

Anchoring on Target: Rethinking Weighting Logic and Paradigm Reconstruction

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Abstract

Indicator-driven weighting methods, represented by the Entropy Weight Method (EWM) and the CRITIC weighting method, have been widely adopted in comprehensive evaluation research owing to their objective weighting attribute. However, these methods carry an underlying logical flaw: they substitute the importance of indicators with the indicators' own statistical characteristics. This flaw further gives rise to a series of problems, including the disconnection between evaluation indicators and evaluation objectives, and the dependence of indicator weights on the given sample. Such a deficiency is not a matter of technical details but a paradigm bias in weighting, which cannot be fundamentally remedied through technical modifications.

To address this issue, we propose a Target-Oriented Weighting (TOW) method that takes the evaluation objective as its core anchor, realizing a fundamental shift of the weighting paradigm from "driven by the statistical characteristics of indicators themselves" to "driven by the correlation with the evaluation goal". The TOW method calculates weights based on benchmark samples and employs unified scaling standardization to ensure the transferability of weights across scenarios. Drawing on the "first differencing, then comparison" rationale of the Difference-in-Differences (DID) approach, it eliminates individual fixed effects via temporal differencing and removes time fixed effects via cross-sectional comparison. This shifts the evaluation focus from cross-sectional level comparison to the assessment of improvement magnitude over periods, providing methodological support for weight design in performance evaluation.

Keywords: Target-oriented weighting; Pooled standardization; Estimation precision adjustment; Comprehensive evaluation method; Entropy weight method

1. Introduction

In comprehensive evaluation, index construction, and multi-criteria decision-making practices, indicator weights not only directly determine evaluation rankings, index measurements, and decision quality judgments, but also profoundly influence the policy implications of research conclusions, resource allocation, and governance orientation. Existing weighting methods are typically classified into three categories: subjective weighting, objective weighting, and combined weighting. Among them, methods such as the entropy weight method, CRITIC method, coefficient of variation

method, standard deviation method, and principal component analysis-based weighting have been extensively applied in comprehensive evaluation field due to their data-driven, “objective” weighting characteristics and operational simplicity.

However, these methods share a common feature in their weighting logic: weights are determined based on indicators’ distributional characteristics or inter-indicator correlation structures—essentially their statistical properties—rather than indicators’ importance or correlation with evaluation objectives. Specifically, the standard deviation method, coefficient of variation method, and principal component analysis belong to typical dispersion-based weighting approaches, assigning weights based on standard deviation (Ioan & Ioan, 2011), coefficient of variation (Zhuang & Li, 2011), and variance contribution (Yan, 1998; Yuan & Yu, 2021), respectively. The CRITIC method incorporates both indicator dispersion and inter-indicator correlation as weighting criteria (Diakoulaki et al., 1995; Li et al., 2025). The entropy weight method converts information entropy—reflecting dispersion—into weights (Yu, 2021). While these methods differ in which statistical features they extract, they share the same weighting paradigm: deriving weights solely from indicators’ intrinsic statistical information without involving evaluation objectives. This paper collectively terms them **Indicator-Intrinsic-Driven Weighting Methods**, emphasizing that weights are endogenously determined by indicators’ statistical distributional characteristics.

Relying solely on indicators’ statistical characteristics for weighting contains a fundamental logical flaw. Statistical characteristics constitute factual descriptions of data distributions, while indicator importance represents value judgments oriented toward evaluation objectives—there exists no necessary correspondence between the two. Directly equating statistical features with indicator importance conflates “statistical properties” with “target relevance,” spawning systematic problems including indicator-objective disconnection and sample-dependent weights, which cannot be fundamentally eliminated through technical fixes such as standardization, outlier adjustment, or parameter optimization (Zhao, 2026).

In fact, the recognition that weights should reflect indicator-objective associations rather than indicators’ intrinsic statistical properties has deep intellectual roots in statistics and econometrics. Wang and Stanley (1970), Green et al. (1978), and others began exploring the use of regression coefficients to identify predictor variable importance. To address contribution allocation problems caused by indicator correlations, Pratt (1987), Budescu (1993), Johnson (2000), Johnson and LeBreton (2004), and Grömping (2007) successively proposed the Pratt measure, dominance analysis, relative weight analysis, and R^2 -based relative importance decomposition methods. Meanwhile, meta-analysis research further explored how to transform regression coefficients from different studies into comparable standardized effect sizes (Peterson & Brown, 2005; Aloe & Becker, 2012).

However, existing research requires further refinement and deepening. First, current methods primarily focus on relative importance ranking among indicators within the same sample, lacking a unified mechanism for stably transferring weights estimated from benchmark samples to external evaluation scenarios. Second, while panel data regression has developed into a mature econometric methodology system serving

parameter estimation, causal identification, and prediction analysis, it has not yet addressed how to construct unified weights suitable for evaluation using panel regression coefficients.

This paper's marginal contributions are threefold. First, it methodologically delineates the fundamental logical defects of the indicator-intrinsic-driven weighting paradigm, demonstrating that such methods' flaws stem from paradigmatic misspecification rather than technical details, and cannot be remedied through technical patches. Second, it constructs the Target-Oriented Weighting (TOW) method, integrating target orientation, external benchmark pooled standardization, panel differencing, and estimation precision adjustment (confidence interval lower bound shrinkage) into a cross-scenario weighting framework (weight transferability). Third, it extends the DID philosophy of "first differencing, then comparing" to the comprehensive evaluation weighting domain: temporal differencing strips away time-invariant individual fixed effects, while cross-sectional comparison neutralizes common time fixed effects, constructing a weight generation pathway suited for performance evaluation.

The remainder of this paper proceeds as follows: Section 2 dissects the fundamental logical defects of indicator-intrinsic-driven weighting paradigms, using the entropy weight and CRITIC methods as representatives to reveal their substitution of statistical characteristics for indicator importance. Section 3 constructs the TOW method, elucidating the fundamental paradigm shift, applicability conditions, benchmark samples and pooled standardization, regression models, weight determination, and comprehensive evaluation procedures. Section 4 demonstrates the weight calculation process using disruptive innovation financial support performance as a case study. Section 5 summarizes research conclusions.

2. Fundamental Logical Defects of Indicator-Intrinsic-Driven Weighting Paradigms

2.1 Underlying Defects of Typical Methods

2.1.1 Entropy Weight Method: The Flaw of Substituting Dispersion for Importance

(1) Calculation Principle of the Entropy Weight Method

Suppose a comprehensive evaluation system contains n evaluation objects and m evaluation indicators, with the original indicator matrix $X = (x_{ij})_{n \times m}$, where x_{ij} represents the original value of the i -th evaluation object on the j -th indicator. The standard calculation procedure of the entropy weight method consists of indicator standardization, information entropy calculation, and weight normalization steps.

First, min-max standardization is applied to original indicators, distinguishing positive and negative indicators to eliminate dimensional and scale differences, yielding the

standardized matrix $(x'_{ij})_{n \times m}$. Second, calculate the proportion of each evaluation object on that indicator:

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^n x'_{ij}}$$

Based on information entropy theory (Shannon, 1948), calculate the information entropy of the j -th indicator:

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij}$$

The information entropy ranges from $[0,1]$, with its statistical connotation being the dispersion degree of the indicator's sample share distribution: the greater the difference in proportions across samples (more dispersed values), the smaller the information entropy and the larger the corresponding variation coefficient; conversely, the more uniform the proportions (more concentrated values), the larger the information entropy and the smaller the variation coefficient.

It warrants special clarification that the "entropy" in the entropy weight method differs fundamentally from classical Shannon information entropy in terms of calculation objects. Classical Shannon information entropy measures the uncertainty of a random variable's values, calculated using the frequency of each value category as probability; whereas the entropy weight method calculates the uniformity degree of samples' share distribution within an indicator's total. Specifically, the entropy weight method first standardizes each sample's value on an indicator as its proportion of that indicator's total, $p_{ij} = x'_{ij} / \sum_{i=1}^n x'_{ij}$, then computes the entropy value for this share distribution as shown in Equation (2).

Consider an extreme case: if all samples have identical values on an indicator, by classical Shannon entropy definition, since only one value exists with probability 1, entropy equals $-1 \cdot \ln 1 = 0$; whereas in the entropy weight method, since each sample's proportion is $1/n$ (perfectly uniform distribution), the calculated entropy value is 1. Furthermore, the entropy weight method does not directly use entropy values as weights, but rather converts entropy values into indicator discrimination through the variation coefficient $g_j = 1 - e_j$, then obtains final weights through normalization:

$$w_j = \frac{1 - e_j}{\sum_{k=1}^m (1 - e_k)}$$

(2) Underlying Defects of the Entropy Weight Method

From the above calculation procedure, one can extract the core implicit assumption underlying the entropy weight method: the higher an indicator's dispersion degree, the smaller its entropy value, the larger its variation coefficient, and the greater its weight; conversely, the lower the dispersion degree, the larger the entropy value, the smaller the variation coefficient, and the smaller the weight. This assumption constitutes the logical cornerstone of the entire entropy weight method system but

lacks rigorous theoretical and mathematical justification, representing a default a priori judgment by researchers and the root source of the method's defects.

The entropy weight method essentially determines indicator weights based on distribution dispersion degree: higher dispersion yields greater weight. However, high dispersion does not necessarily imply greater importance to evaluation objectives; low dispersion may reflect stable and critical explanatory power for evaluation objectives. Directly equating dispersion with importance conflates statistical characteristics with target relevance, causing weights to disconnect from evaluation objectives. Imagine incorporating into evaluation indicators a variable completely unrelated to the evaluation objective but with far higher dispersion than other indicators—following the entropy weight method's standard procedure, its calculated weight would inevitably be inflated. The method's practical manifestations of strong sample sensitivity, insufficient inter-temporal comparability, and frequent underestimation of core indicators while overestimating peripheral indicators all originate from this fundamental flaw.

These defects have been corroborated and discussed across multiple dimensions in existing literature. Zhu et al. (2020) empirically found the entropy weight method's rationality questionable, with weights failing to correctly reflect indicator importance. Chen (2020) discovered that in TOPSIS, entropy weights excessively amplify the weight of the highest-dispersion indicator while weakening low-dispersion indicators' roles. Yan et al. (2019) noted that the entropy weight method considers only indicators' statistical significance without accounting for their actual significance to evaluation objectives, potentially causing important indicators to receive excessively small weights. Wu et al. (2015) pointed out that entropy weight values are attached to sample statistical characteristics, exhibiting insufficient weight stability that varies with sample composition and statistical fluctuations. Yang and Dong (2022) indicated that the entropy weight method over-relies on data objectivity and cannot reflect indicators' actual decision-making importance.

2.1.2 CRITIC Method: The Flaw of Substituting “Dispersion × Conflict” for Importance

(1) Calculation Principle of the CRITIC Method

The CRITIC (CRiteria Importance Through Intercriteria Correlation) method, proposed by Diakoulaki et al. (1995), integrates indicators' contrast intensity (i.e., standard deviation) and inter-indicator “conflict” (calculated from inter-indicator correlation coefficients) into a composite measure termed “amount of information” to determine objective weights. The specific calculation procedure follows:

Let the standardized indicator matrix be $(x_{ij}^*)_{n \times m}$, where n denotes the number of evaluation objects and m the number of indicators.

First, calculate contrast intensity (standard deviation):

$$\sigma_j = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_{ij}^* - \bar{x}_{ij}^*)^2}$$

Second, compute inter-indicator correlation coefficient r_{jk} and conflict degree. The conflict degree of the j -th indicator is defined as:

$$R_j = \sum_{k=1}^m (1 - r_{jk})$$

Third, calculate the amount of information:

$$C_j = \sigma_j \cdot R_j = \sigma_j \sum_{k=1}^m (1 - r_{jk})$$

Finally, calculate objective weights:

$$w_j = \frac{C_j}{\sum_{k=1}^m C_k}, \quad \sum_{j=1}^m w_j = 1$$

(2) Underlying Defects of the CRITIC Method

Superficially, the CRITIC method appears to advance beyond standard deviation, coefficient of variation, and entropy weight methods by capturing not only indicators' intrinsic dispersion characteristics but also inter-indicator correlation structure information. However, upon scrutinizing its underlying logic, the CRITIC method remains trapped within the “indicator-intrinsic-driven” weighting paradigm; its defects, though more concealed, are equally fundamental.

The CRITIC method interprets C_j as information “conflict degree,” asserting that indicators with lower correlation to other indicators contain more independent information and thus merit higher weights. This interpretation contains an obvious logical leap: low inter-indicator correlation merely indicates they describe different dimensional phenomena; it cannot establish that these dimensions are more important to evaluation objectives. For instance, when evaluating enterprise innovation potential, R&D investment intensity and patent counts are often highly correlated, whereas firm age typically exhibits low correlation with both. According to CRITIC logic, when indicators have similar standard deviations, firm age would receive greater weight due to higher conflict degree—clearly contradicting innovation potential evaluation objectives.

The CRITIC method's conflict degree metric essentially equates statistical “independence” with decision-making “importance,” conflating information discrimination with target-oriented contribution. Moreover, when important indicators exhibit strong internal correlation (extremely common in comprehensive evaluation), the CRITIC method's conflict degree term systematically penalizes highly correlated indicator groups, causing core dimensional indicators to be downweighted. For example, if per capita income and per capita GDP are both included in economic development evaluation, their high correlation causes both weights to be compressed.

This anti-redundancy mechanism in CRITIC can paradoxically lead to systematic underestimation of important indicators in information aggregation scenarios.

The CRITIC method shares the same underlying logical defect with the entropy weight method: both derive weighting bases from indicators' intrinsic statistical characteristics (dispersion, correlation structure) rather than indicator-objective associations. Their distinction lies only in which statistical features are extracted from indicators—entropy weights extract dispersion, CRITIC extracts “dispersion × conflict.” This distinction pertains to the technical level, not the paradigmatic level. As long as weighting logic does not originate from evaluation objective-indicator associations, it can never truly answer the core question: “which indicator matters more to the evaluation objective?”

2.2 Theoretical Clarification of Underlying Defects

2.2.1 Conceptual Conflation of Statistical Characteristics and Indicator Importance

From a theoretical essence perspective, indicators' intrinsic statistical characteristics such as dispersion and correlation constitute descriptive attributes, merely depicting data distribution patterns in specific samples—they are objective factual judgments about existing data states. Indicator weights, however, reflect indicators' importance degrees to evaluation objectives—these are value judgments. No natural equivalence exists between the two. The core assumption of indicator-intrinsic-driven weighting methods is that statistical characteristics (e.g., dispersion, independence) can substitute for indicator importance. However, this assumption lacks theoretical support. High dispersion merely indicates large inter-sample differences in indicator values; strong independence merely indicates an indicator describes dimensions different from other indicators. These statistical properties cannot answer the fundamental question: “is this indicator important to the evaluation objective?”

2.2.2 The Essence of Indicator Importance: Association Strength with Evaluation Objectives

The essence of indicator importance lies in the association strength between indicators and evaluation objectives—i.e., indicators' explanatory power, predictive power, or causal contribution to evaluation objectives. In comprehensive evaluation problems with clear objectives, weights should reflect evaluation indicator-objective associations, not indicators' sample statistical characteristics. This definition implies that indicator weights possess inherent objective dependence: the same indicator may have vastly different importance under different evaluation objectives. Judging whether an indicator is important and its importance degree requires situating it within specific evaluation objectives to examine its association strength with those objectives, rather than examining its data distribution divorced from objectives. Indicator-intrinsic-driven weighting methods assign weights based solely on indicators' empirical data characteristics—they can only answer which indicator

exhibits more prominent statistical features in certain dimensions, but cannot address the core evaluation question of which indicator matters more to evaluation objectives. This constitutes the root source of their underlying logical defect.

2.3 Derivative Consequences of Underlying Defects

2.3.1 Disconnection Between Evaluation Indicators and Objectives

Since indicator-intrinsic-driven weighting methods exclude evaluation objective information during weighting, their output weights bind solely to indicators’ intrinsic statistical characteristics rather than genuinely serving evaluation objective orientation. This causes systematic bias in core evaluation scenarios oriented toward objectives such as performance evaluation and policy optimization: indicators with stable explanatory power for evaluation objectives but low dispersion receive small weights due to unremarkable dispersion; indicators weakly associated with evaluation objectives but exhibiting high dispersion or strong independence receive large weights due to prominent statistical features; weight allocation inconsistent with evaluation objectives prevents comprehensive scores from authentically reflecting evaluation objects’ performance on objective dimensions. This disconnection not only undermines evaluation result validity but may also mislead policymakers’ decision directions, producing resource allocations and governance orientations inconsistent with evaluation purposes.

The indicator-objective disconnection prevents weights from adjusting as evaluation objectives change. Consider two indicators in higher education evaluation: “student-faculty ratio” and “proportion of doctoral degree holders among faculty”—both are core measures of university faculty structure, commonly incorporated in university comprehensive strength evaluation and discipline assessment systems. When both are included in an evaluation system, their weights should exhibit fundamental differences as evaluation objectives change. When evaluating “university talent cultivation quality,” student-faculty ratio’s importance far exceeds doctoral degree proportion (directly determining teaching resource abundance available to students); when evaluating “university research innovation capacity,” doctoral degree proportion’s importance far exceeds student-faculty ratio (doctoral faculty constitute crucial human capital foundation for research output). However, under the indicator-intrinsic-driven weighting framework, weights are determined solely by data’s intrinsic statistical characteristics—once indicator sample data are fixed, regardless of how evaluation objectives shift, both indicators’ weights remain fixed values, never adjusting as evaluation objectives switch.

Table 1 presents the defect of indicator-objective disconnection.

Table 1 Defect of Indicator-Objective Disconnection

Evaluation Objective	Evaluation Indicators	Theoretical Indicator	Weight Performance	Core Defect
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		Importance Relationship		
Talent Cultivation Quality	Student-faculty ratio; Doctoral degree proportion	Student-faculty ratio importance > Doctoral degree proportion	Both indicators have fixed weight values	Weights decouple from objectives, fail to reflect evaluation emphasis
Research Innovation Capacity	Student-faculty ratio; Doctoral degree proportion	Doctoral degree proportion importance > Student-faculty ratio	Both indicators maintain identical previous weights	Weights do not dynamically adjust with objective switching, lacking adaptability

2.3.2 Sample Dependence of Indicator Weights

Mathematically, indicator-intrinsic-driven weighting methods' weight values are entirely endogenously determined by indicator distributions in given samples—they are essentially functions of specific sample distributions rather than parameters characterizing indicator-objective associations. This mathematical property ensures indicator-intrinsic-driven weighting methods possess complete sample dependence, lacking cross-sample, cross-scenario, and cross-period stability and transferability. Related defects are inherent to the methodological framework and cannot be fundamentally eliminated through standardization approaches, outlier treatment, or parameter optimization.

Sample dependence manifests first in how sample scope changes directly reconstruct statistical characteristics, triggering systematic weight fluctuations. When evaluation sample regional scope, industry coverage, hierarchical dimensions, or temporal range adjust, weights derived from different sample sets exhibit deviations due to divergent indicator distributions, even experiencing reversals where core indicators become peripheral and vice versa. This directly prevents unified evaluation standards across different sample scopes, rendering evaluation results horizontally incomparable and hindering formation of stable, generalizable evaluation benchmarks.

Second, indicator composition changes exert distortive effects on weight allocation. For example, adding indicators with prominent statistical features but unrelated to evaluation objectives may alter overall weight structure, even creating room for artificial manipulation of evaluation results. Theoretically, merely incorporating such indicators (even random numbers) can artificially compress other indicators' weights,

potentially overturning overall evaluation rankings.

3. Construction of the Target-Oriented Weighting Method

3.1 Construction Logic

3.1.1 Reconstructing Weighting Logic with Evaluation Objectives as the Anchor

The indicator-intrinsic-driven weighting paradigm generates weights entirely enclosed within the indicator set, essentially constituting an “inward-looking” weighting logic—weights are determined by indicators themselves, with evaluation objectives excluded from the weight generation process. The **Target-Oriented Weighting (TOW)** method positions evaluation objectives at the core of weight generation, constructing an “outward-looking” weighting logic: taking evaluation objectives or their observable proxy variables as dependent variables and evaluation indicators as independent variables, it identifies indicator variation-objective variation associations through econometric models. Under this framework, weight meaning becomes clear and explicit: higher weights indicate that unit changes in an indicator contribute greater marginal effects to objective changes, thus warranting greater decision weight in comprehensive evaluation.

3.1.2 Shifting to Incremental Evaluation Perspective Through Panel Structure

Leveraging panel data’s temporal dimension advantages and drawing on the Difference-in-Differences (DID) philosophy of “first differencing, then comparing,” first-order differencing of level models eliminates time-invariant individual fixed effects, redirecting evaluation focus from absolute levels to incremental changes. Building on this foundation, cross-individual comparisons of contemporaneous increments strip away common time fixed effects such as macroeconomic fluctuations, rendering different entities’ indicator increments horizontally comparable. Evaluation results focus on evaluation objects’ improvement magnitudes within specific periods, aligning with performance evaluation’s practical requirements.

3.1.3 Establishing Unified Measurement Benchmarks Through Common-Scale Standardization

Different indicators often possess divergent dimensions and value scales. Directly using raw data to estimate regression coefficients subjects them to interference from both measurement units and data dispersion degrees, failing to authentically reflect indicators’ relative importance to evaluation objectives. The TOW method employs pooled sample z-score standardization of evaluation indicators and objectives based on benchmark samples, preserving inter-sample relative level information. Evaluation

samples similarly adopt benchmark samples' means and standard deviations for standardization transformation rather than independently calculating their own statistics. This design anchors evaluation samples' indicator values to benchmark samples, ensuring the statistical relationships underlying weights can transfer from benchmark samples to evaluation scenarios, rendering final comprehensive evaluation results interpretable and horizontally comparable under unified benchmarks.

3.1.4 Determining Weights by Combining Association Strength and Estimation Precision

The TOW method determines final weights from two dimensions: first, association strength, measured by regression coefficients' absolute values quantifying statistical dependence between indicators and evaluation objectives—larger coefficient absolute values yield higher indicator weights; second, estimation precision, introducing confidence interval lower bound shrinkage mechanisms that compress or even zero out coefficients with large standard errors and insufficient statistical evidence, reducing estimation noise interference on weight systems. Association strength ensures weights reflect indicator importance, while estimation precision ensures weight allocation's statistical robustness. Combining both through normalization yields the indicator weight system.

3.2 Applicability Conditions

The TOW method selects panel data homogeneous to evaluation samples with sufficient sample size as benchmark samples to identify associations between evaluation indicators and objectives, thereby calculating indicator weights. To ensure rationality of weight estimation and transfer application, the TOW method relies on the following basic prerequisites:

1. Objective Observability

Evaluation objectives should possess clear connotations and be measurable through appropriate outcome variables or proxy variables. Proxy variables need not perfectly equate to evaluation objectives but should reasonably reflect objective achievement degrees¹.

2. Association Stability

Within reasonable value ranges covered by samples, evaluation indicators and

¹ When the evaluation objective can be measured by an outcome variable or a proxy variable, the outcome variable or proxy variable itself can be used as the evaluation basis. The necessity of introducing multi-indicator evaluation mainly comes from the time lag, acquisition cost, noise level, non-immediate observability of the outcome variable or proxy variable, as well as the demand for process diagnosis. For example, the outcome variable of enterprise credit risk evaluation can be whether to default in the future, but whether an enterprise defaults can only be observed in the future. Current evaluation needs to find homogeneous benchmark samples and use current indicators such as asset-liability ratio and profitability to evaluate based on historical data and empirical experience.

objectives should exhibit relatively stable associations. The associations referred to here are statistical associations after controlling for other factors, not causal relationships. The TOW method aims to capture indicator-objective co-variation information; weights reflect their statistical dependence strength.

3. Endogeneity Controllability

In model estimation, no severe systematic correlation should exist between disturbance terms and evaluation indicators—i.e., model specifications should mitigate endogeneity interference from omitted variables and reverse causality to some extent. This requires reasonable model specification and appropriate variable selection, with instrumental variable methods adoptable when necessary to address endogeneity issues.

4. Weight Transferability

Evaluation samples should maintain consistency with benchmark samples in evaluation objects' basic attributes, indicator definitions, statistical calibers, and mechanisms/association structures between indicators and evaluation objective proxies, or exhibit no substantial differences.

3.3 Benchmark Samples, Variable Systems, and Pooled Standardization

3.3.1 Benchmark Samples and Variable Specification

Benchmark samples constitute the “weight calibration template” for TOW—their core function is not direct evaluation use but rather extracting stable indicator-objective association structures as weight calculation foundations. Benchmark samples should comprise panel data with sufficient sample size and homogeneity to evaluation samples. Weight transfer essentially constitutes extrapolation based on existing empirical relationships; thus benchmark samples should cover evaluation samples' primary application domains. On this basis, observable outcome variables or proxies of evaluation objectives serve as dependent variables, evaluation indicators as independent variables, constructing an “indicator-objective” variable system. Evaluation objective proxies should effectively reflect objective achievement degrees; evaluation indicators should possess clear theoretical connotations and objective association foundations.

3.3.2 Pooled Sample Standardization

To eliminate different variables' dimensional and scale differences while providing unified benchmarks for indicator weight transfer across application scenarios, the TOW method implements pooled sample z-score standardization of all continuous evaluation indicators and objectives based on benchmark samples:

$$y_{it}^* = \frac{y_{it} - \mu_y^B}{\sigma_y^B}, x_{ijt}^* = \frac{x_{ijt} - \mu_j^B}{\sigma_j^B}$$

where y_{it}^* denotes the standardized evaluation objective variable using benchmark sample statistics; μ_y^B and σ_y^B represent the evaluation objective's mean and standard deviation in the benchmark sample; x_{ijt}^* denotes the j -th standardized evaluation indicator; μ_j^B and σ_j^B represent the j -th indicator's mean and standard deviation across all entities and periods in the benchmark sample.

Pooled standardization means applying the same mean and standard deviation to transform the same indicator across all entities and periods, rather than using each entity's own mean and standard deviation separately. Within-entity standardization, though capturing entities' deviations from their historical means, causes different entities' one standard deviation to correspond to different raw variation magnitudes, lacking unified scale references. In contrast, pooled standardization preserves inter-sample relative level information, enabling different entities and periods' values to share common references, laying foundations for coefficient comparison, weight transfer, and comprehensive score horizontal comparison.

3.4 Regression Models

3.4.1 Level-Value Panel Models and Limitations of Cross-Individual Comparison

After completing pooled standardization, an intuitive approach is constructing a two-way fixed effects panel model with standardized evaluation objective levels (undifferenced values) as the dependent variable and standardized indicator levels as independent variables:

$$y_{it}^* = \sum_{j=1}^m \beta_j^L x_{ijt}^* + \mu_i + \lambda_t + \varepsilon_{it}$$

where β_j^L denotes regression coefficients; μ_i represents individual fixed effects capturing time-invariant entity-specific characteristics (e.g., firms' initial innovation endowments, foundational qualifications); λ_t represents time fixed effects capturing common macroeconomic shocks (e.g., industry policies, cyclical fluctuations); ε_{it} denotes random disturbances.

In panel data models, individual fixed effects μ_i can be controlled through within-group estimation, obtaining within-group coefficients $\hat{\beta}_j^L$. However, these coefficients only reflect associations between indicator and objective variations within the same entity. If directly applied to cross-individual absolute level comparisons, two insurmountable limitations arise:

First, within-group coefficients lack rationality for cross-group level comparisons. In enterprise innovation capacity evaluation, for instance, if R&D investment intensity explains innovation output, within-group coefficients reflect marginal effects when each firm varies around its own mean. If inter-firm individual effect disparities are sufficiently large, even when one firm has higher R&D investment levels, its absolute innovation output may still be lower than another firm (e.g., even if Firm B has higher

R&D investment, if $\mu_A - \mu_B$ is sufficiently large, Firm B's actual innovation output may still be lower than Firm A's). Thus, directly using within-group coefficients to rank firm innovation levels—equivalent to ignoring starting point differences and determining rankings solely from marginal variations—inevitably distorts firm rankings.

Second, between-group estimation's exogeneity assumption is difficult to satisfy in reality. Attempting to estimate between-group coefficients for cross-sectional level comparisons requires the random effects model's key assumption $E(\mu_i | x_{ijt}^*) = 0$ —i.e., individual fixed effects are uncorrelated with evaluation indicators². In most scenarios, however, entities' initial endowments are highly correlated with indicator levels—firms with better foundations typically have higher R&D investments. This causes between-group coefficient estimation bias, limiting their cross-sectional explanatory power.

3.4.2 First-Order Differencing Model for Incremental Evaluation

When evaluation shifts from “absolute level ranking” to “improvement magnitude assessment,” the above dilemmas can be effectively resolved through model transformation. First-order differencing of level models redirects evaluation measurement from absolute levels to incremental changes, eliminating individual fixed effects μ_i . The transformed time-differencing model becomes:

$$\Delta y_{it}^* = \sum_{j=1}^m \beta_j \Delta x_{ijt}^* + \delta_t + v_{it}, t = 2, \dots, T$$

where $\Delta y_{it}^* = y_{it}^* - y_{i,t-1}^*$ denotes the standardized increment of the evaluation objective (i.e., difference between two periods' level values); $\Delta x_{ijt}^* = x_{ijt}^* - x_{ij,t-1}^*$ denotes the j -th indicator's standardized increment; $\delta_t = \lambda_t - \lambda_{t-1}$ represents differenced time effects; $v_{it} = \Delta \varepsilon_{it}$ denotes differenced disturbances; β_j represents differenced model coefficients serving as core weight calculation inputs. When $T > 2$, differenced disturbances typically exhibit serial correlation, requiring cluster-robust standard errors at the entity level. If $T = 2$, the model degenerates into single-period differenced cross-sectional regression, no longer requiring time effect controls.

This differencing transformation aligns with incremental evaluation orientation: through differencing, evaluation measurement shifts from evaluation objectives' absolute levels to improvement magnitudes, focusing on effort achievements within specific periods rather than level disparities from initial endowments³.

² If the Mundlak specification is adopted to introduce individual means to relax this assumption, it needs to satisfy the parameterization condition that the correlation between individual effects and explanatory variables is fully realized through the channel of individual means.

³ When the strict linear model + strict exogeneity holds, “level coefficient + incremental evaluation” is algebraically equivalent to the difference model. However, in practice, when the above conditions are difficult to be strictly established, the coefficients obtained from the level value panel model are biased. The level model coefficient identifies the “correlation between indicator level and target level”, which is mixed with between-group variation driven by initial endowment; even if individual effects offset each other in

Temporal differencing eliminates time-invariant individual fixed effects; model estimation retains only time effects δ_t without controlling individual effects (Wooldridge, 2010). For cross-individual contemporaneous increment comparison between any two entities i and k :

$$\Delta y_{it}^* - \Delta y_{kt}^* = \left(\sum_{j=1}^m \beta_j \Delta x_{ijt}^* - \sum_{j=1}^m \beta_j \Delta x_{ikt}^* \right) + (v_{it} - v_{kt})$$

Time effects δ_t cancel out, neutralizing common factors like macroeconomic cycles and industry-wide shocks from inter-entity performance comparisons.

This paper focuses on incremental evaluation, examining evaluation objects' improvement magnitudes within specific periods. The time-differencing model aligns with this evaluation orientation. After eliminating individual fixed effects through differencing, the model identifies associations between indicator changes and objective changes, redirecting evaluation focus toward controllable period-specific variations rather than absolute levels influenced by initial endowments. Cross-individual increment comparison can eliminate time fixed effect interference, transforming increment comparison into measurement methods combining regression coefficients and indicator increments.

3.4.3 Extension of DID Philosophy to New Application Domains

The core logic of the above differencing transformation inherits the Difference-in-Differences (DID) philosophy. Both avoid centering evaluation on entities' absolute levels, instead stripping time-invariant individual characteristics through temporal differencing and neutralizing common time shocks through cross-sectional comparison.

Classical DID serves causal inference, relying on exogenous policy shocks and treatment/control group quasi-experimental designs to identify policies' net causal effects. This paper's differencing model serves comprehensive evaluation weighting without requiring exogenous shocks or group designs, conducting performance comparison and ranking across all sample entities—extending the differencing philosophy from causal inference to comprehensive evaluation domains.

It should be noted that the time-differencing structure constitutes this method's baseline specification, but TOW is not limited to this baseline model. In actual evaluation, appropriate specifications should be selected based on data structures and theoretical mechanisms, such as dynamic panel models or instrumental variable methods.

increments, the contaminated coefficient itself will still bring endowment effects into the increment score. Only when the level equation is correctly specified will the coefficient of the differenced equation be equal to the level coefficient. Therefore, incremental evaluation must be based on difference model estimation.

3.5 Indicator Weight Determination

3.5.1 Association Strength Measurement

In time-differencing models, since evaluation objectives and indicators are pooled-standardized using the same benchmark sample, regression coefficients $\hat{\beta}_j$ possess unified interpretation: for the same evaluation entity, when the j -th indicator's increment increases by 1 benchmark sample standard deviation, the evaluation objective's increment changes on average by $\hat{\beta}_j$ benchmark sample standard deviations. Thus, different indicators' regression coefficients are comparable on a unified scale.

TOW focuses on the degree of association between indicator changes and objective changes, without directly distinguishing the positive/negative direction of this association. Therefore, the absolute value of regression coefficients serves as the j -th indicator's initial association strength:

$$SA_j = \left| \hat{\beta}_j \right|$$

where larger SA_j indicates stronger statistical association between indicator and objective increments, thus higher potential evaluation contribution. Taking absolute values merely identifies indicators' importance degrees without ignoring indicators' economic meanings. Positive or negative relationships between indicators and evaluation objectives undergo directional adjustment at the comprehensive score calculation stage based on theoretical expectations and coefficient signs.

3.5.2 Estimation Precision Adjustment Mechanism

Determining weights solely based on association strength may overlook different coefficients' estimation precision differences. To reduce statistically under-evidenced indicators' influence on weight systems, continuous shrinkage functions using confidence interval lower bounds as adjusted association strength can be introduced, achieving smooth estimation precision corrections to weights:

$$\tilde{SA}_j = \max \left(\left| \hat{\beta}_j \right| - z_{1-\alpha/2} SE_j, 0 \right)$$

where $\tilde{SA}_j$ denotes association strength after confidence interval lower bound shrinkage adjustment; SE_j represents the j -th coefficient's cluster-robust standard error; $z_{1-\alpha/2}$ denotes the normal distribution critical value at given significance level α .

The confidence interval lower bound shrinkage mechanism essentially subtracts estimation uncertainty from coefficient absolute values: higher estimation precision yields smaller shrinkage; lower precision yields larger shrinkage. When the confidence interval lower bound is ≤ 0 , adjusted association strength directly becomes zero—equivalent to filtering out indicators lacking statistically significant support from the weight system. Compared to binary “significant/non-significant”

classification, continuous shrinkage filters pure statistical noise while preserving significant indicators' information, enabling weights to simultaneously carry association strength and statistical evidence attributes.

3.5.3 Normalization to Calculate Weights

Normalizing adjusted association strengths yields the j -th evaluation indicator's final weight:

$$w_j = \frac{\tilde{SA}_j}{\sum_{k=1}^m \tilde{SA}_k}$$

satisfying⁴:

$$w_j \geq 0, \sum_{j=1}^m w_j = 1$$

3.6 Comprehensive Evaluation of Evaluation Samples

After calculating indicator weights from benchmark samples, the weight system must be transferred to evaluation samples following common-scale and common-caliber principles, generating performance comprehensive scores suitable for horizontal ranking and longitudinal comparison through evaluation sample common-scale standardization and indicator directional adjustment steps.

3.6.1 Evaluation Sample Common-Scale Standardization Transformation

After obtaining benchmark sample weights, evaluation sample indicators are still standardized using benchmark sample means and standard deviations. For entity i in evaluation sample S at period t on the j -th indicator:

$$x_{ijt}^{S*} = \frac{x_{ijt}^S - \mu_j^B}{\sigma_j^B}$$

where x_{ijt}^{S*} denotes the standardized evaluation sample indicator value; x_{ijt}^S denotes the evaluation sample's raw indicator value; μ_j^B and σ_j^B , as previously defined, represent the j -th indicator's mean and standard deviation in the benchmark sample.

After common-scale standardization, evaluation sample indicator values consistently reference the benchmark sample. For example, $x_{ijt}^{S*} = 1$ indicates that entity's indicator value exceeds the benchmark sample mean by 1 standard deviation. Thus,

⁴ In extreme cases, if the estimation precision of all indicators fails to meet the requirements, the sum of weights is not equal to 1. This indicates that under the current sample and model setting, there is not enough evidence to support the construction of a target-oriented weight system based on this set of indicators. At this time, the applicability of the evaluation objective, indicator system, model setting or benchmark samples should be re-examined.

standardized indicator values enable both horizontal comparison among evaluation objects and reflection of their deviations from benchmark population means, providing unified references for subsequent comprehensive score interpretation.

3.6.2 Indicator Directional Adjustment

The weight calculation stage uses regression coefficients' absolute values to measure association strength, only depicting indicators' importance degrees without distinguishing their directional effects on objectives. Therefore, before calculating comprehensive scores, directional coefficients calibrate indicators' effect directions, aligning indicator contribution directions with their impact directions on evaluation objectives.

Directional coefficient d_j is determined by estimated coefficient signs: $d_j = \text{sign}(\hat{\beta}_j)$, i.e., +1 for positive signs, -1 for negative signs. If signs contradict theoretical expectations, indicator definitions, data calibers, and model specifications should be reviewed to eliminate data or specification biases before application. Through directional adjustment, each indicator's contribution direction to comprehensive scores aligns with its effect direction on evaluation objectives; higher comprehensive scores indicate better evaluation object incremental performance on objective dimensions.

3.6.3 Comprehensive Score Calculation

This paper focuses on incremental comparison, corresponding to differencing model specifications. Comprehensive scores similarly calculate based on indicator increments rather than absolute levels. First calculate evaluation sample indicator increments:

$$\Delta x_{ijt}^{S*} = x_{ijt}^{S*} - x_{ij,t-1}^{S*}$$

On this basis, calculate evaluation object i 's incremental comprehensive score at period t :

$$S_{it} = \sum_{j=1}^m w_j d_j \Delta x_{ijt}^{S*}$$

Under unified benchmark samples, indicator calibers, and weight systems, comprehensive scores possess dual comparability: horizontally, directly enabling performance ranking among different evaluation objects; longitudinally, score numerical magnitudes reflect evaluation objects' performance changes. Final evaluation results serve both performance ranking needs and provide quantitative bases for individual diagnosis and improvement directions.

4. Case Study: Weight Calculation Using the Target-Oriented Weighting Method

This case demonstrates TOW's weighting process. The evaluation project is

“enterprise disruptive innovation financial support performance,” focusing on the financial dimension’s support role for innovation activities by measuring statistical associations between financial indicator changes and disruptive innovation increments to assess enterprise financial strategy adjustment performance.

4.1 Benchmark Sample Selection and Empirical Analysis

We select panel data of A-share listed companies from 2012–2021 from Yu (2025) as benchmark samples. Financial indicators originate from Wind and CSMAR databases; disruptive innovation levels and patient capital funding ratio indicators are sourced from Yu (2025)’s measurement results. Using differencing models to identify association strengths between financial indicator changes and disruptive innovation increments determines indicator weights. In the regression model, the dependent variable is the standardized increment of disruptive innovation level; independent variables are standardized financial indicator changes, incorporating standardized patient capital funding ratio changes to examine their impact on disruptive innovation.

$$\Delta y_{it}^* = \sum_{j=1}^m \beta_j \Delta x_{ijt}^* + \delta_t + v_{it}$$

Since disruptive innovation’s input-output exhibits long lags, annual differencing is susceptible to short-term fluctuation interference and struggles to capture stable associations. This paper adopts two-year differencing specifications. Controlling time fixed effects and employing entity-level cluster-robust standard errors, regression results follow in Table 2.

Table 2 Regression Results

Dependent Variable: Disruptive Innovation Level Change	Coefficient	Cluster-Robust SE	t-value	p-value
Patient Capital Funding Ratio Change	0.0355039	0.0113956	3.12	0.002
Asset-Liability Ratio Change	−0.0514631	0.016395	−3.14	0.002
Return on Assets Change	0.001857	0.0085799	0.22	0.829

Receivables- to-Assets Ratio Change	-0.016948	0.0182178	-0.93	0.352
Tangible Assets Ratio Change	-0.0052449	0.0114253	-0.46	0.646
Shareholder Return Ratio Change	0.006734	0.007056	0.95	0.340

Both patient capital funding ratio change and asset-liability ratio change coefficients are significant at the 1% level—the former positive, the latter negative. Return on assets change, receivables ratio change, tangible assets ratio change, and shareholder return ratio change are all non-significant.

4.2 Calculating Indicator Weights

Employing continuous shrinkage functions to reduce estimation noise influence on weights, the association strength calculation formula after confidence interval lower bound shrinkage adjustment is shown in Equation (13).

Taking $\alpha = 0.05$, corresponding normal distribution critical value $z_{0.975} = 1.96$. According to the above formula, combining indicators' regression coefficients and cluster-robust standard errors, calculate indicator weights as shown in Table 3.

Table 3 TOW Weight Calculation Process

Indicator	Coefficient Absolute Value $ \hat{\beta}_j $	Cluster- Robust SE SE_j	$1.96 \times SE_j$	Adjusted Association Strength $\tilde{SA}_j$	TOW Weight
Patient Capital Funding Ratio Change	0.0355039	0.0113956	0.022335	0.013169	40.5%
Asset- Liability Ratio Change	0.0514631	0.016395	0.032134	0.019329	59.5%

Return on Assets Change	0.001857	0.0085799	0.016817	0	0%
Receivables Ratio Change	0.016948	0.0182178	0.035707	0	0%
Tangible Assets Ratio Change	0.0052449	0.0114253	0.022394	0	0%
Shareholder Return Ratio Change	0.006734	0.007056	0.001383	0	0%

Final weights: Asset-liability ratio change 59.5% (negative direction), patient capital funding ratio change 40.5% (positive direction). The former indicates that debt level declines closely associate with disruptive innovation increments—i.e., financial constraint alleviation releases funding space for long-cycle, high-risk disruptive innovation. The latter's positivity indicates patient capital continuous injection substantially supports disruptive innovation. This weight system can evaluate enterprise disruptive innovation financial support performance; higher comprehensive scores indicate more pronounced support improvements across both dimensions.

5. Conclusions

Indicator-intrinsic-driven weighting methods constitute widely applied statistical evaluation approaches—the entropy weight method alone yields over 45,000 CNKI database articles (with “entropy weight” in topics). However, such methods contain fundamental logical defects requiring theoretical-level clarification. This paper systematically deconstructs indicator-intrinsic-driven weighting methods' underlying logical defects and constructs TOW, forming two core conclusions: First, indicator-intrinsic-driven weighting methods possess irreparable systematic methodological defects—indicators' intrinsic dispersion or information independence cannot establish associations with their importance to evaluation objectives; their core assumptions lack theoretical support; technical patches cannot fundamentally remedy inherent defects, necessitating complete weighting paradigm replacement. Second, TOW anchors on evaluation objectives with association strength as its core, enabling weights to possess clear economic semantic interpretations.

The TOW method constructed in this paper retains certain application boundaries and limitations. First, the method relies on observable singular evaluation objectives, rendering it difficult to directly apply to scenarios lacking clear objectives or

dominated by subjective value judgments. Second, this paper constructs models based on linear relationship assumptions, exhibiting insufficient adaptability for complex nonlinear association scenarios. Future research can deepen and extend along two dimensions: First, extending nonlinear evaluation frameworks by introducing nonparametric estimation and machine learning methods to enhance adaptability for complex association scenarios—though nonlinear evaluation transcends linear weighted evaluation paradigms, requiring synchronized adjustment of comprehensive score calculation approaches. Second, conducting weight transfer boundary research through heterogeneity testing to further expand weighting method applications.

Data Availability

The datasets used and/or analyzed during the current study are available in the China Industrial Economics repository, <https://ciejournal.ajcass.com/Magazine/show/?id=121325>.

The data for this study are drawn from Yu Yongze (2025), using a panel dataset of Chinese A-share listed companies from 2012 to 2021 as the baseline sample. Financial indicators are sourced from the Wind and CSMAR databases. The two key variables—the level of disruptive innovation and the proportion of patient capital funding—are derived from the measurement results of Yu Yongze (2025). All data can be downloaded from the *China Industrial Economics journal* website at <https://ciejournal.ajcass.com/Magazine/show/?id=121325>.

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