and performance evaluation are conducted. Due to limited informatization, data relies heavily on manual reporting, making real-time monitoring and performance evaluation largely dependent on post-hoc statistics, with difficulties in promptly identifying deviations and issues. In recent years, S University has urgently needed to improve resource allocation efficiency and budget execution quality, prompting a decision to conduct a virtual budget performance management experiment supported by AI technology to explore digital and intelligent solutions.

4.2 Experimental Design

To validate the role of AI in budget performance management, the study designed the following experiment: First, based on the university's strategic goals and key tasks, a performance indicator system covering six dimensions (teaching, research, student development, logistics, social services, and financial management) was constructed (see Table 1), with weights assigned to reflect their relative importance in budget performance evaluation. The system includes quantitative indicators (e.g., enrollment target completion rate, research project completion rate, graduate employment rate) and qualitative indicators (e.g., student satisfaction, teaching quality evaluation), using a hierarchical weight allocation to ensure comprehensiveness and scientific rigor (Table 2).

Table 2. University Budget Performance Indicator System

Dimension	Indicator	Weight (%)
Teaching Quality	Undergraduate Teaching Compliance Rate Graduate Employment Rate Student Satisfaction	20
Research Output	Number of SCI Papers Research Funding Acquisition Research Project Completion Rate	20
Financial Management	Budget Execution Rate Budget Cost Control Rate Internal Audit Issue Rate	15
Student Development	Number of Student Innovation Projects Employment Rate Student Scholarship Award Rate	15
Logistics Support	Facility Utilization Rate Administrative Efficiency Indicator Service Satisfaction	15
Social Service & Collaboration	Number of Industry Collaboration Projects Social Training Participation Rate University-Enterprise Collaboration Count	15

Building on this, the experiment deployed various AI tools. The research team selected key technologies: RPA (Robotic Process Automation) for automated financial data collection and performance reporting; ARIMA time-series forecasting for income and expenditure predictions; BI dashboards for real-time budget execution and performance visualization; machine learning classification for root-cause analysis of budget deviations; NLP for automated performance report summaries; and a reserved large language model-based decision support tool for simulating executive-level budget decision interactions. Table 2 matches each AI tool's functions to budget management stages, clarifying their applications(Table 3).

Table 3. AI Tool Functions and Budget Management Phase Matching Matrix

Tool Name	Budget Planning Phase	Budget Execution Phase	Performance Evaluation Phase
RPA Robot	√ (Data Collection, Preprocessing)	√ (Regular Data Extraction)	—
ARIMA Forecasting Model	√ (Revenue, Expenditure Forecasting)	—	—
BI Dashboard	—	√ (Real-time Monitoring, Visualization)	√ (Performance Results Display)
Machine Learning Analysis Algorithm	—	√ (Anomaly Detection, Attribution Analysis)	√ (Performance Clustering Analysis)
NLP Auto-Report	—	—	√ (Auto-Generated Performance Report Summary)
Decision Support System (Large Model)	√ (Budget Proposal Suggestions)	√ (Adjustment Strategy Suggestions)	√ (Evaluation Result Interpretation)

4.3 Experimental Process

The experiment involved three phases: data preprocessing, AI model operation, and decision support. In data collection and preprocessing, RPA bots extracted structured data (e.g., budget and expenditure details, performance records) from college financial and academic systems over three years, while parsing unstructured reports and forms into a centralized data warehouse. The system cleaned and standardized the data, calculating historical key performance indicators (KPIs) for baseline analysis.

During budget formulation and forecasting, the ARIMA model predicted next-year financial metrics (e.g., teaching income, research funding, administrative expenses) and compared them with college draft budgets. The AI flagged deviations (e.g., lower income forecasts due to reduced funding or growth slowdowns) and suggested adjusted budget amounts. Optimization algorithms simulated budget scenarios, generating options for leadership. The final budget balanced historical performance and future trends, achieving higher accuracy than traditional methods.

For execution monitoring and evaluation, BI dashboards tracked real-time budget execution, visualizing expenditure deviations for managers. Machine learning identified abnormal spending patterns (e.g., rapid overspending) and potential causes. Year-end evaluations automatically scored performance against Table 1's targets, with NLP summarizing results into reports highlighting achievements and risks. The experiment simulated a full AI-aided cycle:

"formulation–execution–monitoring–evaluation."

4.4 Data Presentation

Simulated results (Table 4) compared pre- and post-AI performance for select budget items. "Budget Execution Rate" (actual vs. planned expenditure) and "Performance Score" (0–100 scale) improved post-AI. For example, research funding execution rose from 84% to 96%, with scores increasing from 78 to 89.

Table 4. Simulated Comparison of Budget Execution and Performance Scores for University S

Item/Department	Budget (10k CNY)	Actual Expenditure (10k CNY)	Execution Rate (%)	Performance Score (Before/After AI)
Teaching Expenditure	12000	11400	95	82 / 90
Research Investment	8000	7700	96	78 / 89
Student Development & Aid	5000	4900	98	85 / 92
Logistics Support	3000	2900	97	80 / 88
Administration	2000	1840	92	75 / 85
Total	30000	29200	97	80 / 89

Additionally, Table 5 compares budget management efficiency before and after adopting AI technology. The "Manual Workload" metric is estimated in person-days, covering tasks like data collection, analysis, and report drafting. Results show significant efficiency gains post-AI adoption. For example, data collection workload dropped from 20 to 5 person-days, and performance report generation time reduced from 15 to 3 person-days, with overall efficiency improving by over 70%.

Table 5. Efficiency Comparison Before and After AI Adoption

Work Process	Manual Workload (Pre-AI)	Manual Workload (Post-AI)	Efficiency Gain (%)
Data Collection & Processing	20 person-days	5 person-days	75
Budget Planning & Forecasting	15 person-days	4 person-days	73
Execution Monitoring (Report Generation)	10 person-days	2 person-days	80
Performance Evaluation & Reporting	15 person-days	3 person-days	80
Total	60 person-days	14 person-days	77

4.5 Analysis

The simulation data shows that AI-powered budget performance management has a significant effect on improving resource allocation precision and decision-making efficiency at S University. First, the budget deviation rate has dropped notably. In Table 3, the budget execution rates for various projects are generally close to 100%, with the overall budget execution rate increasing from approximately 92% to 97%. This indicates more accurate budget execution, reducing idle funds and blind spending. Correspondingly, performance evaluation scores have also improved. The average performance score rose from 80 points before AI intervention to 89 points afterward, with a more than 10% increase in target achievement. This suggests that AI-assisted analysis enables the university to make more reasonable estimates of target completion during budget formulation and allows for more timely adjustments during execution, thereby promoting the realization of performance goals.

Second, decision-making and management efficiency have improved significantly. As shown in Table 6, the manual workload for multiple key tasks has been substantially reduced, freeing up significant time for management staff. During budget formulation, AI's predictive models reduce repetitive calculations and data integration steps. During execution monitoring, automated reports eliminate the need for manual compilation by financial staff, enabling immediate presentation of abnormal indicators and deviation information to management. In the performance evaluation stage, intelligent algorithms automatically generate performance analysis results and report summaries, allowing school leaders to obtain clear and comprehensive performance feedback in a shorter time. Estimates show that after introducing AI technology, the average processing efficiency at each stage improved by more than 70%. This not only means cost savings for the finance department but also enhances the responsiveness of management decisions, enabling the university to adjust budget execution deviations more swiftly.

Overall, the experimental results demonstrate that digitally empowered budget performance management can achieve the following quantifiable improvements within the university: increased scientific rigor in budget formulation (reduced prediction error rates), decreased deviation rates in budget execution (improved fund utilization), enhanced completion of performance indicators (notably higher scores), and significantly improved timeliness in decision-making (shortened management cycles). These improvements correspond to a marked enhancement in achieving the university's management objectives, providing positive signals for future promotion and optimization.

Table 6. Comparison between Traditional Budget Performance Management and HUPM-Intelligence Model

Comparison Dimension	Traditional Budget Performance Management	HUPM-Intelligence Model
Management Philosophy	Focuses on fund allocation and expenditure control; prioritizes spending over performance	Emphasizes a closed-loop of "goal-execution-evaluation-feedback" with clear performance orientation
Indicator System	Primarily financial metrics; lacks non-financial indicators (e.g., teaching, research)	Comprehensive evaluation across six dimensions (finance, teaching, research, HR, infrastructure, social service)
Management Process	Concentrates on post-hoc evaluation; lacks pre- and mid-process phases	Covers full lifecycle: pre-planning, mid-execution control, post-evaluation
Data Processing	Relies on manual entry and static reports; inefficient and error-prone	Automated collection via RPA/ETL; AI-assisted data cleaning, forecasting, and analysis
Monitoring Approach	Lacks real-time monitoring; delayed risk detection	BI visualization + anomaly detection for real-time progress and risk monitoring
Resource Allocation	Static allocation; lacks dynamic adjustment mechanisms	Reinforcement learning-driven dynamic optimization for flexible resource allocation
Result Application	Underutilized results; evaluation disconnected from next budget cycle	Automated report generation; direct feedback drives closed-loop improvement
Promotion Value	Struggles with complex multi-dimensional goals and resource constraints	Enhances transparency and scientific rigor; advances governance modernization and strategic alignment

The comparison highlights how the HUPM-Intelligence model surpasses conventional approaches in every key area—from its underlying principles to workflows, technical execution, and practical outcomes. Its standout strengths lie in three features: a seamless closed-loop process, integration across six critical dimensions, and AI-driven automation. Beyond boosting the efficiency and precision of budget performance management, this model also serves as a powerful tool for advancing university governance and reshaping education funding systems.

5. Discussion and Conclusions

This study focuses on "Digital Intelligence Empowering Comprehensive Budget Performance Management in Universities," proposing and constructing the HUPM-Intelligence model. The model is based on the Balanced Scorecard (BSC), PDCA cycle, and public finance theory, integrating AI empowerment and information platform support to form a closed-loop management system covering the pre-event, in-process, and post-event stages. It uses six core performance evaluation dimensions: finance, teaching, research, personnel, infrastructure, and social services.

Compared with traditional budget performance management models, the model proposed in this study achieves breakthroughs in both concept and methodology. In traditional models, university budgets primarily focus on fund allocation and expenditure control, lacking a performance-oriented approach, which leads to issues such as vague objectives, delayed process control, and insufficient application of results. In contrast, the HUPM-Intelligence model emphasizes a closed-loop logic of "objective–execution–evaluation–feedback," leveraging AI tools to automate data collection, trend prediction, process monitoring, and result optimization, thereby transforming performance management from a formal exercise into a substantive practice.

Specifically, in the pre-implementation phase, strategic goals are translated into concrete performance targets through demand forecasting and indicator decomposition. During the implementation phase, real-time monitoring and intelligent scheduling enhance the dynamic adjustment capability of budget execution. In the post-implementation phase, causal analysis, automated report generation, and simulation optimization ensure that evaluation results effectively inform the next round of budget planning, truly enabling continuous improvement.

The model's application value lies not only in the refinement and transparency of financial management but also in advancing the modernization of university governance. Through comprehensive assessment across six dimensions, universities can better understand the relationship between funding inputs and outcomes in talent cultivation, research achievements, and social services, leading to more scientific and rational resource allocation. Meanwhile, AI integration throughout the process not only improves data processing and decision-making efficiency but also reduces subjective biases from human intervention, making performance evaluation more objective and actionable.

However, this study has certain limitations. On one hand, the model requires a high level of informatization support and data governance capabilities, which some universities currently lack in terms of system construction and staff training. On the other hand, universities vary significantly in development goals and resource endowments, necessitating contextual adjustments during model implementation. Additionally, data security and privacy protection are critical concerns when applying AI at scale.

Overall, the HUPM-Intelligence model offers a new framework for university budget performance management, with its core contribution being the deep integration of AI and performance management to construct a multidimensional, full-process, and iterative performance evaluation system. Future research could further explore the model's adaptability and optimization paths through empirical case studies of different types of universities, providing stronger academic support and practical insights for rational resource allocation and the reform of educational fiscal systems.

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