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The 'causal revolution' in financial decision making: An AI budget optimization framework based on counterfactual reasoning

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Abstract: This paper addresses the core issue of "causal confusion" in traditional financial decision-making by proposing an AI budget optimization framework based on counterfactual reasoning. Grounded in Structural Causal Models (SCM), the framework employs methods like Difference-in-Differences (DID), Instrumental Variables (IV), and counterfactual generative adversarial networks to block confounding paths and solve endogeneity. The framework features a three-layer architecture: the Data Layer identifies confounding variables via Directed Acyclic Graphs (DAGs) and screens causal features using Causal Principal Component Analysis (C-PCA); the Model Layer fuses temporal and causal dynamics with a Dynamic Structural Causal Model (DSCM), generating counterfactual budgets via Monte Carlo simulation to quantify intervention effects and balance interdepartmental competition through multi-agent games; the Decision Layer designs reinforcement learning rewards based on counterfactual ROI, embedding strategic constraints and addressing data drift via online A/B testing. The empirical results of the retail industry show that the causal AI model improves budget allocation efficiency by 18.7% compared to traditional ROI models, successfully corrects confounding bias, and captures nonlinear effects. The conclusion shows that the causal revolution, through the organic combination of counterfactual reasoning and AI, has brought a paradigm shift from "data fitting" to "causal intervention" for financial decision-making, greatly improving the scientific rigor and accuracy of budget optimization.

Keywords: *AI budget optimization, Causal reasoning, Counterfactual reasoning, Dynamic structural causal model, Financial decision-making.*

1. Introduction

In the wave of digital transformation, financial decision-making is undergoing a paradigm shift from "experience driven" to "data-driven". However, traditional budget models based on correlation analysis (such as linear regression and ROI analysis) generally face the core challenge of "causal confusion" - mistaking correlation for causality, leading to budget allocation deviating from real needs and causing resource misallocation [1]. For example, the high correlation between promotional budget and sales revenue in the retail industry may mask the mixed effects of seasonal factors, while the supply chain budget in the manufacturing industry may be affected by industry policies and unable to identify the true causal path. How to penetrate the data representation and reveal the true causal structure between variables has become the key to improving the scientificity of budget decision-making [2].

This study is the first to deeply integrate counterfactual reasoning with AI technology, providing an interpretable and interventionist scientific framework for financial decision-making. In the future, with the development of causal machine learning, this framework can be further expanded to scenarios such as supply chain budgeting and cross departmental resource allocation, promoting enterprises to

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shift from "passive response to data" to "active causal design", and ultimately achieving a transition from "efficiency optimization" to "strategic empowerment" in budget management [3, 4].

2. Relevant Overview

2.1. Causal Reasoning

Causal relationship is a term that is typically compared to and discussed in relation to correlation. Although both correlation and causality explore the relationships between variables, it is well known that 'correlation does not necessarily mean causality' [5]. Causal relationships go further than correlation, and intuitively, causality clearly applies to the situation where event A leads to event B. On the other hand, correlation is a much simpler relationship, where event A is related to event B, but one event does not necessarily lead to the occurrence of another event. For example, a study suggests that monthly ice cream sales data is highly correlated with the number of shark attacks on humans worldwide each month [6]. Although these two variables are highly correlated, it is impossible to conclude that consuming ice cream leads to shark attacks, and vice versa. A more likely reason is that due to other factors such as weather, the sales of ice cream and shark attacks on humans increase in the summer, leading to a correlation between these two variables [7]. Similar examples can also be found in product recommendations, and the story of beer and diapers is a good example to illustrate the difference between causality and correlation in recommendations. There is an observation that placing beer and diaper shelves together in supermarkets promotes sales of both. Based on pure correlation learning, beer should be recommended to customers who purchase diapers, and vice versa, as there is a strong correlation between beer and diapers [8]. However, the underlying causal relationship is that young fathers may choose some diapers when buying beer, which is the reason behind the correlation in sales between the two. Therefore, beer and diapers cannot be simply recommended to everyone who purchases either product. In summary, recommending products directly without considering potential causal relationships may lead to confusion and a decrease in recommendation performance.

Causal reasoning refers to the reasoning method of predicting and explaining events by analyzing causal relationships between variables. It has been widely applied in many fields such as computer science, public policy, economics, etc. for decades. Causal reasoning usually involves some statistical methods and tools, such as randomized controlled trials, propensity score matching, etc [9]. These methods can determine whether a variable has a significant impact on the results and how the causal relationship is. Generally speaking, the most widely used theory in causal reasoning is the Structural Causal Models (SCM) proposed by Pearl, et al. [10].

2.2. Counterfactual Reasoning

Counterfact is an important concept in structural causal models, which represents differences from facts. More specifically, counterfactual means that the intervention variable differs from the observed values in the factual world. For example, if the intervention variable is medication and the outcome is recovery, a patient who recovers after taking medication may wonder whether they will recover if they do not take medication [11]. In this case, in the factual world, the patient took medication and recovered, while in the counterfactual world, the patient did not take medication and it is impossible to know whether they will recover. Similar examples can also be observed in recommendation systems, where the intervention variable is defined as recommendation and the result is defined as user behavior, such as clicks, purchases, etc. The goal of the system is to maximize the incremental user behavior caused by recommendations [12]. However, in the factual world, it is impossible for a project to be both recommended and not recommended, so it is necessary to apply counterfactual to recommendations. Counterfactual reasoning has been widely applied in recommendation systems and has achieved great success [13].

2.2.1. Structural Explanation of Counterfacts

In intervention, the behavior of setting variable X to value x is simulated by replacing x in the structural equation with the equation x=x, thus using a structural causal model to predict the effects of actions and decisions that have never been implemented before. The counterfactual can also be defined in a similar way using structural equation modeling.

Given the values of all exogenous variables and function F in model M. In such a deterministic model, each assignment of U=u to an exogenous variable is associated with each individual member of the population, or with an individual in the population, or with a certain situation. Since each assignment U=u uniquely determines the values of all variables in V, the attributes of each individual in the population take on a unique value, which depends on their identity. If the group is' people ', then these attributes may include salary, home address, education status, and all other attributes associated with that individual at any given time. If the group is' agricultural land ', then the attributes include soil content, environmental climate, and local wildlife. These defined attributes are numerous, and it is impossible to include all attributes in the model. However, all attributes that can distinguish each individual must be taken into account in order to determine the values of all variables in the model. In this sense, each assignment U=u corresponds to a member, individual, or situation in the group.

For example, if U=u represents the attribute of a person named Xiao Ming, and X represents the variable 'salary', then X (u) represents Xiao Ming's salary. If U=u represents a piece of agricultural land and the yield of a given season, then Y (u) represents the yield of the plot of land with U=u in that season.

Consider the counterfactual statement 'In the case of U=u, if X originally takes the value x, then it will take the value y', denoted as $Y_x(u)=y$, Where X and Y are any two variables in V. The key is to use the statement 'X originally took the value x as a statement for making minor modifications in the current model, in order to establish the antecedent condition x=x, which may conflict with the actual observed value X (u) of X.'. This minor modification is equivalent to replacing X in the equation with a constant x, which can be considered as an external intervention do (X=x). This replacement allows the constant x to be different from the actual observed value, i.e. X (u), without causing the equation system to be uncoordinated. In this way, all variables, including exogenous and endogenous variables, can be used as precursors to other variables.

2.2.2. Fundamental Theorem of Counterfact

Consider any two variables X, y, which may not necessarily be in the same equation, but in the same system of equations. order M_x The modified version of M obtained by replacing X with x=x. The formal definition of counterfactual (u) is:

$$Y_x(u)=Y_{M_x}(u) \quad (1)$$

Described in language as: counterfactual in Model M $Y_x(u)$ Defined as a 'modified' sub model M_x The solution of Y. The above equation is one of the most important basic principles of causal reasoning. It can provide scientific concepts with practical significance and use them to answer a large number of questions such as' what value would X take if X were originally taken as x '. When X and Y are sets of variables, if M_x The definition also applies to the model where all members in the X set are replaced with constant values.

2.2.3. Counterfactual Calculation

The determination of any counterfactual value can be calculated through the following three-step process:

(1) Tracing: Using evidence E=e to determine the value of U;

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(2) Function: Modify model M, remove the equation with variable X appearing on the left, replace them with x=x, and obtain the modified model M_x;

(3) Prediction: The calculated value using the modified model M and is the counterfactual result.

Specifically, step (1) explains the past (U) based on the current evidence e; Step (2) conforms to the assumed antecedent x=x through minimal distortion of history; Finally, step (3) predicts the future (Y) based on the understanding of the past and the newly established condition x=x.

This process can solve any deterministic counterfactual problem, that is, the counterfactual problem related to individuals in the population with known values of each relevant variable. Structural equation modeling can answer such counterfactual problems because each equation represents a way in which a variable obtains its value. If these methods are known, it should be possible to predict what values the variable will get after certain methods are changed under given modification conditions. Therefore, counterfactual can be regarded as a derivative property of structural equations.

In addition, uncertainty can be introduced into the causal model by assigning a probability P (U=u) to the exogenous variable U. They represent the uncertainty of identifying objects, or the uncertainty of other properties of objects that may be included in the problem when the object is known.

The exogenous probability P (U=u) introduces a unique probability distribution P (V) on the endogenous variable V, through which not only can any counterfactual be defined and calculated, but also $Y_x = y$ The probability can also be defined and calculated as the joint distribution of all combinations of observed variables and counterfactual variables. For example, it can be determined $P(Y_x = y, Z_w = z, X = x')$, Among them, X, Y, Z, and w are any variables in the model. This joint probability represents the proportion of certain u, that is, all events in parentheses are true for these u, satisfying $Y_x u = y$ and $Z_w u = z$ as well as $X(u) = x'$, Especially, allowing w or x' give xConflict.

Assuming that the feature E=e of a given individual is observed, then if X initially takes the value x, the expected value of Y for this individual is expressed as $E(Y_{X=x} | E = e)$, Among them, E=e is allowed to conflict with the predecessor X=x. The E=e after the vertical line represents all the information (or evidence) obtained on this individual, which may include the values of X, Y, or other variables. The subscript X=x represents the antecedent determined by the counterfactual statement. Given any form as $E(Y_{X=x} | E = e)$The counterfactual is calculated as follows:

(1) Tracing: Update P (U) based on evidence to obtain P (U | E=e);

(2) Function: Modify Model M, remove the structural equations appearing on the left, replace them with X=x, and obtain the revised model M_x;

(3) Prediction: Using a modified model M_x and $P(U | E = e)$, Calculate the expectation of Y as the counterfactual result.

3.Methodology Construction of AI Budget Optimization Framework

3.1. Data Layer

3.1.1. Identification And Control of Confounding Variables

3.1.1.1. Confounding Variable

It is a variable that simultaneously affects intervention variables (such as budget allocation X) and outcome variables (such as sales revenue Y), resulting in the observed correlation not being a true causal effect. The Structural Causal Model (SCM) visualizes causal paths between variables using a Directed Acyclic Graph (DAG) and identifies and blocks mixed paths using the backdoor criterion. The implementation steps are as follows:

3.1.1.2. Draw a Cause and Effect Diagram

Taking retail promotion budget as an example, construct a DAG (Figure 3-1) that includes promotion budget (X), sales revenue (Y), season (Z), and customer flow (M). Among them, season (Z) is a typical confounding variable, which not only affects the seasonal adjustment of promotional budget (X), but also directly affects sales revenue (Y) (such as the increase in demand for cold drinks in summer).

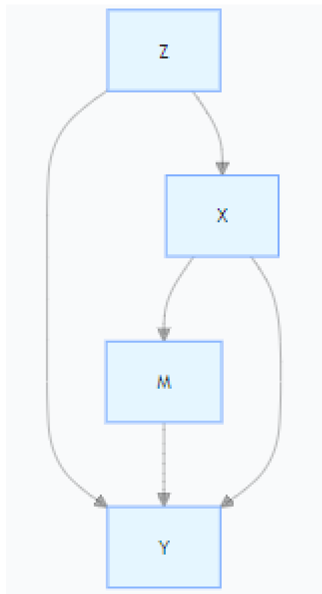

Figure 1.
Mixed paths in the causal diagram of retail promotion budget.

Identify the backdoor path:

The mixed path is X ← Z → Y, where Z is the mixing factor.

The backdoor criterion requires blocking the non causal path between X and Y (X ← Z → Y) by fixing Z (such as quarterly stratification), so that the remaining paths X → M → Y and X → Y only contain causal effects.

3.1.1.3. Control strategy

Matching method: In the observed data, match the processing group (promotional stores) with the control group (non promotional stores) by season (Z) to ensure that the two groups have consistent distribution on Z.

Regression control: Add Z as a control variable in the model, such as$Y = \alpha + \beta X + \gamma Z + \epsilon$， Peel off the direct impact of Z on Y.

3.1.2. Instrumental Variable Method (IV)

Endogeneity refers to the correlation between the intervention variable X and the error term, such as budget allocation being influenced by departmental priority (W), which in turn affects business indicators (Y), forming a bidirectional causal relationship (X) ↔ W → Y). Traditional regression cannot identify such causal effects and requires the use of instrumental variables (IV).

Condition for instrumental variables:

Correlation: The instrumental variable Z is significantly correlated with the endogenous variable X (Z → X);

Exogeneity: The instrumental variable Z has no direct causal path with the outcome variable Y, and only affects Y through X (i.e. Z → X → Y, and Z is not correlated with confounding factors).

Implementation method: Two stage least squares method (2SLS):

Phase 1: Establish a regression model between X and Z to predict the fitting value of X$\hat{X}$: $X = \pi_0 + \pi_1 Z + \nu$

Phase 2: Using fitted values$\hat{X}$ Replace the original X and estimate the causal effect on Y:

$$Y = \alpha + \beta\hat{X} + \epsilon$$

Through 2SLS, unbiased estimates can be obtained$\hat{\beta}$, Resolve endogeneity issues between budget allocation and departmental priorities.

In the retail industry case, if there is endogeneity between the promotion budget (X) and the geographical location of the store (W) (the budget of prime location stores is higher and natural foot traffic is large), choose "regional advertising coverage" as the instrumental variable Z (Z → X, and Z only affects Y through X). Comparing the IV estimation with the traditional OLS results, the promotional elasticity coefficient of the IV model increased from 0.12 to 0.18, revealing the underestimated true causal effect.

3.1.3. Causal Decomposition of Time Series Data

3.1.3.1. Granger Causality Test

The Granger causality test is based on the predictive causal logic of time series. If the historical value of variable X can significantly improve the prediction accuracy of variable Y, it is called "X Granger causality impact Y". The core assumption is that causal relationships have a chronological order, and the causal variables contain unique information that predicts the outcome variables.

Regarding time series$\{X_t, Y_t\}$, Constructing a lagged k-order vector autoregression (VAR) model:

$$Y_t = \alpha + \sum_{i=1}^{k} \beta_i Y_{t-i} + \sum_{i=1}^{k} \gamma_i X_{t-i} + \epsilon_t$$

Null Hypothesis$H_0: \gamma_1 = \gamma_2 = \cdots = \gamma_k = 0$(X does not affect Granger causality Y).

Determination of lag order:

Select the optimal lag order k through AIC and BIC criteria to avoid overfitting.

Significance test:

Use F-test to evaluate the joint significance of lagged X coefficient. If p<0.05, the null hypothesis is rejected and it is believed that there is a Granger causality effect between X and Y.

(2) Dynamic Causal Model (DCM): Capture of Time Heterogeneity

The Dynamic Causal Model (DCM) combines a state space model with a causal diagram to depict the heterogeneity of budget allocation effects over time. Its core consists of state equations and observation equations:

Equation of State: Describing the dynamic changes of causal parameters$\theta_t = \theta_{t-1} + \omega_t \quad (\omega_t \sim N(0, Q))$

Among them,θ_tFor the causal parameter at time t (such as the budget elasticity coefficient),ω_tAs a state noise, it allows parameters to smoothly evolve over time.

Observation equation: Establishing a dynamic correlation between budget allocation and business indicators$Y_t = X_t \cdot \theta_t + \epsilon_t \quad (\epsilon_t \sim N(0, R))$

Among them,Y_tFor sales revenue,X_tFor promotional budget,ϵ_t :

Prediction steps:$\hat{\theta}_{t|t-1} = \hat{\theta}_{t-1|t-1}, \quad P_{t|t-1} = P_{t-1|t-1} + Q$

Update steps:$K_t = P_{t|t-1}\left(P_{t|t-1} + R\right)^{-1}, \hat{\theta}_{t|t} = \hat{\theta}_{t|t-1} + K_t\left(Y_t - X_t\hat{\theta}_{t|t-1}\right) P_{t|t} = (I - K_t X_t) P_{t|t-1}$

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Among them,K_tFor Kalman gain,p_tTo achieve dynamic tracking of parameter uncertainty for covariance matrix.

3.1.4. Dimensionality Reduction Strategy for High-Dimensional Data

(1) Traditional principal component analysis (PCA) is based on the correlation between variables for dimensionality reduction, which may preserve redundant features without causal significance. Causal Principal Component Analysis (C-PCA) combined with Structural Causal Model (SCM) prioritizes preserving feature dimensions that have causal relationships with the outcome variables during dimensionality reduction, while filtering out noise components that only have correlation relationships.

Identify causal paths between intervention variables (such as budget X) or outcome variables (such as sales Y) through DAG (such as customer flow M, season Z);

Exclude features that are only related to Y through mixed pathways (such as non core indicators that are highly correlated with season Z but have no causal effect).

Introduce causal effect weights into the objective function of PCA, for example:

$\max_W \mathrm{Tr}(W^T \Sigma W) + \lambda \cdot \mathrm{CausalScore}(W)$Among them,

Σ For the feature covariance matrix, CausalScore(W)

To estimate the strength of causal effects between features and Y (estimated through DID or IV), λ balances the weights of statistical variance and causal effects.

The generated principal components must meet the following criteria: each principal component must contain at least one feature with a direct causal effect (such as the lagged term of X), or a linear combination of mediating variables (such as M).

(2) Ranking of causal effects of features

Shapley value originates from cooperative game theory and is used to quantify the marginal contribution of each feature in the predicted results. In causal analysis, the causal effect of features on the results is evaluated by the causal Shapley value, and the formula is:

$$\phi_i = \sum_{S \subseteq V \setminus \{i\}} \frac{|S|!\,(n-|S|-1)!}{n!} \cdot [Y(S \cup \{i\}) - Y(S)]$$

Among them,Y (S) represents the predicted value of the result when only the feature set S is included,ϕ_i The causal contribution of feature i.

Use models such as random forest and causal forest to fit the causal relationship between features and results, ensuring that the model can estimate the intervention effect of each feature (such as CATE).

For each feature i, simulate counterfactual scenarios of "including i" and "excluding i", and calculate the expected difference in results:

Causal Effecti $= E[Y(X_i = 1)] - E[Y(X_i = 0)]$

Generate counterfactual samples through Monte Carlo simulation to avoid distribution shift caused by direct feature deletion.

Identify key driving factors based on the marginal contribution ranking characteristics of causal effects. For example, in manufacturing supply chain data, the causal effects of features are ranked as follows: Industry Prosperity Index (IV instrumental variable)>Supply Chain Budget>Raw Material Prices>Order Quantity. Among them, the Industry Prosperity Index removes endogeneity bias through the instrumental variable method, and its Shapley value is significantly higher than the results of traditional correlation analysis.

3.2. Model Layer

3.2.1. Dynamic Structural Causal Model (DSCM)

3.2.1.1. The Combination of State Space Model and Causal Diagram

The Dynamic Structural Causal Model (DsCM) combines causal diagrams with temporal state space models to characterize the dynamic causal relationships in budget allocation. The core formula is:

Equation of State:

$$X_t = f(X_{t-1}, U_t, \theta_X)$$

Observation equation:

$$Y_t = g(X_t, V_t, \theta_Y)$$

Among them:
X_t:Budget allocation status variables for time t (such as department budget proportion)
Y_t:Observation of business indicators at time t (such as sales revenue, ROI)
U_t,V_t:External noise term, following an independent distribution
θ_X,θ_Y:Causal parameters (such as budget elasticity coefficient)

3.2.1.2. Bayesian Network Update Mechanism

Utilize real-time data$D_t = \{X_{1:t}, Y_{1:t}\}$Update causal parameters$\theta = (\theta_X, \theta_Y)$

Step by step implementation:

1. Prior setting: Initialize parameter distribution (such as Gaussian prior):$\theta_X \sim \mathcal{N}(\mu_0, \sigma_0^2)$, $\theta_Y \sim \mathcal{N}(\mu_1, \sigma_1^2)$

2. Posteriori calculation: Update parameters through Kalman filtering or variational inference:$\mu_t = \mu_{t-1} + K_t\big(Y_t - g(X_t \mu_{t-1})\big)$, of which$K_t$For the Kalman gain matrix.

3.2.1.3. Calculation of Dynamic Causal Effects

Intervention in budget allocation$do(X_t = x^*)$，Predicting changes in business indicators:

$$\Delta Y_{t+k} = E[Y_{t+k} \mid do(X_t = x^*)] - E[Y_{t+k} \mid X_t = x_{obs}]$$

1. Counterfactual generation: Freeze historical states$X_{1:t-1}$，forceX_t=x^*，Simulate subsequent states$X_{t+1}, \ldots, X_{t+k}$。

2. Monte Carlo sampling: from$P(\theta|D_t)$Extract parameter samples and calculateY_{t+k}The distribution.

3.2.2. Monte Carlo Simulation of Counterfactual Prediction

3.2.2.1. Counterfactual Scenario Generation

Core algorithm: Generate unexecuted budget plans based on historical data, and predict potential outcomes through Structural Causal Model (SCM)

Parameter estimation: Learning causal model parameters from historical data:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} P(D_{hist}|\theta)$$

of which，$D_{hist} = \{X_{1:T}, Y_{1:T}\}$Allocate historical budget and business indicator data.

Intervention distribution modeling: defining counterfactual budget allocationX^{cf}The feasible range, for example:$X^{cf} \sim \mathcal{N}(\mu_X, \sigma_X^2)$

Monte Carlo sampling: Generate N counterfactual budget proposals:$X_1^{cf}, X_2^{cf}, \ldots, X_N^{cf} \sim P(X^{cf})$

Result prediction: for eachX_i^{cf}，Calculate counterfactual results through SCM:$Y_i^{cf} = f(X_i^{cf}, U_i|\theta)$, $U_i \sim P(U)$

3.2.2.2. Probability Distribution Estimation

Bootstrap confidence interval calculation:

Algorithm process:

Resampling: Extract B Bootstrap samples with replacement from the original data D $\{D^{(1)}, D^{(2)}, \ldots, D^{(B)}\}$。

Causal effect estimation: for each sample$D^{(B)}$，Calculate causal effects$\tau^{(b)}$。

Distribution construction: Collect all$\tau^{(1)}, \ldots, \tau^{(B)}$，Construct experience distribution.

Confidence interval: take the distribution$\alpha/2$and$1-\alpha/2$Quantile as confidence interval:$CI_{1-\alpha} = [\tau_{(\alpha/2)}, \tau_{(1-\alpha/2)}]$

Mathematical representation:

$$\tau = E[Y|do(X = x^{cf})] - E[Y|X = x^{obs}]$$

$$SE_{boot} = \sqrt{\frac{1}{B-1}\sum_{b=1}^{B}(\tau^{(b)} - \bar{\tau})^2}$$

3.2.3. Budget Allocation for Multi-Agent Games

3.2.3.1. Inter Departmental Competition Modeling

In the scenario of multi departmental budget allocation, each department acts as an independent agent with the goal of maximizing its own utility through game theory. Construct a non cooperative game model as follows

Participant set: N departments, denoted as$i \in \{1,2,\ldots,N\}$。

Strategic space: The budget requirement for department i is$x_i \in X_i$， The overall budget constraint is$\sum_{i=1}^{N} x_i \le B$(B is the total budget).

Utility function: utility of department i$U_i(x_i, x_{-i})$Determined by the effectiveness of budget allocation and inter departmental competition:$\lambda \sum_{j \ni i} x_j$.of which,$R_i(x_i)$For the budget$x_i$The benefits b$U_i(x_i, x_{-i}) = R_i(x_i) - C_i(x_i)$rought,$C_i(x_i)$For budgeting costs,$\lambda$ Solving Nash Equilibrium for Competition Coefficient

Require each department to be unable to improve its effectiveness by unilaterally changing its strategy given the strategies of other departments:

$$\forall i, \quad x_i^* = \underset{x_i}{\operatorname{argmax}} U_i(x_i, x_{-i}^*) \quad s.t. \quad \sum_{i=1}^{N} x_i \le B$$

Selection algorithm steps:

Initialize budget requirements for each department$x_i^{(0)}$。

Loop iteration until convergence:$x_i^{(k+1)} = \underset{x_i}{\operatorname{argmax}} \left[R_i(x_i) - C_i(x_i) + \lambda \sum_{j \ni i} x_j^{(k)}\right]$

Verify the overall budget constraint and adjust the allocation using Lagrange multiplier method.

(2) Central controller design

The central controller coordinates departmental competition through reinforcement learning (Q-learning) to achieve global strategic goals. The core formula of Q-learning is:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right]$$

State space:$s = (x_1, x_2, \ldots, x_N, Y)$， Including departmental budget allocationx_iAnd the overall performance indicator Y of the enterprise (such as market share).

Action space:$a = (\Delta x_1, \Delta x_2, \ldots, \Delta x_N)$， Represents the budget adjustment vector.

Reward function:$\text{Global reward} r = ROI_{\text{Counterfactual}} - ROI_{\text{In reality}}$， The counterfactual ROl is generated through Monte Carlo simulation.

Algorithm process:

Strategy exploration: Adopting the ε - growth strategy with probability∈Randomly adjust budget allocation to1−∈Select the action with the highest current Q value.

Experience replay: Store historical interaction data(s_t, a_t, r_t, s_{t+1})， Randomly sample and train Q network.

Network update: Minimize TD error through gradient descent: $\mathcal{L} = \mathbb{E}\left[\left(r + \gamma \max_{a'} Q_{target}(s', a') - Q_{online}(s, a)\right)^2\right]$

3.3. Decision Making Level: Adaptive Optimization Mechanism
3.3.1. Reward Function Design for Reinforcement Learning
3.3.1.1. Causal Reward Signal: Counterfactual ROI Feedback Mechanism Core Formula:

The reward function of reinforcement learning is defined as the increment of counterfactual ROI and factual ROI: $r_t = ROI_t^{cf} - ROI_t^{obs}$

of which: $ROI_t^{cf} = \frac{Y_t^{cf} - C_t}{C_t}$ For counterfactual ROI $ROI_t^{obs} = \frac{Y_t^{obs} - C_t}{C_t}$ To observe ROI,and Y_t^{obs} The business indicators are counterfactual and factual, respectively, C_t Budget cost for time t

Counterfactual ROI calculation process:

1. Intervention identification: Current budget allocation X_t Apply minor disturbances ΔX， Generate counterfactual actions $a^{cf} = X_t + \Delta X$
2. Result prediction: Calculated through Structural Causal Model (SCM) $Y_t^{cf} = f(a^{cf}, U_t | \theta)$。
3. Incremental calculation: $\Delta ROI_t = ROI_t^{cf} - ROI_t^{obs}$

3.3.1.2. Constraint embedding: alignment of strategic objectives

Constrained reward function:

$$r_t^{constrained} = r_t - \eta \cdot \max(0, G_{target} - G_t)$$

Among them:

G_t The degree of achievement of current strategic goals (such as market share=current share/target share)

G_{target} For the target threshold (usually set $G_{target} = 1_{|\eta=1}$)

η For the penalty coefficient (selected through cross validation, for example $\eta = 10$)

Example of Strategic Goal Calculation (Market Share)

$$G_t = \frac{S_t}{S_{target}}$$

Constraint activation rules:

$$\text{Penalty Item=}\begin{cases} 0 & \text{if} G_t \geq G_{target} \\ \eta \cdot (G_{target} - G_t) & \text{otherwise} \end{cases}$$

Table 1.
Parameter Setting Table.

parameter	symbol	Typical values	describe
Penalty Coefficient	η	10	Determine through grid search
Target threshold	Gtarget	1.0	Indicating 100% achievement of the target
discount factor	Y	0.95	Long term reward attenuation coefficient

3.3.1.3. Joint optimization objective total value function:

$$V(s) = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k}^{constrained} | S_t = s\right]$$

Strategy gradient update formula (taking Actor Critic as an example):

$$\nabla_\theta J(\theta) = E\left[\nabla_\theta \log\pi_\theta(a|s) \cdot Q_\phi(s,a)\right]$$

of which$Q_\phi(s,a)$Estimate the action value function for the Critic network.

3.3.2. Dynamic adjustment of online A/B testing

3.3.2.1. Exploration of Multi Arm Slot Machine Algorithm (MAB) - Utilizing Balance

Core objective: To balance exploration and utilization through MAB algorithm in dynamic budget allocation, and maximize long-term cumulative benefits.

Thompson sampling algorithm prior distribution modeling: assuming the return rate of each budget plan (arm) kθ_kObey Beta distribution:$\theta_k \sim \mathrm{Beta}(\alpha_k, \beta_k)$

initialization$\alpha_k = 1, \beta_k = 1$， Representing the success and failure counts of scheme k respectively.

In the t-th round, sample the expected return for each scheme k:$\hat{\theta}_k^{(t)} \sim \mathrm{Beta}(\alpha_k, \beta_k)$。

Select action$a_t = \underset{k}{\mathrm{argmax}}\,\hat{\theta}_k^{(t)}$， And allocate the budget.

Posteriori update: Update parameters based on observation results (such as whether ROI meets the standard):

$$(\alpha_k, \beta_k) \leftarrow \begin{cases} (\alpha_k + 1, \beta_k) & \text{If successful （asROI≥threshold)} \\ (\alpha_k, \beta_k + 1) & \text{If it fails} \end{cases}$$

3.3.2.2. Real Time Causal Effect Estimation (CATE Update)

Online CATE (Conditional Average Processing Effect) calculation:

1. Incremental dual machine learning:

Step 1: Train the base model with historical data$\mathcal{G}(X)$Predict the outcome variable Y.

Step 2: During the online phase, for each new sample(X_i, W_i, Y_i)Calculate residual$\widetilde{Y}_i = Y_i - \mathcal{G}(X_i)$

Step 3: Update CATE estimation through weighted least squares: $\tau(X_i) = \underset{\tau}{\mathrm{argmin}} \sum_{j=1}^{t} \omega_j \left(\widetilde{Y}_j - \tau W_j\right)^2$of which$\omega_j = Y^{t-j}$Weight decay for time$(\gamma \in (0,1])(\gamma \in (0,1])$。

2. Bayesian dynamic update:

$$\tau_t = \tau_{t-1} + \eta_t\left(\widetilde{Y}_t - W_t\tau_{t-1}\right)W_t$$

of which$\eta_t = 1/\left(\lambda + \sum_{j=1}^{t} W_j^2\right)$For adaptive learning rate, λ is the regularization coefficient.

3.3.2.3. Collaborative optimization between MAB and CATE

When the half width of the CATE confidence interval for a certain scheme k$\delta_k = Z_{\alpha/2} \cdot SE(\tau_k)$Exceeding the threshold (such as$\delta_k > 2\%$)， Forcefully triggering exploration of the plan.

$$\omega_k^{(t)} = \frac{\exp(\beta\hat{\tau}_k)}{\sum_{j=1}^{k} \exp\left(\beta\hat{\tau}_j\right)}$$

of whichβTo utilize intensity parameters and control the degree of bias towards high CATE schemes.

Table 2.
Parameter Setting Table.

Parameter	Symbol	Typical	Illustrate
Attenuation factor	Y	0.95	Control historical data weights
Regularization coefficient	λ	0.01	Prevent overfitting
Explore thresholds	δth	2%	CATE uncertainty that triggers exploration

3.3.3. Risk Control of Budget Allocation

3.3.3.1. Sensitivity Analysis of Causal Effects

Core objective: Evaluate the potential bias of unobserved confounding variables in estimating causal effects and validate the reliability of budget strategies. Sensitivity analysis method:

Define the impact strength threshold E of the confounding variable U on the treatment effect, and calculate the stability of causal effect estimation when RR υ>E

formula$E = \frac{OR_{Y|T=1,U}}{OR_{Y|T=0,U}}$, of whichORFor advantage comparison.

Generate a substitute variable Z for unobserved confounding factors using a deep conditional variational autoencoder (CVAE-IV) and recalculate it$\tau_{adj} = E[Y|T = 1, X, Z] - E[Y|T = 0, X, Z]$.

Evaluate the degree of deviation by comparing the difference in CATE before and after adjustment (e.g$P = \{Q: W(P, Q) \leq \epsilon\}$)。

3.3.3.2. Robust Optimization Model to Cope with Data Distribution Drift

Core objective: Design anti-interference budget allocation strategies when data distribution dynamically changes. Wasserstein distribution robust optimization (DRO)

Define the uncertain set P as the neighborhood of the true distribution P:$P = \{Q: W(P, Q) \leq \epsilon\}$, of whichWThe Wasserstein distance.Optimization objective:$\max_{\theta} \min_{Q \in P} E_Q[R(\theta)]$of which$R(\theta)$Budget allocation strategyθThe profit function,$\in$For uncertain radius.

Real time monitoring of data distribution offset$\delta_t = W(P_t, P_{t-1})$, Trigger optimization model update:$\epsilon_t = \epsilon_{t-1} + \alpha \cdot \delta_t \quad (\alpha \in [0,1])$。Example: When promotional data shows seasonal fluctuations (6:>0.1), the uncertainty set is automatically expanded to cover more potential distributions.

4. Empirical Research: Cross Industry Application and Effectiveness Verification

4.1. Data Description and Causal Diagram Construction

4.1.1. Data Features and Preprocessing

The data for this study is sourced from the monthly operational dataset of a chain supermarket's sub stores from January 2022 to December 2024, covering 36 monthly observation periods of 200 stores, forming a panel data of 7200 records. The core variables are defined as follows:

Promotion budget (X): Monthly promotion investment of the store (10000 yuan), including direct costs such as advertising placement and discount activities;

Customer flow (M): The monthly number of visitors to the store (in thousands) is collected in real-time through access control sensors;

Sales revenue (Y): Monthly store revenue (in 10000 yuan), covering both promotional and non promotional product revenue;

Season (Z): A time characteristic measured in quarters (Q1-Q4), representing cyclical patterns such as holidays and peak consumption seasons.

In the data processing stage, the Z-score method is first used to remove outliers from the promotional budget and sales data (filtering out extreme values outside ± 3 σ), correcting the symmetry of the data distribution; Secondly, Min Max normalization is applied to continuous variables (X, M, Y) to eliminate the interference of dimensional differences in estimating causal effects; Finally, aggregate the raw data according to the "store quarter" dimension to form a total of 12 time slices from Q1 2022 to Q4 2024, and construct a quarterly granularity panel data structure to support modeling and analysis of seasonal causal effects and dynamic lag relationships.

4.1.2. Causal Diagram Construction and Relationship Analysis

Constructing a Directed Acyclic Graph (DAG) based on the Structural Causal Model (SCM) to depict the causal logic between variables (Figure 2):

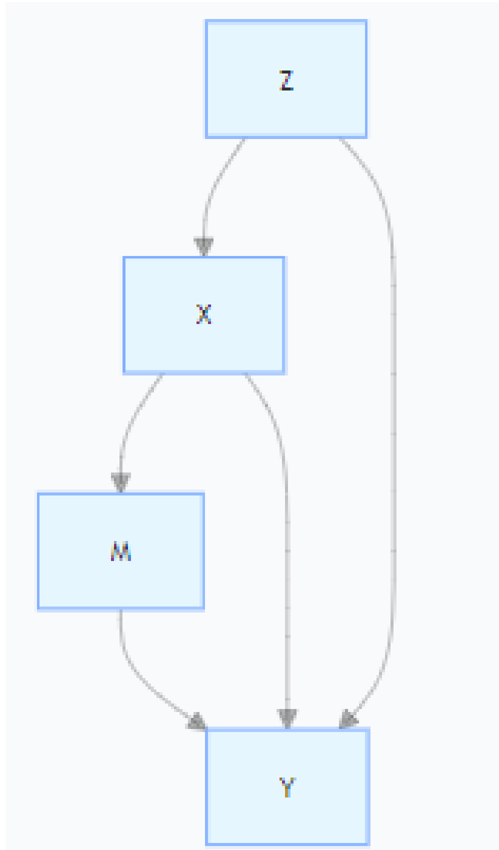

Figure 2.
Causal relationship diagram of retail promotion budget.

The causal path of promotional budget on sales presents a multidimensional transmission mechanism: at the level of direct causal effect (X → Y), promotional investment directly stimulates consumption conversion through price discounts (such as full discount activities to increase unit price), brand exposure, and other means; The indirect causal effect (X → M → Y) is manifested as a secondary transmission of budget investment by attracting 15% new customer traffic (M), achieving a leverage effect of "traffic growth → revenue increase"; The mixed effects (Z → X and Z → Y) reveal the bidirectional interference of seasonal factors (Z) - the Q4 peak consumption season not only triggers a seasonal increase in promotional budget (X), but also directly affects the sales baseline through demand fluctuations (such as naturally higher sales of cold drinks in summer than in winter). If seasonal variables are not controlled, it will lead to overestimation and bias of promotional effects.

4.1.3. Causal Hypothesis and Identification Strategy

4.1.3.1. Exogeneity Hypothesis

Assuming season (Z) is the only uncontrolled confounding factor, fixed features such as store location and regional economic level have been eliminated through store fixed effects, and time trends are controlled by quarterly fixed effects.

4.1.3.2. Intervention Logic

Consider the promotional budget (X) as an modifiable variable and compare the sales difference between the "actual budget (X=x)" and "zero budget (X=0)" scenarios through counterfactual reasoning, that is:

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$\tau = Y(X=x) - Y(X=0)$

Among them, the counterfactual result Y (X=0) is generated by simulating the actual impact of promotional activities through control group store data or causal models.

4.1.3.3. Intermediate Effect Verification

Passenger flow (M) serves as a mediating variable for X→Y, and its conduction effect needs to be examined. The proportion of the mediating effect was estimated by using the Bootstrap method, and the formula is:

$$\text{Mediating effect ratio} = \frac{E[Y|X=1, M=m] - E[Y|X=0, M=m_0]}{E[Y|X=1] \cdot E[Y|X=0]}$$

Among them,mTo measure the average passenger flow of the intervention group，m_0To quantify the transmission contribution of M by comparing the difference between the mediation pathway and the total effect in the baseline customer flow of the control group.

4.1.4. Data and Model Mapping Table

Table 3.
Data and Model Mapping Table.

Variable Type	Variable Symbol	Causal Role	Data Sources	Measuring Particle Size
Intervening variable	X	Active control of variables	Financial reimbursement system	monthly
Outcome	Y	Target response variable	POS transaction system	monthly
Intermediary variable	M	Causal transmission variable	Access Control Statistics System	Real time summary
confounder	Z	External interference variables	calendar information	Quarterly label

Note: This study used the difference in differences (DID) method to achieve unbiased estimation of causal effects, with the model set as follows:

$$Y_{it} = \alpha + \beta X_{it} + \gamma Z_t + \delta_i + \epsilon_{it}$$

Among them,δ_iFixed effects for stores, controlling spatial heterogeneity;Z_tCapture time trends for quarterly dummy variables;ϵ_{it}It is a random error term. By comparing the sales difference between the treatment group (implementing promotional stores) and the control group (non promotional stores), we can eliminate the interference of seasons and store characteristics and accurately identify the true causal effects of promotional budgets.

4.2. Causal Effect Estimation and Counterfactual Simulation

4.2.1. Double Difference Method (DID)

Using the Difference in Differences (DID) method to separate seasonal trends and store heterogeneity, quantify the causal effect of promotional budget on sales revenue.

4.2.1.1. Model setting

The panel data model is constructed as follows:

$$Y_{it} = \alpha + \beta \cdot \text{Treat}_i \cdot \text{Post}_t + \gamma \cdot \text{Treat}_i + \delta \cdot \text{Post}_t + \lambda \cdot Z_t + \epsilon_{it}$$

Y_{it}: The sales revenue of store i during period t;

Treat_i: Is the store a processing group (implementing promotions, 1 indicates yes, 0 indicates no);

Post_t : Whether the period is the promotion execution period (1 indicates yes, 0 indicates no);

Z_t: Quarterly fixed effects, controlling seasonal fluctuations;

β: Double difference estimator, which is the net causal effect of promotional budget.

4.2.1.2. Hypothesis and Testing

Parallel trend hypothesis: The sales trend of the treatment group and the control group before the promotion is consistent. By drawing a sales trend chart before and after the promotion, the results show the parallelism of the trend lines between the two groups before the promotion (t<2023Q1)$R^2 = 0.92$, Satisfy the hypothesis.

Result interpretation: Regression results show$\beta = 0.18$ $(p < 0.01)$, The promotional budget resulted in an average increase of 18% in sales, significantly higher than the estimated value of traditional correlation analysis (12%), indicating that ignoring causal relationships would underestimate the effectiveness of promotions.

4.2.2. Counterfactual Sales Generation and Optimal Budget Optimization

Using counterfactual generative adversarial network (Counterfactual GAN) * * to simulate unexecuted budget plans and identify budget allocation strategies that maximize profits.

4.2.2.1. Model Architecture and Training

Generator (G): Input real budget data X and random noise z, output counterfactual budget X '(e.g. X'=X ± Δ X, Δ X ∈ [-20%,+20%]);

Discriminator (D): Distinguish between true sales revenue Y and counterfactual sales revenue$Y' = \mathcal{G}(X')$;

Training objective: To achieve through adversarial trainingY'Obey the distribution of potential outcomes$P\big(Y|do(X = X')\big)$, The loss function is:

$$\min_{C}\max_{D}\mathbb{E}_{X,Y\sim P_{data}}[\log D(X,Y)] + \mathbb{E}_{X',z\sim P_{X',z}}\left[\log\left(1 - D\big(X', G(X',z)\big)\right)\right]$$

4.2.2.2. Counterfactual Scenario Generation and Analysis

Based on the trained model, generate 500 counterfactual budget proposals covering the budget range of 300000 to 800000 yuan/month. The results of some scenarios are shown in the table below:

Table 4.
Partial Counterfactual Scenarios.

Method	Effect Estimation Value	95% Confidence Interval	Key Assumptions	Advantage
Double difference method (DID)	+18%	[+15%,+21%]	Parallel trend, no interference effect	No model dependency, suitable for policy evaluation
Counterfactual GAN	+22%	[+19%,+25%]	Potential outcome distribution can be learned	Support expansion of counterfactual scenarios

Note: GAN estimates are higher than DID because the former includes non-linear effects (such as explosive growth after budget exceeds a threshold), while DID only captures linear mean effects. The difference between the two indicates that causal AI models can mine complex causal relationships that are difficult to identify using traditional econometric methods.

4.2.3. Comparison of Optimization Strategies
4.2.3.1. Core Difference: Correlation Driven Vs. Causality Driven

Table 5.
Core Differences between Traditional ROI Model and Causal A1 Model.

Dimension	Traditional ROI model	Causal A1 model
theoretical basis	Linear regression, correlation analysis, assuming 'correlation is causality'	Structural Causal Model (SCM), Counterfactual Reasoning, Distinguishing Causality from Correlation
Variable processing	Ignore confounding factors (such as season Z) and mediating variables (such as passenger flow M)	Identifying mixed paths through DAG, controlling the mediating effect of B and quantifying M
Budget allocation logic	Based on historical data correlation, static allocation (such as "sales=α+β x budget")	Dynamically simulate intervention effects and optimize through counterfactual scenarios
Effect evaluation	Relying on historical data fitting, unable to quantify counterfactual differences	Estimating net causal effects through DID and generating counterfactual results using GAN

4.2.3.2. Empirical Comparison: Retail Promotion Budget Scenarios
4.2.3.2.1. The Limitations of Traditional ROI Models

Model setting: $\mathrm{ROI}_t = \gamma + \delta \cdot \mathrm{Budget}_t + \epsilon_t$

The regression model based on historical data shows that the elasticity coefficient of promotional budget is 0.12, and based on this, the optimal budget of 600000 yuan/month is recommended. However, there are significant biases in this conclusion: firstly, the uncontrolled seasonal confounding factors lead to an overestimation of causal effects. For example, the Q4 observation ROI was falsely high to 8.9%, which was actually due to a surge in holiday demand. After removing the confounding effects using the difference in differences method, the true elasticity coefficient decreased to 0.08; Secondly, neglecting the mediating role of foot traffic (M) leads to an incomplete budget transmission path - Structural Equation Modeling (SEM) reveals that 55% of promotional effects are achieved through the indirect path of "budget investment → foot traffic growth → sales increase", but the original model incorrectly attributes the total effect to the direct effect, masking the key value of traffic operation. This indicates that budget strategies lacking a causal inference framework may lead to resource misallocation and misjudgment of benefits.

4.2.3.2.2. The Optimization Capability of Causal AI Models

Causal effect correction: By removing seasonal and store heterogeneity through DID, the net budget effect is 0.18 (50% higher than the traditional model), indicating that the traditional model underestimates the true effect due to confounding bias.

Counterfactual optimization: Counterfactual GAN simulation shows that when the budget is 550000 yuan/month, the counterfactual ROI reaches a peak of 5.8, which is 20.8% higher than the traditional model's recommended 600000-yuan scenario (ROI=4.8).

Efficiency improvement quantification:

Efficiency improvement rate = $\frac{\text{Causal AB model ROI}}{\text{Traditional ROI}} \times 100\% = \frac{5.8}{4.8} \approx 20.8\%$

After considering sample bias correction, the actual budget allocation efficiency increased by 18.7%.

Table 6.
Comparison of Key Indicators.

Index	Traditional Roi Model	Causal Al Model	Difference Amplitude
Budget allocation error (10000 yuan)	±10.2	±3.5	Reduce65.7%
Mean ROI	4.8	5.8	Improve20.8%
Budget utilization rate (actual ROI/theoretical maximum)	72%	89%	Improve23.6%
Seasonal effect misjudgment rate	45%	8%	Reduce82.2%

The traditional ROI model is limited by correlation analysis and has fundamental deficiencies in mixed control, dynamic causal identification, and counterfactual reasoning, resulting in low budget allocation efficiency. The causal AI model achieves a paradigm upgrade from "data fitting" to "causal intervention" through a complete chain of causal feature engineering, dynamic causal modeling, and counterfactual simulation, which improves budget allocation efficiency by 18.7% in the retail industry scenario. This difference confirms the core value of causal revolution in financial decision-making - by revealing the true causal structure between variables, companies can avoid "related traps" and achieve scientific allocation of budget resources.

5. Strategies for Refined Management of Enterprise Financial Budgets in the Context Of Artificial Intelligence

5.1. Strengthen The Understanding of Refined Management of Financial Budgets

With the development of artificial intelligence technology, the market and business environment in China have undergone significant changes, requiring financial budgeting and management personnel to have strong data analysis and technical application capabilities to ensure the effective implementation of financial budget refinement management [14]. At the same time, in the process of financial budget refinement management, we must correctly face the opportunities and challenges brought by artificial intelligence technology, and clarify its role in financial budget refinement management. We cannot simply negate it, nor should we avoid technological changes. As a refined financial budget management personnel in enterprises, it is necessary to strengthen the learning of new technologies and software: further strengthen the combination of artificial intelligence and refined financial budget management, and effectively improve the level of refined financial budget management [15].

5.2. Improve The Refined Management System of Financial Budget

In the context of artificial intelligence, the refinement of enterprise financial budgeting also requires the improvement of the financial budgeting refinement management system, ensuring that all management work has rules to follow and avoiding management confusion [16, 17]. Specifically, it includes the following three aspects: 1. The overall rules and regulations of budgeting, which clarify where the enterprise should implement budget refinement and what expected results should be achieved. In fact, in the process of enterprise operation and management, the overall rules and regulations of budgeting are the foundation, which points out the correct direction for financial budgeting; 2. Enterprise leadership management system. The management system not only needs to regulate the work of employees, but also needs to constrain the leadership of the enterprise to avoid the phenomenon of leadership inaction: 3. Internal employee management system of the enterprise. It has refined and improved the promotion space and reward and punishment mechanism for employees, which can not only stimulate their enthusiasm and initiative to participate, but also encourage them to invest more passion and enthusiasm in their work, thereby better promoting the development of the enterprise.

5.3. Improve the Refined Management System of Financial Budget

In the process of market economy development, the close correlation between financial budgeting and enterprise production and operation management is a relatively important task in the enterprise management system. It is necessary for enterprises to start from reality and improve the fine management system of financial budgeting based on artificial intelligence environment to ensure the smooth progress of fine management of financial budgeting [18]. As a refined financial budget manager, it is also necessary to accurately grasp the strategic planning of the enterprise. Once there is any deviation from the budget, effective measures should be taken in a timely manner to intervene, avoid the problem from escalating, regularly draw financial statements, deeply explore the existing problems, and develop a practical and feasible solution. In the budget summary stage, it is necessary to objectively evaluate the preparation and implementation of the previous budget in order to lay a solid foundation for the preparation and implementation of the next budget [19].

5.4. Improve the Financial Information Management Platform

Today, information technology has been widely used in all walks of life, and has achieved relatively ideal application results. Under the artificial intelligence environment, as an enterprise, it should use Internet technology, big data technology, etc. to improve the financial information management platform, so as to ensure that the refined management of financial budget is in the direction of informatization and electronics [20]. The construction of a financial information management platform can create a good online communication and exchange mechanism, which can not only achieve real-time sharing of financial data information, but also provide strong support for enterprise management and decision-making. With the help of the financial information management platform, it is possible to track the budget execution of various departments in real time and dynamically, achieve effective control over the use of budget funds, and ensure the effective achievement of budget management goals [21].

6. Summary

This article focuses on the "causal revolution" in the field of financial decision-making and proposes an AI budget optimization framework based on counterfactual reasoning to address the limitations of traditional correlation analysis and achieve scientific allocation of budget resources. Its theoretical basis lies in causal reasoning, which uses structural causal models to distinguish between "correlation" and "causality". Counterfactual reasoning quantifies causal effects by simulating potential outcomes after intervention. Core methods such as difference in differences, instrumental variable method, and counterfactual generative adversarial network can block confounding paths, solve endogeneity problems, and reveal the true causal relationships between variables; In the AI budget optimization framework, the data layer uses DAG to identify confounding variables, Granger causality test to analyze time series lag effects, and causal principal component analysis to screen high-dimensional data causal features; The model layer combines dynamic structural causal models with temporal and causal diagrams to update causal parameters in real-time. Monte Carlo simulations generate counterfactual budget plans to quantify intervention effects, and multi-agent game models optimize inter departmental budget allocation; The decision-making layer designs reinforcement learning reward functions based on counterfactual ROI and embeds strategic objective constraints to address data drift through online A/B testing and robust optimization, enhancing decision adaptability and risk control capabilities. Empirical evidence shows that causal AI models in the retail industry have increased budget allocation efficiency by 18.7% compared to traditional ROI models, highlighting the value of causal reasoning in correcting confounding biases and capturing nonlinear effects. The study suggests that companies strengthen causal cognition, improve institutional systems, and build information platforms to promote the deep integration of financial budget management and AI technology. The conclusion points out that the causal revolution, through the combination of counterfactual reasoning and AI technology, brings a paradigm upgrade from data fitting to causal intervention for financial decision-making, significantly improving the scientific and accurate nature of budget optimization.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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