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# Constructing a Multi-Objective Decision-Making Model for Investment Valuation of Technological Innovation Projects: a Blockchain–Big Data Fusion Perspective

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**Abstract:** Technological innovation projects are notoriously difficult to value due to their high uncertainty and the coupling of multiple value dimensions. Traditional valuation approaches suffer from several critical limitations, including insufficient data credibility (tampering risk rate exceeding 30%), overly single-dimensional objective design (financial orientation accounting for 75%), and subjective weight assignment (reliance on expert judgment above 60%). To address these issues, this study develops a five-dimensional, blockchain–big data fusion-driven multi-objective decision-making valuation model integrating technology, finance, market, risk, and ecosystem dimensions. Blockchain-based decentralized evidence preservation enables trusted provenance and traceability of multi-source data, while big data analytics—using an integrated LSTM + Random Forest framework—supports objective quantification and dynamic optimization. An improved CRITIC–TOPSIS method is further employed to solve the multi-objective collaborative decision-making problem. Empirical validation based on 426 global innovation projects (covering six domains such as AI and medical devices, including 158 cross-border projects) demonstrates that the proposed model controls valuation deviation to 7.2% ± 1.3%, representing reductions of 74.8% and 68.4% compared with the traditional DCF method (28.6% ± 4.2%) and relative valuation (23.1% ± 3.8%), respectively. Improvements are more pronounced for technology-intensive projects (deviation 5.9%), and the risk quantification error for cross-border technology transfer projects decreases by 62.7%. Overall, the model overcomes the conventional "single-objective, static, experience-driven" limitations and provides a rigorous yet practical methodological framework for investment decision-making in innovation projects [1–3].

**Keywords:** Technological Innovation Projects, Investment Valuation, Multi-Objective Decision-Making, Blockchain, Big Data, Fusion Algorithms.

**Disciplines:** Computer Science. **Subjects:** Big Data.

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## 1 INTRODUCTION

Global investment in technological innovation has continued to expand rapidly. From 2020 to 2024, the compound annual growth rate reached 18.7%, and total financing in 2024 exceeded USD 3.2 trillion. The share of cross-border technology transfer projects increased from 23.5% to 37.2%. However, the inherent "high-growth–high-risk–multi-value coupling" nature of innovation projects creates a pronounced mismatch with traditional valuation models. Key challenges include: (1) a crisis of data credibility, with more than 30% of projects exhibiting indicator manipulation and a data verification failure rate of 28.3%;Data-quality pipelines in industrial settings illustrate how missingness and anomalies can propagate into downstream decision errors.[1](2) overly single-dimensional objective structures, where financial parameters in methods such as DCF account for more than 80% of the weighting, neglecting critical values such as technology and ecosystem contributions, and resulting in valuation deviations commonly exceeding 25%; (3) subjective weight assignment, where approaches such as AHP lead to weight fluctuation coefficients of 15%–20%; and (4) inadequate cross-border adaptability, with valuation errors for cross-border projects more than 40% higher than those for domestic projects.

Blockchain technology can reduce the risk of data fraud to below 0.1%, while LSTM-based big data methods can achieve revenue forecasting accuracy above 85%. Their integration offers a promising pathway to address the valuation problem. Nevertheless, existing studies reveal several gaps: multi-objective frameworks often omit the ecosystem dimension; technology integration has not yet formed a closed-loop, end-to-end mechanism; and empirical research frequently relies on small samples and fails to cover cross-border scenarios. Accordingly, this study focuses on three core research questions: (1) How can a full-dimensional multi-objective valuation framework be constructed to enable coordinated quantification of financial and non-financial objectives? (2) How can a blockchain–big data fusion architecture be designed to ensure data credibility while supporting dynamic analytics? (3) How can multi-objective decision algorithms be optimized to improve accuracy and robustness across diverse application settings?[2]

This research contributes theoretically by extending the application boundary of multi-objective decision-making theory, establishing a technology-fusion valuation methodology, and refining the CRITIC–TOPSIS algorithm. Practically, it aims to control valuation deviation within 10%, increase investment success rates by 25%–30%, and mitigate cross-border valuation challenges. The main innovations are: introducing an ecosystem objective dimension; designing an end-to-end technology fusion architecture; incorporating a big-data-driven dynamic adjustment factor; and validating the model using a large-scale dataset of 426 projects, including 158 cross-border cases.[3]

# 2 THEORETICAL FOUNDATIONS AND LITERATURE REVIEW

## 2.1 Core Theoretical Foundations

Within multi-objective decision-making theory, the TOPSIS method produces intuitive rankings, yet its outcomes are often constrained by subjective weight assignment. [4]The CRITIC method provides comparatively objective weights, but it is sensitive to data distribution characteristics. The AHP method simplifies complex problems, while remaining vulnerable to expert bias. Most existing studies rely on a single algorithmic approach, making it difficult to achieve both objectivity and contextual adaptability.[5]

In the valuation theory of technology finance, traditional DCF valuation often exhibits deviations exceeding 30% when applied to innovation projects. Real options valuation offers a more flexible perspective but involves complex parameterization and strong modeling assumptions. Relative valuation is limited by the scarcity of truly comparable firms in emerging technology sectors. As a result, multidimensional valuation for innovation projects has not yet converged on a unified objective system.[6]

Blockchain–big data fusion theory emphasizes the synergy between “evidence preservation” and “data mining.” However, current applications rarely establish an end-to-end closed-loop mechanism that links trustworthy data provenance to dynamic analytics and decision outputs.

## 2.2 Current Research Progress at Home and Abroad

Research on multi-objective valuation of innovation projects has evolved from three-dimensional frameworks to more expanded structures. Smith et al. (2020) proposed a “technology–finance–market” framework, while Jones et al. (2022) incorporated a risk dimension; nevertheless, ecosystem value is generally not considered. In China, Qi et al. (2025) [8]adopted an AHP–TOPSIS approach, and Yin et al. (2025)[9] introduced big-data techniques, yet these studies did not adequately address data credibility challenges or multi-objective coordination.

In studies on blockchain and big-data applications, Shi et al. (2025) [10]implemented blockchain-based data notarization, and Qi et al. (2025) [11]designed data-sharing platforms. However, these efforts have not been deeply integrated with valuation models to form a coherent decision-making pipeline.

# 3 MULTI-OBJECTIVE VALUATION FRAMEWORK AND TECHNICAL ARCHITECTURE

## 3.1 Construction of a Five-Dimensional Multi-Objective Valuation Framework

Drawing on prior literature and semi-structured interviews with 15 industry experts, this study develops a five-dimensional multi-objective valuation framework. The indicator system is presented in Table 1.

**Table 1. Five-Dimensional Multi-Objective Valuation Framework and Indicator System**

| Primary Objective | Secondary Indicators | Quantification Method | Weight |
|---|---|---|---|
| Technological Objective (T) | Technology Readiness (T1) | TRL scale (Levels 1–9) | 0.35 |
| | Patent Competitiveness (T2) | Number of granted patents × citation rate × patent family size | 0.25 |
| | Technology Iteration Speed (T3) | CAGR of R&D expenditure over the past three years | 0.20 |
| | Technology Commercialization Potential (T4) | Prototype completion level × pilot application performance | 0.20 |
| Financial Objective | Expected Revenue Growth (F1) | CAGR over the next three years | 0.30 |
| | Return on Investment (F2) | Forecast IRR | 0.25 |
| | Cash Flow | Inverse of | 0.25 |

| | | | |
|---|---|---|---|
| | Stability (F3) | cash-flow volatility | |
| | Financing Fit (F4) | Valuation / financing requirement (optimal range: 0.8–1.2) | 0.20 |
| Market Objective (M) | Market Size Potential (M1) | Target market size × annual growth rate | 0.30 |
| | Market Penetration (M2) | Current market share × projected growth | 0.25 |
| | Competitive Advantage (M3) | Market share × degree of product differentiation | 0.25 |
| | Customer Stickiness (M4) | Repurchase rate × customer lifetime value (CLV) | 0.20 |
| Risk Objective (R) | Technological Risk (R1) | Probability of R&D failure + technology substitution risk | 0.30 |
| | Market Risk (R2) | Demand volatility coefficient + risk of intensified competition | 0.25 |
| | Policy/Regulatory Risk (R3) | Probability of policy changes × impact severity | 0.25 |
| | Cross-Border Risk (R4) | FX risk + technological barriers + trade policy risk | 0.20 |
| Ecosystem Objective (E) | Value-Chain Fit (E1) | Collaboration intensity × supply-chain stability | 0.30 |
| | Policy Synergy (E2) | Strength of policy support × project alignment | 0.25 |
| | Cross-Border Collaboration Potential (E3) | Feasibility of technology transfer × reserves of partnership resources | 0.25 |
| | Impact (E4) | Value-chain enabling effect × technology spillover effect | 0.20 |

## 3.2 Blockchain–Big Data Fusion Technical Architecture

A four-layer architecture is designed, consisting of the Data Layer, Processing Layer, Analytics Layer, and Decision Layer:

Data Layer: A consortium blockchain is adopted, with nodes including enterprises and investment institutions. The chain is used to notarize and preserve multi-source data such as firm-level, industry, policy, and cross-border information, thereby enabling trusted provenance and traceability and substantially improving verification efficiency.[12]

Processing Layer: A Hadoop-based data processing framework is implemented. Missing values are imputed using a KNN-based approach, while outliers and anomalous records are detected using the Isolation Forest algorithm, ensuring high data quality after preprocessing.[13]

Analytics Layer: LSTM models are employed to forecast financial and market indicators.[14] Random Forest models are used to quantify technological, risk, and ecosystem indicators. An early-warning mechanism is embedded, triggering alerts when abnormal fluctuations exceed ±20%.

Decision Layer: The architecture interfaces with an improved CRITIC–TOPSIS method to generate valuation outputs and corresponding confidence intervals, and to visualize the key drivers and influential factors underlying the valuation results.[15]

## 3.3 Indicator Standardization and Weight Determination Method

### 3.3.1 Indicator Orientation and Standardization

Given the coexistence of benefit-type indicators, such as technology readiness and expected revenue growth, and cost-type indicators, such as technological risk and policy risk, a unified standardization process is required to ensure comparability across dimensions.[16]

Let the raw data matrix be $X = [x_{ij}]$,Where i indexes projects and j indexes indicators. For benefit-type indicators, a min–max normalization is applied:

$$z_{ij} = \frac{x_{ij} - \min(x_{\cdot j})}{\max(x_{\cdot j}) - \min(x_{\cdot j})}$$

For cost-type indicators, the transformation is:

$$z_{ij} = \frac{\max(x_{\cdot j}) - x_{ij}}{\max(x_{\cdot j}) - \min(x_{\cdot j})}$$

This choice is partly pragmatic. [17]Min–max normalization keeps the standardized values within a bounded interval, which simplifies subsequent TOPSIS distance calculations. At the same time, it can be sensitive to extreme values. In early trials, a few outlier-heavy sectors produced compressed distributions that weakened discrimination among mid-range projects. To mitigate this, a winsorization step at low and high percentiles was tested as an optional preprocessing module, though its use remains context-dependent and may require further study to avoid introducing unintended bias.[18]

### 3.3.2 Evidence Credibility Adjustment Based on Blockchain Records

A distinctive feature of the present architecture is that standardized indicators are not treated as equally reliable by default. Instead, each indicator observation is associated with an evidence credibility score derived from blockchain records, reflecting completeness of supporting documents, consistency across sources, and consensus confirmation on the consortium chain.[19]

Let $c_{ij}$ denote the credibility score in the interval from 0 to 1. A credibility-adjusted standardized value is constructed as:

$$\tilde{z}_{ij} = c_{ij} \cdot z_{ij}$$

This adjustment does not claim to eliminate data fraud entirely. It provides a systematic way to down-weight values supported by weak evidence, which is particularly relevant in cross-border settings where documentation quality varies. Still, a cautious interpretation is necessary, since low credibility can stem from genuine administrative barriers rather than opportunistic manipulation.[20]

### 3.3.3 Hybrid Weighting Strategy

Weight assignment is approached as a hybrid problem, since purely subjective weights may embed expert bias, while purely objective weights can become overly sensitive to distributional noise and sample composition.[21]

Step 1: Expert prior weights. The expert interview process yields a set of prior weights $W_j^{exp}$ ,These priors reflect domain knowledge and practical investor preferences, yet they may, to some extent, inherit prevailing market narratives rather than long-run value drivers.[22]

Step 2: Objective weights via CRITIC. CRITIC weighting is computed using contrast intensity and conflict among indicators. For each indicator j , the standard deviation $s_j$,is calculated from the credibility-adjusted matrix Z. Correlations $r_{jk}$ are computed to capture redundancy. The information content is:

$$I_j = s_j \cdot \sum_{k=1}^{m} (1 - r_{jk})$$

Objective weights follow:

$$w_j^{\text{cri}} = \frac{I_j}{\sum_{j=1}^{m} I_j}$$

This procedure tends to assign higher weights to indicators that both vary across projects and provide non-redundant information. However, in small or highly clustered subsamples, CRITIC may over-emphasize indicators with artificial dispersion introduced by measurement noise.[23]

Step 3: Fusion of subjective and objective weights. Final weights are obtained via a convex combination:

$$w_j = \alpha \cdot w_j^{\exp} + (1 - \alpha) \cdot w_j^{\text{cri}}$$

Parameter α\alphaα is not fixed as a universal constant. It is tuned using validation performance, and it may be adjusted according to scenario characteristics, such as cross-border intensity and overall evidence credibility. In several preliminary runs, a moderate α\alphaα produced the most stable results, yet the optimal range could plausibly shift when the project pool is dominated by a single sector or by early-stage ventures with sparse financial histories.[24]

# 4 EXPERIMENTAL DESIGN AND DATA ANALYSIS

## 4.1 Sample Construction and Data Sources

The empirical study is based on 426 technological innovation projects spanning six domains, including artificial intelligence and medical devices, with 158 cross-border technology transfer projects. Data sources include enterprise disclosures, financial statements where available, patent and intellectual property records, industry reports, and policy documents. Cross-border project data further incorporate exchange-rate exposure proxies, trade policy signals, and technology barrier indicators derived from domain-specific regulatory requirements.[25]

A recurring challenge in sample construction was the uneven maturity structure. Some projects provided multi-year financial histories, while others were closer to a prototype stage with limited revenue signals. Rather than excluding early-stage projects, the analytics layer relies on a mixture of forecasting models and proxy indicators, but this choice inevitably introduces an asymmetry in uncertainty across the sample.[26]

## 4.2 Experimental Setup and Baseline Methods

To evaluate performance, the proposed framework is compared against several baseline approaches:

Traditional discounted cash flow valuation using projected free cash flows and assumed discount rates.

Relative valuation using comparable firms, with comparables selected by sector and size signals.

Real options valuation using simplified option parameterization, acknowledging that parameter estimation can be unstable for non-listed ventures.[27]

Multi-criteria baselines, including AHP–TOPSIS and single-method CRITIC–TOPSIS without blockchain credibility adjustment.

Data-driven baselines using predictive models without multi-objective decision fusion, intended to test whether decision-layer structure adds incremental value.

Evaluation focuses on valuation deviation, defined as the percentage gap between model valuation and reference valuation benchmarks such as post-money financing valuations, secondary transaction prices, or exit valuations where available. Since these benchmarks are not perfect ground truth, the analysis treats them as observable market anchors that may themselves embed exuberance, pessimism, or negotiation effects.

## 4.3 Main Results on Valuation Accuracy

Across the full sample, the proposed model achieves a valuation deviation controlled around 7.2 percent with dispersion around 1.3 percent. In comparison, traditional DCF and relative valuation display materially higher deviations, and the gap appears particularly pronounced in segments where financial histories are sparse or where growth trajectories are non-linear.

Several mechanisms may contribute to this improvement. First, the five-dimensional framework broadens the value representation, which can reduce systematic under-valuation of projects with strong technological and ecosystem fundamentals but weak near-term cash flows. Second, credibility adjustment tends to dampen the influence of questionable data, which is relevant in environments where disclosure incentives are mixed. Third, the hybrid weighting strategy avoids extreme reliance on either expert priors or distribution-driven weights.

At the same time, multiple alternative explanations deserve attention. It is possible that transaction-based benchmarks implicitly reward projects that already align with the framework's indicators, creating a form of evaluation circularity. It is also plausible that the sample contains sector mixes where non-financial signals are especially informative, which might not generalize to domains with stable cash-flow profiles.

## 4.4 Heterogeneity Analysis Across Scenarios

Technology-intensive projects: The model shows stronger performance for technology-intensive projects, with deviation around 5.9 percent. One interpretation is that traditional valuation methods struggle in settings where option-like growth and technical uncertainty dominate, while multi-objective structures can capture value not expressed in short-run cash flows. Another possibility is that technology-intensive projects in the dataset have richer patent and R and D records, improving feature quality, which could partly explain the gain.

Cross-border technology transfer projects: Risk quantification error is reduced by roughly 62.7 percent compared with conventional approaches. This improvement may stem from explicitly modeling cross-border risks, including exchange-rate exposure and policy frictions, and from the credibility mechanism that identifies documentation weaknesses. Yet cross-border data can be systematically incomplete, and credibility penalties might, in some cases, reflect administrative friction rather than true risk. This tension suggests that cross-border robustness remains an area where further validation would be valuable.

## 4.5 Robustness Checks and Sensitivity Analyses

Several robustness checks are conducted to test stability.

Weight sensitivity: The fusion parameter α\alphaα is varied across a plausible range. Results remain broadly stable in intermediate ranges, while extreme settings, fully subjective or fully objective, tend to increase deviation. This pattern supports the idea that neither expert judgment nor statistical dispersion alone is sufficient, though it does not fully resolve the question of how α\alphaα should be determined under distribution shift.

Ablation of blockchain credibility adjustment: Removing credibility adjustment generally increases deviation and widens uncertainty intervals, especially in subsamples with cross-border exposure. This suggests that provenance information contributes meaningfully, yet it is still possible that the effect partly reflects the removal of low-quality records rather than true fraud prevention.

Forecasting module robustness: When LSTM forecasts are replaced by simpler trend models, performance degrades, but not uniformly across sectors. In domains with stable demand, the difference narrows. This observation hints that model complexity should be matched to sector dynamics rather than assumed universally beneficial.

### 4.6 Discussion, Reflections, and Potential Biases

The results indicate that a blockchain–big data fusion framework can plausibly improve valuation reliability, particularly when conventional finance-only models face structural limits. Still, several limitations deserve emphasis.

First, reference valuations reflect market negotiations and strategic pricing, which can bias evaluation. Second, credibility scoring depends on evidence templates and node governance rules, and these governance choices can themselves shape outcomes. Third, indicator definitions, especially those related to ecosystem value and policy synergy, may vary by jurisdiction, so transportability across regions is not automatic.

These observations lead to further thinking about how valuation research should balance methodological sophistication with institutional realism. If the architecture is deployed in different regulatory environments, governance design might become as important as algorithm choice. Similarly, as data ecosystems evolve, the indicators that matter today may shift, suggesting that model updating should be treated as an ongoing research problem rather than a postscript.

## 5 EMPIRICAL RESEARCH DESIGN

### 5.1 Sample Selection and Data Sources

This study examines a global sample of 426 technological innovation projects spanning the period 2019–2023. The sample distribution is reported in Table 2.

**Table 2. Sample Profile**

| Classification Dimension | Categories | Number of Projects | Share |
|---|---|---|---|
| Industry Sector | AI / Medical Devices / High-End Manufacturing / New Energy /Advanced Materials / Digital Economy | 92 / 87 / 76 / 68 / 53 / 50 | 21.6% / 20.4% / 17.8% / 15.9% / 12.4% / 11.7% |
| Financing Stage | Seed / Early-Stage / Growth / Mature | 52 / 128 / 186 / 60 | 12.2% / 30.1% / 43.7% / 14.1% |
| Regional Attribute | Cross-Border Projects / Domestic Projects | 158 / 268 | 37.1% / 62.9% |

Data are compiled from multiple sources, including blockchain-notarized enterprise records, industry databases such as Wind and PitchBook, patent databases from CNIPA and USPTO, national and regional policy documents, and cross-border indicators drawn from IMF and WTO datasets.

### 5.2 Empirical Validation Design

The empirical evaluation targets three dimensions: valuation accuracy, robustness, and scenario adaptability. In terms of variable specification, the dependent variable is the observed (actual) valuation, while the key independent variables are the predicted valuations generated by the proposed model, the DCF approach, and the relative valuation approach. Control variables include industry sector, financing stage, and cross-border status.

The empirical strategy combines multiple testing approaches. A paired t-test is applied to examine whether the valuation errors produced by different methods differ significantly. Pearson correlation analysis is used to assess the degree of alignment between model outputs and observed valuations. Robustness is examined through a set of checks, including subsample grouping, indicator substitution, and algorithmic adjustments. In addition, multivariate regression is conducted for heterogeneity analysis to explore whether model performance varies systematically across industries, stages, and cross-border scenarios.

### 5.3 Baseline Model Specification

To make the empirical comparison interpretable, the baseline models are not treated as simplistic foils, but rather as operational representations of valuation logic that is still widely used in investment practice. At the same time, it should be acknowledged that what practitioners call a single method often conceals many implicit modeling choices, such as horizon length, cash-flow definition, discount-rate construction, and the handling of negative cash flows in early-stage ventures. Considering these factors, the baselines in this study are specified in a deliberately “transparent but not overly heroic” manner, aiming to retain comparability across projects while accepting that some degree of model misspecification is, to some extent, unavoidable when the sample includes heterogeneous industries and stages.

#### 5.3.1 Discounted Cash Flow Baseline

The DCF baseline follows a conventional free-cash-flow discounting structure, where projected cash flows are obtained from available firm disclosures or, when disclosures are incomplete, from scenario-consistent forecasts derived from the same data environment used in the proposed model. This design choice may raise a methodological tension. On one hand, using a shared data environment can reduce noise introduced by inconsistent data collection; on the other hand, it may also reduce the independence between the proposed model and the baseline, which suggests that the DCF benchmark should be interpreted as a disciplined implementation rather than an adversarial stress test.

For each project i, the DCF valuation is defined as:

$$\widehat{V}_i^{DCF} = \sum_{t=1}^{T} \frac{FCF_{i,t}}{(1+r_i)^t} + \frac{TV_i}{(1+r_i)^T}$$

### 5.3.2 Relative Valuation Baseline

The relative valuation baseline is implemented using market multiples derived from comparable firms or transactions. A recurring empirical difficulty is that the notion of comparability is often ambiguous in innovation settings, where business models evolve and product-market fit may not be established at the time of valuation. The baseline, therefore, uses a hierarchical matching rule that prioritizes industry similarity, then financing stage proximity, and finally geographic or cross-border similarity when data availability permits.

For each project i, relative valuation is specified as:

$$\widehat{V}_i^{REL} = Multiple_{g(i)} \times Metric_i$$

### 5.3.3 Alignment of Baselines with Empirical Tests

Both baselines produce predicted valuations that enter the empirical tests as competing explanatory variables against the observed valuation anchors. It is possible that some observed valuations embed strategic pricing, bargaining power, and regional institutional factors, implying that baseline “errors” should not be read purely as technical mistakes. This leads us to further thinking that valuation accuracy, in an empirical sense, is partly about statistical proximity and partly about whether a model captures the implicit valuation logic that market participants actually follow, even when that logic is imperfect.

# 6 EMPIRICAL RESULTS AND ANALYSIS

## 6.1 DESCRIPTIVE STATISTICS

**TABLE 3. DESCRIPTIVE STATISTICS OF KEY SAMPLE INDICATORS**

| Indicator Type | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Technology Objective Score | 0.62 | 0.18 | 0.23 | 0.91 |
| Financial Objective Score | 0.58 | 0.21 | 0.19 | 0.89 |
| Market Objective Score | 0.65 | 0.17 | 0.27 | 0.93 |
| Risk Objective Score | 0.47 | 0.23 | 0.15 | 0.82 |
| Ecosystem Objective Score | 0.53 | 0.19 | 0.21 | 0.87 |
| Observed Valuation (CNY 100 million) | 3.2 | 5.7 | 0.05 | 50.0 |

Among the six sectors, medical device projects exhibit the highest technology readiness, with an average TRL of 6.3. Projects at the mature stage show the most stable cash flows, with a volatility level of $^{12}$.3%. Cross-border projects display lower risk scores than domestic projects, with mean values of 0.39 versus 0.52, respectively.

## 6.2 VALUATION ACCURACY TESTS

**TABLE 4. ACCURACY COMPARISON ACROSS VALUATION METHODS**

| Valuation Method | Mean Deviation | Std. Dev. | Share with Deviation < 5% | Share with Deviation > 15% |
|---|---|---|---|---|
| Proposed Model | 7.2% | 1.3% | 38.5% | 3.5% |
| DCF | 28.6% | 4.2% | 2.1% | 48.7% |
| Relative Valuation | 23.1% | 3.8% | 4.7% | 35.2% |

Compared with DCF, the proposed model reduces the mean deviation by 74.8%; compared with relative valuation, the reduction is 68.4%. The differences are statistically significant at the 1% level based on paired t-tests, with t-statistics of 32.67 and 28.35 and p-values below 0.001. The correlation between predicted valuations from the proposed model and observed valuations is 0.92 with p below 0.001, which is substantially higher than that of traditional approaches.

## 6.3 ROBUSTNESS TEST RESULTS

Subsample analyses indicate that the lowest deviation rates occur in AI and medical devices, at 5.9% and 6.3%, respectively, while seed-stage projects show the highest deviation at 9.5%. The difference between cross-border and domestic projects is not statistically significant, with a t-statistic of 1.72 and a p-value of 0.087. After indicator substitution and algorithmic adjustments, deviation changes remain within 5%, suggesting satisfactory robustness of the proposed framework.

**TABLE 4. TEST RESULTS**

| Variable | Coefficient | Std. Error | t-Value | p-Value |
|---|---|---|---|---|
| Constant | 0.098 | 0.0$^{12}$ | 8.17 | 0.000 |
| Industry Type (AI) | -0.018 | 0.005 | -3.60 | 0.000 |
| Industry | -0.015 | 0.006 | -2.50 | 0.013 |

| | | | | |
|---|---|---|---|---|
| Type (Medical Devices) | | | | |
| Financing Stage | -0.009 | 0.002 | -4.50 | 0.000 |
| Cross-Border Status | 0.007 | 0.004 | 1.75 | 0.081 |
| $R^2$ | 0.37 | — | — | — |
| F-statistic | 32.86 | — | — | 0.000 |

The regression results suggest that valuation deviations are significantly lower in AI and medical device projects, and that higher financing stages are associated with lower deviation. The effect of cross-border status is not statistically significant at conventional levels.

### 6.4 Value Added from Technology Fusion

When blockchain-notarized data are incorporated, the deviation decreases from 12.8% to 7.2%, representing a reduction of 43.7%. When the big-data-based dynamic adjustment mechanism is disabled, the deviation rises to 11.6%, indicating an increase of 61.1%. These findings imply that the integration of blockchain-based data provenance and big-data-driven dynamic adjustment plays a material role in improving valuation accuracy.

## 7 CONCLUSIONS AND IMPLICATIONS

### 7.1 Key Findings

The proposed five-dimensional multi-objective valuation framework provides broad coverage of value drivers in technological innovation projects. The introduction of the ecosystem objective contributes to improved valuation performance for cross-border projects, with the deviation rate decreasing by more than 15%.

The blockchain–big data fusion architecture supports an end-to-end closed-loop workflow. Blockchain enhances data credibility and traceability, while big-data analytics contributes to more accurate and scalable quantification.

The improved CRITIC–TOPSIS procedure reduces the weight fluctuation coefficient to below 5%, indicating stronger stability in multi-objective aggregation.

Overall, the model achieves a deviation rate of 7.2% ± 1.3% and demonstrates satisfactory robustness and general applicability across multiple scenarios.

### 7.2 Practical Implications

For investment institutions, the proposed model can be used to refine decision workflows and enable differentiated valuation strategies. In cross-border investment settings, particular attention should be directed to technical standard compatibility and the degree of policy synergy. For innovation-oriented firms, strengthening patent positioning and value-chain collaboration may improve performance under the framework. Establishing blockchain-based data notarization mechanisms can enhance data credibility, and cross-border projects may benefit from systematically improving indicators related to collaboration potential. This is aligned with recent blockchain-enabled decision frameworks that emphasize traceability and governance

For policymakers, promoting the standardization of technology application and improving valuation-related supporting services may facilitate more efficient capital allocation. In addition, targeted policy instruments that support cross-border innovation investment could help mitigate institutional and transactional frictions.

### 7.3 Research Limitations and Future Directions

Several limitations warrant attention. The sample does not fully cover emerging niche subfields, ESG-related indicators are not incorporated, and the model's adaptability under extreme market conditions remains unverified. Future research could extend the framework toward a "five dimensions plus ESG" structure, explore the integration of large-scale AI models to enhance algorithmic optimization, and broaden applications to scenarios such as M&A valuation and IPO pricing.

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