Performance Evaluation Mechanisms in Digital Transformation

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***Abstract*—This study develops an integrated performance evaluation system combining financial outcomes with digital transformation. Indicator weights are determined using both Analytic Hierarchy Process (AHP) (subjective) and the entropy method (objective), reconciled through game theory and the Lagrange multiplier approach. Applied to Haier Smart Home, results show profitability indicators remain key, while digital transformation measures also carry substantial weight. The fusion coefficient (*a* = 0.25) reflects predominance of expert judgment while preserving objective data. The framework offers a robust, scientifically grounded basis for TOPSIS-based evaluation and managerial decision-making.**

***Keywords*—digital transformation, evaluation system, entropy method, Analytic Hierarchy Process (AHP)**

I. Introduction

The rapid diffusion of digital technologies has reshaped industries, challenging traditional performance evaluation approaches. Emerging technologies such as cloud computing, big data, and artificial intelligence enhance operational efficiency while redefining value propositions, customer engagement, and revenue models. Consequently, performance evaluation systems must integrate both financial and digital dimensions to provide a holistic view of enterprise competitiveness. Traditional tools like DuPont analysis and Economic Value Added (EVA) remain relevant but fail to capture value generated through digital capabilities such as IT infrastructure, data governance, and innovation-driven investment.

To address these limitations, this study develops a hybrid performance evaluation framework combining financial and digital indicators. We determine weights using both the entropy method and the Analytic Hierarchy Process (AHP), with fusion optimization via game theory and the Lagrange multiplier approach. Applied to Haier Smart Home, the methodology demonstrates how profitability and digital transformation jointly drive enterprise performance, offering insights for academic research and managerial decision-making.

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II. Literature Review

Digital transformation is widely recognized as a systemic change driven by emerging technologies such as cloud computing and big data, leading to product innovation, process automation, and the reconfiguration of business models (Schwertner, 2017; Chanias, Myers, & Hess, 2019; Armenia, Tsaples, Papathanasiou, Barnabé, & Nazir, 2022;). It is also understood as a structural transformation, characterized by flatter hierarchies, process redesign, and data-driven organizational culture (Hanelt, Bohnsack, Marz, & Antunes, 2021; Feng, 2024). From a strategic perspective, it is considered a continuous and iterative process of renewal that reshapes value propositions, customer interactions, and revenue models (Warner & Wäger, 2019; Grover & Lyytinen, 2023).

Digital capabilities generally encompass technological, organizational, and data dimensions. Technological capabilities, including IT infrastructure, cloud computing, and artificial intelligence, enhance efficiency, flexibility, and responsiveness (Westerman, Tannou, Bonnet, Ferraris, & McAfee, 2012). Organizational capabilities emphasize leadership support, collaboration across functions, and adaptability in culture (Sun, He, & Qian, 2024). Data capabilities, covering governance, quality, and analytics, have become central drivers of competitiveness (Davenport, Guha, Grewal, & Bressgott, 2018). Empirical studies confirm that big data and algorithmic capabilities directly promote innovation and enterprise performance (Zhang & Yuan, 2023).

Performance evaluation has shifted from traditional control-oriented systems to multidimensional and strategically aligned frameworks. Early approaches emphasized standardization and efficiency (Taylor, 1911; Drucker, 1954). The Balanced Scorecard introduced financial and non-financial indicators (Kaplan & Norton, 1992), but still showed rigidity. Subsequent models such as harmonious management and dual-track systems sought to balance KPI-driven control with innovation-oriented OKRs (Lau, Qian, & Roland, 2000; Cao, Zhang, & Xi, 2011). Recent developments highlight agile performance management and data-driven approaches that prioritize strategic alignment, flexibility, and real-time feedback (Darino, Sieberer, Vos, & Williams, 2019; Li, Yao, & Yan, 2021).

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Performance evaluation frameworks are increasingly incorporating digital dimensions, including data assets, algorithmic capacity, and organizational readiness (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013). Studies demonstrate industry-specific differences: in manufacturing, digitalization enhances production efficiency and supply chain intelligence (Müller, Buliga, & Voigt, 2018); in retail, it improves customer experience through analytics and e-commerce (Grewal, Roggeveen, & Nordfält, 2017); and in finance, fintech adoption supports automation and risk control (Scardovi, 2017). The effects extend to innovation and environmental performance as well (Xu, Li, & Guo, 2023). However, most research continues to focus on outcomes rather than systematically embedding digitalization within integrated evaluation models.

Traditional tools such as DuPont analysis and EVA remain in use, but objective multi-criteria methods such as entropy-weighted TOPSIS have gained prominence (Nistor & Stefanescu, 2017; Liu & Zhang, 2023; Özarı & Demirkale, 2024). These methods better address nonlinear relationships compared with factor analysis (Na-Nan, Chaiprasit, & Pukkeeree, 2018) and minimize subjectivity in weight assignment. Nevertheless, hybrid models integrating managerial judgment and objective data analysis are still necessary, particularly for sustainability-oriented performance evaluation (Abran & Buglione, 2003; Tokos, Pintarič, & Krajnc, 2012).

Current research provides valuable insights into the definition of digital transformation, the composition of digital capabilities, and their impacts on performance. Yet three limitations remain. First, most studies examine the causal effects of digital transformation without constructing integrated frameworks that combine financial and digital dimensions. Second, measurement approaches are fragmented, relying mainly on text-based indices or partial financial proxies. Third, weighting methods are often one-sided, emphasizing either subjectivity or objectivity.

III. Construction of Performance Evaluation System

A. *Objectives and Approaches*

The objective of this study is to construct a performance evaluation system that integrates financial outcomes with digital transformation achievements. The framework not only measures profitability, solvency, operational efficiency, and growth potential, but also captures the progress of digital investment and capability building. In doing so, it provides managers with reliable decision-making support and establishes a transferable benchmark for cross-industry comparisons.

The design follows a clear process of "dimension integration—indicator selection—weight optimization—comprehensive evaluation." Specifically, performance is divided into financial and digital dimensions: the former relies on traditional indicators, while the latter encompasses technology application, business models, smart manufacturing, and information systems, supplemented by digital investment measures. Indicator weights are determined through a combination of the entropy method and Analytic Hierarchy Process, further refined using the Lagrangian multiplier approach to balance objectivity and rationality. For overall assessment, the TOPSIS method is employed to measure firms' proximity to an ideal solution and thus enable ranking.

B. *Indicator Selection*

Based on literature and data availability, performance indicators are divided into two categories. Financial indicators: include profitability, solvency, operational efficiency, and growth, such as return on equity, debt-to-asset ratio, total asset turnover, and revenue growth. Digital transformation indicators: are measured using a text analysis-based annual index, covering technology adoption, organizational support, and data capabilities, including R&D intensity, IT investment ratio, digital patents, online channel share, and data governance.

Additionally, we extract digital-related investments from firms' asset structures to construct quantitative measures: software investment ratio and digital hardware investment ratio. The software investment ratio is the share of software-related intangible assets in total assets, reflecting investment in software systems, information platforms, and analytics tools. The digital hardware investment ratio is the share of digital equipment in fixed assets, reflecting investment in smart terminals, automated devices, and network infrastructure. These indicators complement the text-based index, improving multidimensionality and providing a more complete measure of firms' digital capabilities for performance evaluation. The specific indicators are shown in Table I.

TABLE I. Performance Evaluation Index

Primary Indicator	Secondary Indicator	Indicator Nature
Profitability	Economic Value Added (EVA)	Positive
	ROA	Positive
	Net Profit Margin	Positive
Solvency	Current Ratio	Moderate
	Quick Ratio	Moderate
	Debt-to-Asset Ratio	Negative
Operational Efficiency	Total Asset Turnover	Positive
	Inventory Turnover	Positive
	Accounts Receivable Turnover	Positive
Growth Capability	Total Asset Growth Rate	Positive
	Operating Profit Growth Rate	Positive
	R&D Expense to Revenue Ratio	Positive
Digital Capability	Digital Text Analysis	Positive
	Software Investment Ratio	Positive
	Digital Hardware Investment Ratio	Positive

In the process of data collection and processing, standardized financial indicators were obtained from the Wind database. For digital transformation indicators that could not be directly retrieved, we used text analysis and manually reviewed Haier Smart Home's annual reports. Based on the detailed disclosures under intangible and fixed assets, together with the company's notes on asset usage, we applied classification and estimation methods to extract the relevant data.

C. Indicator Weight Confirmation

To ensure robust weight assignment, this study integrates the entropy weight method (objective) and the Analytic Hierarchy Process (AHP, subjective). Their results are further reconciled using game theory with the Lagrange multiplier approach to balance objectivity and subjectivity.

1) Entropy weight method

The entropy weight method is an objective approach to weight determination, based on the principle that indicators with greater variability contain more information and therefore should be assigned higher weights in the evaluation system.

The procedure applied in this study involved three main steps. First, the original data were normalized to eliminate the influence of different measurement scales. Second, entropy values were calculated for each indicator, followed by the determination of divergence coefficients. Finally, the objective weights were obtained according to the degree of divergence.

Use formulas to calculate information entropy (e_j); information redundancy (d_j) and Indicator weights (ω_j). The final results of the entropy-based weights are summarized in Table II.

TABLE II. ENTROPY WEIGHTING OF PERFORMANCE EVALUATION INDEX

Indicator	e_j	d_j	ω_j
EVA	0.8748	0.12	0.0624
ROA	0.8218	0.17	0.0889
Net Profit Margin	0.8475	0.1524	0.0760
Current Ratio	0.8945	0.1054	0.0526
Quick Ratio	0.8917	0.1082	0.0540
Debt-to-Asset Ratio	0.9026	0.0973	0.0486
Total Asset Turnover	0.6918	0.3081	0.1538
Inventory Turnover	0.8643	0.1356	0.0677
Accounts Receivable Turnover	0.8706	0.1293	0.0645
Total Asset Growth Rate	0.8965	0.1034	0.0516
Operating Profit Growth Rate	0.9483	0.0516	0.0257
R&D Expense to Revenue Ratio	0.8928	0.1071	0.0534
Digital Text Analysis	0.8761	0.1238	0.0618
Software Investment Ratio	0.8438	0.1561	0.0779
Digital Hardware Investment Ratio	0.8791	0.1208	0.0603

2) Analytic hierarchy process

The performance evaluation system is structured in three levels: the goal level (enterprise performance), the criterion level (profitability, solvency, operational efficiency, growth, and digital capability), and the indicator level (15 specific indicators, including EVA, ROA, net profit margin, liquidity ratios, asset turnover, growth rates, R&D intensity, and digitalization measures).

The Analytic Hierarchy Process (AHP) was applied to allocate indicator weights. Experts conducted pairwise comparisons using a 1–9 scale, and judgment matrices were constructed to reflect relative importance. The Consistency Ratio (CR) was used to test matrix validity. A matrix is considered consistent when CR < 0.1; otherwise, expert scores are revised until the threshold is met.

To ensure robustness, sensitivity analysis was performed by adjusting the relative importance of selected indicators within a reasonable range (e.g., ±10%) and recalculating weights. Stable rankings under such perturbations indicate that the final weight distribution is reliable and well-aligned with expert consensus. The final results of the AHP are summarized in Table III.

TABLE III. AHP WEIGHT OF PERFORMANCE EVALUATION INDEX

Primary Indicator	weight	Secondary Indicator	weight
Profitability	0.2747	EVA	0.0794
		ROA	0.0888
		Net Profit Margin	0.1066
Solvency	0.1991	Current Ratio	0.0382
		Quick Ratio	0.0721
		Debt-to-Asset Ratio	0.0888
Operational Efficiency	0.1655	Total Asset Turnover	0.0335
		Inventory Turnover	0.0520
		Accounts Receivable Turnover	0.0800
Growth Capability	0.1755	Total Asset Growth Rate	0.0343
		Operating Profit Growth Rate	0.0598
		R&D Expense to Revenue Ratio	0.0815
Digital Capability	0.1851	Digital Text Analysis	0.0441
		Software Investment Ratio	0.0714
		Digital Hardware Investment Ratio	0.0697

3) Game theory and Lagrange multiplier method

Game theory is widely applied in weight integration for multi-indicator evaluation systems, aiming to balance objectivity and subjectivity through the principle of minimum deviation. The Lagrange multiplier method is employed to solve constrained optimization problems. This study adopts a combined approach: game theory is first used to derive fusion coefficients between the entropy method and AHP, producing an initial weight vector. The Lagrange multiplier method is then applied with normalization constraints to optimize the results, ensuring both consistency and robustness in the final weight distribution for performance evaluation.

Step 1: Game theory determines the fusion coefficient α There are 15 evaluation indicators, and two sets of weight vectors from different methods:

Outcome of the entropy approach (Eq. (1)):

$$W^{(1)} = w_1^{(1)}, w_2^{(1)} \cdots, w_{15}^{(1)} \tag{1}$$

Outcome of the AHP (Eq. (2)):

$$W^{(2)} = w_1^{(2)}, w_2^{(2)} \cdots, w_{15}^{(2)} \tag{2}$$

The goal is to build the final combined weight vector $W = w_1, w_2 \cdots, w_{15}$, so that it minimizes the deviation from the weights of each method. Under the two weighting methods (such as the entropy weighting method $W^{(1)}$ and the AHP method $W^{(2)}$, the objective function is constructed as (Eq. (3)):

$$\min_{\alpha} \sum_{i=1}^{n}\{[\alpha W_i^{(1)} + (1-\alpha)W_i^{(2)} - W_i^{(1)}]^2 + [\alpha W_i^{(1)} + (1-\alpha)W_i^{(2)} - W_i^{(2)}]^2\} \quad (3)$$

The solution yields an optimal $\alpha^* \in [0,1]$, indicating which source the fusion weight should lean towards.

Step 2: Introducing α into the Lagrange multiplier method to construct the objective function as (Eq. (4)):

$$\min \sum_{i=1}^{n}\{w_i - [\alpha^* w_i^{(1)} + (1-\alpha^*)w_i^{(2)}]\}^2 \quad (4)$$

By taking the α^* weighted fusion value as the 'target weight', and the Lagrange multiplier method is used to optimize so that $\sum w_i = 1$ and $w_i > 0$. The results of the weighted composite are shown in Table IV.

TABLE IV. COMPREHENSIVE WEIGHT

Primary Indicator	Comprehensive weight	Secondary Indicator	Comprehensive weight
Profitability	0.2629	EVA	0.0751
		ROA	0.0888
		Net Profit Margin	0.0989
Solvency	0.188	Current Ratio	0.0418
		Quick Ratio	0.0675
		Debt-to-Asset Ratio	0.0787
Operational Efficiency	0.1956	Total Asset Turnover	0.0635
		Inventory Turnover	0.0559
		Accounts Receivable Turnover	0.0761
Growth Capability	0.1644	Total Asset Growth Rate	0.0386
		Operating Profit Growth Rate	0.0512
		R&D Expense to Revenue Ratio	0.0744
Digital Capability	0.1889	Digital Text Analysis	0.0485
		Software Investment Ratio	0.0730
		Digital Hardware Investment Ratio	0.0673

IV. RESULT AND DISCUSSION

By integrating the entropy weight method with the AHP, the final fusion coefficient was determined to be $\alpha = 0.25$. This indicates that the results are primarily guided by expert judgment derived from AHP, while still preserving 25% of the objective information provided by the entropy-based weighting. Such a configuration not only captures the strategic insights and experiential expertise of domain specialists but also incorporates the objectivity, differentiation, and stability inherent in quantitative data.

With respect to specific indicators, profitability-related measures (e.g., ROA, net profit margin, and EVA) retained relatively high weights after the fusion process, underscoring their continued importance in comprehensive performance assessment. Simultaneously, indicators reflecting digital transformation (e.g., the proportion of software investment and R&D intensity) also received substantial weights, reflecting the increasing emphasis on digitalization alongside financial performance in the current research context.

In summary, the fused weighting scheme offers a balanced reconciliation of subjective expert judgment and objective statistical evaluation, thereby providing a scientifically sound and methodologically robust foundation for the subsequent TOPSIS-based comprehensive assessment.

V. CONCLUSION

This study develops and validates a comprehensive performance evaluation system that integrates financial outcomes with digital transformation achievements. By combining the entropy weight method with the AHP and optimizing through game theory and the Lagrange multiplier method, the framework balances subjective expertise with objective data-driven insights, ensuring robust and reliable weight assignment.

Results indicate that profitability indicators, such as ROA, net profit margin, and EVA, remain central, while digital transformation measures—including software investment ratio and R&D intensity—also carry substantial weight, reflecting the growing strategic importance of digitalization. With a fusion coefficient of α = 0.25, expert judgment predominates while preserving objective data influence. The proposed system enhances methodological rigor and offers practical guidance for enterprises balancing financial performance and digital innovation, with potential for cross-industry and longitudinal applications in future research.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

BX designed the study, conducted the research, analyzed the data, and drafted the manuscript; TJ and KZ contributed to the literature review, assisted in manuscript preparation, and provided critical revisions; all three authors collaboratively refined the final draft to ensure clarity and coherence; all authors approved the final version of the manuscript.

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