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Do AI Markets Drive Financial Performance in Chinese Banks? A Quantum-Inspired (QI) MCDM Approach

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Abstract

This paper proposes a novel quantum-inspired multi-criteria decision-making (QI-MCDM) framework to assess the structural performance of Chinese banks considering emerging AI technological contexts. By embedding classical bank performance indicators within a quantum probability space, the model captures inter-criteria entanglement, decoherence from ideal benchmarks, and robustness under noise—constructs traditionally absent in conventional MCDM models. Empirical results reveal significant divergence in structural efficiency across bank types. Top-performing banks exhibit higher adaptability, often tied to agile governance and fintech integration, whereas lower-performing institutions are encumbered by legacy systems and structural fragmentation. Regression and random forest analyses further show that larger AI and smart city markets are paradoxically associated with reduced systemic entanglement, suggesting that contextual technological maturity fosters functional decoupling among traditional banking metrics. These findings provide theoretical and managerial insights into how technological complexity reshapes financial performance structures in emerging economies.

Keywords Quantum-inspired · MCDM · Chinese banks · Artificial intelligence · Market size · Benchmarking · Partial dependence

1 Introduction

The increasing complexity of financial systems in the era of digital transformation has challenged traditional frameworks for evaluating institutional performance (Al-Ansi et al., 2024). In emerging economies such as China, where artificial intelligence (AI), smart city development, and digital finance are rapidly reshaping the macroeconomic landscape (Fan & Liu, 2021; Song et al., 2023; Ding & Ding, 2024), there is a growing need for more nuanced and structurally sensitive evaluation methods. Chinese banks, in particular, have experienced dramatic shifts in their operating environments (Xie & Wang, 2023), requiring new tools that move beyond conventional indicators to capture deeper interdependencies, dynamic trade-offs, and adaptive capabilities (Qi et al., 2022; Cheng et al., 2023).

Conventional multi-criteria decision-making (MCDM) models, such as TOPSIS, VIKOR, and COPRAS, provide useful scalar rankings (Seçme et al., 2009; Dincer & Hacioglu, 2013; Ünvan & Ergenç, 2022) but often rely on linear independence and static assumptions. These models may fail to account for hidden structural couplings, such as the entanglement of credit risk, liquidity, and capital adequacy, especially when banks operate within highly interconnected technological ecosystems (Brunnermeier & Pedersen, 2009; Greenwood et al., 2015). In this context, a new generation of models is required - models that can accommodate the probabilistic interdependence of financial criteria, contextual sensitivity, and performance under noisy, volatile environments (Farmer & Foley, 2009; Guidolin & Timmermann, 2007; Brownlees & Engle, 2017).

This study introduces a quantum-inspired multi-criteria decision-making (QI-MCDM) framework to assess the performance of Chinese banks. Drawing on concepts from quantum information theory—such as entanglement, decoherence, and fidelity (Keyl, 2002) - the model maps classical

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bank performance indicators onto a quantum density matrix representation (Liu et al., 2019). This allows for the explicit measurement of systemic interdependencies among criteria and the computation of a composite performance score that incorporates both structural coherence and contextual robustness.

The model is empirically tested using a panel dataset of Chinese banks over multiple years, incorporating financial, operational, and contextual indicators—such as AI market size, smart city investments, and innovation intensity. The resulting QI scores are then compared with those derived from traditional MCDM approaches. In addition to providing improved discrimination and continuity in ranking outcomes, the model reveals distinct patterns of entanglement and decoupling across bank types and over time. These patterns are further interpreted through network visualization, and partial dependence plots, offering insights into how macro-technological forces reconfigure internal banking structures.

By blending advanced decision-theoretic modeling with empirical data from one of the world's largest banking systems (Shi et al., 2007; Twum et al., 2022), this paper contributes both methodologically and theoretically to the literature on performance evaluation under complexity (Martynova & Vogel, 2022). It opens new directions for analyzing systemic risk, digital adaptation, and structural coherence in financial institutions operating at the frontier of technological change (Xu et al., 2024; Liu et al., 2025).

By advancing decision-theoretic modeling with empirical evidence from one of the world's largest banking systems, this study extends the performance evaluation literature toward contexts characterized by interdependence, technological disruption, and systemic uncertainty. Contributions of this study can be summarized as follows. First, on the methodological side, we introduce a quantum-inspired multi-criteria decision-making (QI-MCDM) framework that operationalizes concepts of entanglement, decoherence, and fidelity to model structural interdependencies among performance criteria. This represents a departure from DEA, SFA, and hybrid MCDM approaches that largely assume separability or rely on linear aggregation, thereby advancing performance evaluation toward structurally sensitive and resilience-aware models. Second, on the theoretical side, the study uncovers counterintuitive dynamics in the Chinese banking sector: while agile joint-stock and regional banks exhibit higher systemic coherence, larger AI and smart city markets are paradoxically associated with reduced entanglement among financial criteria. These findings refine existing views by showing that technological maturity can promote functional decoupling rather than tighter integration. Third, on the practical side, the QI-MCDM framework offers managers and policymakers a diagnostic tool for identifying when bank operations are structurally entangled or decoupled, and for tailoring strategies—such as modularization, targeted integration, or risk buffering—to the phase of technological development.

Accordingly, this study is guided by the following research questions: (1) How can a quantum-inspired multi-criteria decision-making framework be designed to capture structural interdependencies—such as entanglement, decoherence, and robustness—that are overlooked by traditional MCDM models in evaluating bank performance? (2) What patterns of structural coherence and fragmentation can be observed among different types of Chinese banks when assessed through this framework? (3) How do contextual factors, such as AI market development and smart city expansion, influence the degree of entanglement and systemic coherence in the Chinese banking sector?

The rest of the paper is structured as follows: Sect. 2 provides a review of literature on measuring performance in the Chinese banking industry including the evaluation of bank profitability, bank efficiency and bank productivity, in this section, we also review the literature on the proposal and applications of MCDM methods in the evaluation of bank performance in generally and Chinese banking sector specifically. Section 3 presents the methodology proposed in the current study, followed by Sect. 4 providing the analysis and discussions of the results. Section 5 provides the concluding remarks.

2 Literature Review

The traditional literature evaluating bank performance in China mainly focuses on various accounting indicators reflecting bank profitability, such as return on assets, return on equity, net interest margin and profit margin (Tan, 2016, 2017). Financial performance is also shaped by structural and institutional changes, as shown in studies of merger and spin-off effects (Heralová, 2024). Because of the advent and development of operational research, a growing number of studies have evaluated the performance of Chinese banking industry from the efficiency or productivity perspective through the non-parametric data envelopment analysis and parametric stochastic frontier analysis (Tan & Floros, 2013a, b; Tan et al., 2021a, b). Operational research scholars have been making consistent efforts in developing more innovative DEA and SFA models and applying them to evaluating bank performance in the Chinese context. For instance, a network DEA model was developed by Fukuyama and Tan (2022a) to decompose the overall bank efficiency in China into different sub-efficiencies, reflecting different aspects of banking operation, including innovation efficiency, stability efficiency, profitability efficiency and corporate social responsibility efficiency, the study also contributes to the literature by proposing the concept of strategic disposability for an intermediate undesirable output and an intermediate undesirable input. The network DEA model was also proposed by Fukuyama & Tan, (2022b, 2024) to evaluate bank efficiency in China. Fukuyama et al. (2023) and Fukuyama et al. (2024) further build on the static network DEA by proposing dynamic network DEA in which the carryover variables are considered and incorporated in the production process. Most recently, Fukuyama et al. (2025) extend these DEA-based approaches by introducing a Bayesian likelihood-based DEA framework to jointly estimate marginal costs, Lerner indices, and cost efficiency in a multi-output setting for Chinese banks. This framework retains the non-parametric flexibility of DEA but integrates Bayesian statistical inference into the multiplier DEA model, allowing for posterior estimation of input/output weights, marginal costs, and efficiency scores while explicitly quantifying statistical uncertainty. In doing so, it overcomes the deterministic limitations of earlier DEA, network DEA, and dynamic network DEA models, and provides credible intervals for efficiency and market power measures—thus offering richer policy-relevant insights into the competitive dynamics and cost structures of the Chinese banking sector.

Beyond the non-parametric DEA approaches, recent research has extended the traditional parametric stochastic frontier analysis (SFA) in evaluating Chinese bank performance. Tan and Tsionas (2022) employ an output distance function within a multi-output SFA framework to decompose sustainability efficiency into internal (economic and stability) and external (social and environmental) components, allowing simultaneous estimation of multiple inefficiency types while accounting for joint production and output endogeneity. Galán and Tan (2024) develop a dynamic SFA model with inefficiency heterogeneity to assess cost and profit efficiency and the impact of green credit, incorporating bank-specific fixed effects in both the frontier and inefficiency terms to separate time-invariant heterogeneity from inefficiency persistence. Using Bayesian estimation, they derive posterior distributions for efficiency and persistence parameters, providing richer inference than conventional SFA. These advances move beyond static single-equation frontiers, introducing multi-dimensional efficiency concepts, dynamic adjustment processes, and explicit treatment of heterogeneity.

Recent work has further advanced operational research methods for evaluating Chinese bank performance. Antunes et al. (2024a) develop a trigonometric envelopment analysis for ideal solutions (TEAIS) model, which extends DEA through trigonometric aggregation functions. This approach enables refined benchmarking of Chinese banks under nonlinear frontier conditions and avoids compensatory distortions in performance assessment. Tan and Walheer (2024) adopt a nonparametric framework to jointly measure stability and economic performance, introducing the concepts of risk indicator shadow prices and stability rents to capture the trade-offs between efficiency and stability. Fukuyama and Tan (2021) incorporate corporate social responsibility into DEA, using indicators such as employee numbers, donations, green credits, and SME loans. Their results highlight that CSR dimensions can exert heterogeneous effects on allocative and technical efficiency. Collectively, these studies illustrate how innovative extensions of DEA and related methods are providing a richer and more nuanced understanding of Chinese banking performance.

MCDM approaches have been widely applied to evaluate banking performance by integrating diverse financial and non-financial indicators into structured decision frameworks. Dincer and Hacioglu (2013), for example, combine fuzzy AHP and VIKOR to incorporate customer service and satisfaction into the performance evaluation of Turkish banks, revealing systematic differences by ownership type and illustrating how qualitative service dimensions can complement quantitative measures. Extending the methodological scope, Guo and Wu (2024) develop a hybrid pseudo-Malmquist–Grey TOPSIS model to compare credit allocation efficiency among seven categories of Chinese banks over a decade, finding joint-stock commercial banks to be consistently more efficient and demonstrating that such differences are largely driven by structural characteristics inherent to each bank type. Gupta et al. (2021) apply a hybrid AHP–TOPSIS, enhanced with interval-valued TOPSIS, to benchmark Indian private sector banks over a five-year period, identifying persistent leaders (HDFC Bank) and laggards (South Indian Bank) while confirming the robustness of rankings through sensitivity analysis. Lin and Chang (2019) adopt a DEMATEL–DANP–SAW hybrid to evaluate the sustainability performance of Taiwanese banks, highlighting the non-performing loan ratio as the most critical factor, and showing that financial holding companies—particularly those with insurance subsidiaries—outperform non-holding and state-owned banks. Collectively, these studies underscore the versatility of hybrid MCDM techniques in capturing multidimensional bank performance, accounting for both temporal dynamics and interdependencies among criteria, and providing actionable insights for managerial decision-making in diverse banking contexts.

Building on these hybrid designs, recent work has pushed MCDM for bank performance in three notable directions. First, Işık et al. (2025) propose an integrated fuzzy framework—F-LBWA and F-LMAW for criteria weighting combined with MARCOS for ranking—to assess publicly listed Pakistani banks across 13 indicators spanning CAMELS variables, customer service network, and market performance. Their combinative weighting mitigates expert subjectivity, the overall scheme is reported as rank-reversal-resistant, and extensive sensitivity checks indicate stable, dependable rankings that help decision-makers isolate the most influential factors for improvement. Second, a stochastic-neural hybrid MCDM study by Marezda et al. (2022) on SADC countries links banking performance with social welfare by marrying COPRAS (utility-based aggregation) and TOPSIS (distance-to-ideal) under bias-controlled SWARA weights set via the maximum-entropy principle. The authors then estimate endogeneity among performance and welfare variables using neural-network residuals and entropy-guided covariance minimization, showing how epistemic uncertainty can be handled explicitly in both weighting and causal structure estimation. Third, on the sustainability front, Raut et al. (2017) assemble a strategic multi-criterion evaluation model for banks that integrates the balanced scorecard with fuzzy AHP and fuzzy TOPSIS. Their contribution emphasizes a multidimensional (economic–social–environmental) perspective for developing-economy banking.

Recent studies continue to expand the toolkit of MCDM techniques applied to bank performance evaluation, often fusing fuzzy logic with multi-criteria frameworks. For example, Wu et al. (2009) propose a fuzzy Balanced Scorecard (BSC) framework where FAHP is used to weight 23 financial and non-financial indicators, and then SAW, TOPSIS, and VIKOR are applied to rank banks. This approach demonstrated that integrating qualitative BSC perspectives via fuzzy AHP and multiple ranking methods yields nuanced insights into banks' performance gaps. Wang et al. (2020) evaluate innovation performance of Turkish banks by identifying eight mixed financial/non-financial criteria and applying interval type-2 fuzzy DEMATEL to derive weights, followed by interval type-2 fuzzy VIKOR for ranking. They find that market share and return on investment (ROI) dominate innovation capability, illustrating how higher-order fuzzy extensions (IT2 FDEMATEL and VIKOR) can capture epistemic uncertainty in criteria weighting and clustering. In a related vein, Seçme et al. (2009) integrate fuzzy AHP with TOPSIS for Turkey's largest banks, combining expert-determined weights on financial and service indicators with a fuzzy TOPSIS ranking. Their results emphasize that non-financial (customer service) measures materially affect relative performance. Together, these fuzzy MCDM studies underscore the value of embedding linguistic scales and uncertainty modeling in bank ranking tasks, ensuring that both financial and qualitative dimensions are systematically incorporated.

Building on fuzzy MCDM, other works introduce novel fuzzy set extensions to enrich performance analysis. Tuysuz and Yildiz (2020) develops a *simulation-integrated hesitant fuzzy AHP* approach to weight criteria, and couples it with Grey Relational Analysis (GRA) to rank bank branches within an agricultural bank in Turkey. This hybrid method, grounded in both probability theory and fuzzy set theory, better captures judgment uncertainty inherent in decision making process. More recently, Yang et al. (2025) propose an *improved scenario fuzzy set* model for bank employee performance evaluation, expanding fuzzy sets to four categories (positive, neutral, negative, invalid) and introducing a Hamming-distance-based TOPSIS procedure. They demonstrate that this enhanced "scenario fuzzy" framework provides more comprehensive discrimination among alternatives than classical fuzzy TOPSIS. These advances highlight how enriched fuzzy representations and distance metrics (e.g. hesitant or scenario fuzzy sets with novel similarity measures) can refine multi-attribute evaluation in banking contexts, a direction that is still relatively unexplored in the literature.

Several recent works emphasize combined weighting schemes and robustness checks. Unlü et al. (2022) fill a pandemic-era gap by assessing Turkish banks' efficiency and productivity pre- and during COVID-19 using a three-phase MCDM approach. They first segment banks by ownership (state, foreign, private) and then derive criteria weights via subjective SWARA II (expert judgment) and objective MEREC (data-driven dissonance) methods, finally synthesizing them for a MARCOS ranking analysis. This dual weighting (subjective–objective) hybrid mitigates biases inherent in single-method weights, yielding stable rankings where foreign-investor banks excel and state banks lag post-COVID. Such designs illustrate the trend of integrating multiple weight derivation techniques and rigorous sensitivity analysis to bolster the credibility of MCDM results in banking.

Another strand of literature merges MCDM with data-driven or optimization models. Wanke et al. (2016) analyze 114 Islamic banks across 24 countries using a two-stage TOPSIS–neural network framework. In Stage 1, they apply TOPSIS to compute efficiency scores based on commonly used financial ratios. In Stage 2, these TOPSIS outcomes feed into a neural network model to predict bank performance and infer the impact of institutional factors. Their findings show that country-specific variables and cost structures significantly affect efficiency, and suggest that global Islamic banking would benefit from more competition. Likewise, Wu et al. (2018) integrate DEA cross-efficiency and VIKOR to rank 16 major Chinese banks. They introduce a cross-efficiency interval (capturing all possible DEA weighting schemes) and then apply VIKOR to the resulting global scores. This hybrid reveals that China's banking efficiency improved over 2007–2014, with joint-stock banks outperforming state-owned ones and the efficiency gap narrowing. Both studies exemplify how combining classical efficiency analysis with distance-based MCDM (and even machine learning) can overcome limitations of each approach alone.

Finally, cutting-edge research is exploring new decision frameworks and optimization for banking MCDM. Yazdi et al. (2025) propose a hybrid second-order cone programming (SOCP)–MCDM method to perform cost–benefit analysis (CBA) across global banks. By formulating CBA as an SOCP problem, they efficiently handle large-scale financial data, then embed it within a MCDM analysis to compare countries. Their empirical results highlight that endogenous factors (capital, labor, loans) heavily influence CBA scores, whereas exogenous variables (FDI, GDP) matter less, and domestic regulation has a strong effect on banking performance. Notably, Chinese banks consistently rank highest, attributed to robust industry standards. This innovative use of convex optimization methods in an MCDM context opens a promising avenue: accurately optimizing weights and incorporating convex quadratic constraints to enhance decision robustness in banking performance studies. Recent research increasingly explores novel MCDM models that extend beyond traditional TOPSIS, VIKOR, or DEA hybrids (Arman et al., 2025; Yalçın et al., 2025; Çobanoğulları et al., 2025). Although many of these applications lie outside the banking sector—such as sustainability or digital innovation—they underscore the methodological frontier that this study builds upon in proposing a quantum-inspired extension.

Recent advances further illustrate the trend toward information-theoretic and stochastic extensions of MCDM in banking. For example, Wanke et al. (2023) develop a hybrid stochastic MCDM framework based on sign decomposition and transfer entropy to disentangle endogenous and exogenous sources of performance in Asian banks, showing how liquidity, capitalization, and contextual factors such as accounting standards interact to shape outcomes. Similarly, Antunes et al. (2024b) introduce a stochastic entropic analysis of ideal solutions (SEA-IS) for Japanese banks, which combines DEA and TOPSIS with mutual information and entropy analysis to capture uncertainty, learning feedback, and continuous improvement dynamics. These studies underscore the emerging emphasis on stochasticity, entropy, and causality in performance evaluation, reinforcing the need for novel frameworks capable of capturing complex interdependencies—such as the quantum-inspired approach proposed in the present study.

In summary, the literature demonstrates a clear trajectory toward increasingly sophisticated MCDM frameworks—integrating fuzzy logic, hybrid weighting, optimization, and machine learning—to capture the multifaceted nature of bank performance. However, existing models still largely treat criteria relationships as linear or static, with limited ability to represent deep systemic couplings, structural degradation, or resilience under uncertainty. This gap is especially salient in China's rapidly evolving AI and smart city context, where bank performance indicators are shaped by complex, often non-classical interdependencies. To address this, the present study proposes a quantum-inspired MCDM framework that embeds classical performance metrics into a quantum probability space, enabling explicit measurement of entanglement among criteria, decoherence from ideal structural benchmarks, and robustness under noise. This approach not only extends the methodological frontier of MCDM but also offers novel insights into how technological complexity reshapes the structural performance of Chinese banks.

3 Methodology

This paper proposes a novel quantum-inspired framework for multi-criteria decision making (QI-MCDM), where each alternative is treated as a quantum state and the relationships among performance criteria are modeled using concepts from quantum mechanics: entanglement, decoherence, and noise. The framework incorporates inter-criteria dependencies (entanglement), degradation from ideal benchmarking conditions (decoherence), and measurement uncertainty (quantum noise). We formalize the QI-MCDM methodology in distinct computational steps and demonstrate how each contributes to a structurally informed benchmarking of alternatives in light of the entangled criteria.

3.1 The QI-MCDM Model

Let $A \in \mathrm{R}^{m \times n}$ be a performance matrix, where m is the number of alternatives (observations), n is the number of criteria, and A_{ij} is the performance of alternative i under criterion j. Each row $\overrightarrow{a}_i \in \mathrm{R}^n$ represents the performance vector of alternative i, and the entire matrix A captures the multi-dimensional evaluation landscape. In classical MCDM, this matrix is typically analyzed through normalization, weighting, and aggregation (Zavadskas et al., 2014; Behzadian et al., 2012). However, such methods often assume criteria-independence and ignore higher-order interdependencies (Wang & Chang, 2007; Greco et al., 2001).

In the QI-MCDM framework, A serves as the input layer to a quantum-inspired transformation process, where each alternative $\overrightarrow{a}_i$ is viewed not merely as a point in R^n, but as a projection of a latent quantum state (Yukalov & Sornette, 2011; Pothos & Busemeyer, 2022). On the other hand, each criterion is treated as an observable dimension whose interaction with others may be nonclassical (e.g., entangled)

(Haven & Khrennikov, 2013). The overall decision structure will be examined not just in scalar space, but within a Hilbert space representation (Khrennikov et al., 2018; Moreira & Wichert, 2016). These assumptions set the stage for mapping classical observations into a quantum probability framework that captures both linear and non-linear interdependencies (Busemeyer et al., 2011; Basieva et al., 2018), enabling a richer and more flexible representation of decision information.

3.1.1 Quantum State Normalization

Each alternative $\overrightarrow{a}_i \in \mathrm{R}^n$ is mapped to a quantum state $|\psi_i>$ in an n-dimensional complex Hilbert space H_n. The transformation ensures that the quantum state is normalized:

$$\left|\psi_i >= \frac{\overrightarrow{\alpha}}{\|\overrightarrow{\alpha}\|}, \text{ where } \|\overrightarrow{\alpha_i}\| = \sqrt{\sum_{j=1}^{n} A_{ij}^2}\right. \quad (1)$$

This mapping preserves the proportional relationships among criteria while embedding them within a formal quantum framework. The normalization transforms each row vector into a unit vector (also referred to as a "ket" (Kibble, 1979), ensuring that the quantum state lies on the unit sphere in H_n (Brody & Hughston, 2001). From a quantum mechanical perspective, $|\psi_i>$ corresponds to a pure quantum state (Jozsa, 1994), and its squared components $|\psi_{ij}|^2$ can be interpreted as the probability amplitude of observing a particular criterion level relative to the entire alternative's performance profile. In practical terms, normalization removes magnitude differences between alternatives and allows focusing on the shape of performance patterns. This is particularly important when interpreting performance as a distribution of relative strengths across entangled criteria.

Since all normalized vectors $|\psi_i>$ reside on the surface of a hypersphere, the inner product $\langle\psi_i\ |\psi_j\rangle$ works as a similarity metric on the unit hypersphere, not only allowing angular distances to represent relative proximity in performance structure but also allowing projections and density matrices to be computed, which are helpful in measuring coherence (Streltsov et al., 2017) and entanglement (Horodecki et al., 2009) properties among criteria.

3.1.2 Density Matrix Representation

The quantum state of each alternative *i* is represented by a pure-state density matrix:

$$\rho_i = |\psi_i >< \psi_i| \quad (2)$$

Each $\rho_i \in \mathrm{C}^{n\times n}$ is Hermitian, positive semi-definite, and satisfies $\mathrm{Tr}(\rho_i) = 1$. The density matrix encodes all the statistical and structural information of the quantum state, including both the observable probabilities (diagonal terms) and the interference or coherence between criteria (off-diagonal terms) (Breuer & Petruccione, 2007).

The diagonal elements $(\rho_i)_{jj} = |\psi_{ij}|^2$ represent the relative strength or importance of each criterion in the normalized performance profile. The off-diagonal elements $(\rho_i)_{jk} = \psi_{ij}\psi_{ik}$ capture the mutual coherence or phase-aligned correlation between criteria j and k, analogous to the wave-like interference patterns in quantum physics (Haroche & Raimond, 2006).

Based upon this representation it is possible to perform structural comparisons in the MCDM using trace distances, fidelities, or entropy measures between ρ_i and benchmarks or other alternatives (Bengtsson & Życzkowski, 2006). Moreover, by analyzing ρ_i as a full operator rather than a point estimate, alternatives are no longer isolated points but structured distributions within the decision space (Keyl, 2002).

3.1.2.1 Entanglement Between Criteria In classical MCDM, criteria are typically considered independent unless explicit weighting or correlation analysis is performed (Dyer & Sarin, 1979; Keeney, 1974). However, in the QI-MCDM framework, criteria can exhibit entangled relationships, where the performance in one dimension inherently influences or aligns with the performance in others due to systemic or operational interdependencies (Aerts, 2009; Modi et al., 2012). To measure this entanglement, we define an entanglement index $EI(\rho_i)$ for each alternative i as:

$$EI(\rho_i) = \sum_{j\neq k} \left|(\rho_i)_{jk}\right| \quad (3)$$

This sum of the absolute values of the off-diagonal entries in ρ_i quantifies the degree to which performance criteria are coherently interrelated (Xi et al., 2015). A higher EI suggests stronger entanglement meaning that improvements or deteriorations in one criterion are likely to be reflected in others due to coherent MCDM structure. So, if $EI \approx 0$, the criteria are nearly orthogonal or independent; the alternative behaves classically. Conversely, when $EI \gg 0$, the criteria are entangled, suggesting latent synergies or trade-offs within the alternative's configuration.

From a managerial standpoint, high entanglement may suggest the presence of leverage points: improvements in one area may yield cascading benefits across others. Conversely, low entanglement may reflect siloed or fragmented operations. In other words, $EI(\rho_i)$ can be used to identify alternatives that may benefit most from coordinated, multi-criteria improvement strategies.

3.1.2.2 Decoherence Distance to Quantum Benchmark The concept of decoherence in QI-MCDM captures how much an observed alternative diverges from a theoretically ideal, fully coherent quantum benchmark state. This ideal benchmark ρ^* reflects a state in which all performance criteria are assumed to contribute equally, besides being perfectly entangled. Hence, we define the benchmark matrix as:

$$\rho^* = \frac{1}{n} 1_n 1_n^T \tag{4}$$

where 1_n is the column vector of ones of length n, and ρ^* is a rank-one projector scaled by $1/n$, representing a uniform superposition over all criteria. To evaluate how close an observed state ρ_i is to the benchmark, we use the trace overlap:

$$D_{\text{decoh}}(i) = 1 - \text{Tr}\left(\rho_i \rho^*\right) \tag{5}$$

Here, $\text{Tr}\left(\rho_i \rho^*\right)$ measures the similarity or alignment between the observed density matrix and the ideal benchmark. A low $D_{\text{decoh}}(i)$ indicates that ρ_i retains much of the coherence and entanglement of ρ^* (Vedral et al., 1997), while a higher value suggests that the system has decohered (Blume-Kohout & Zurek, 2006)-i.e., lost its structure due to external influence or internal inefficiency.

Decoherence thus provides a structural degradation index, identifying alternatives that are not merely underperforming but structurally disconnected from optimal configurations. It distinguishes between poor outcomes due to noise and those due to fundamental structural limitations.

3.1.2.3 Quantum Noise and Robust Benchmarking While decoherence quantifies the structural deviation of an alternative from the ideal benchmark, quantum noise accounts for inherent uncertainty in the measurement or observation process. In QI-MCDM, this uncertainty is modeled using a depolarizing channel (King & Ruskai, 2001), which simulates random disturbances in the quantum state.

Let ρ_i be the density matrix of alternative i, and $p \in [0,1]$ be the noise intensity parameter. The noisy version of ρ_i is given by:

$$\text{N}_p(\rho_i) = (1-p)\rho_i + p \cdot \frac{I_n}{n} \tag{6}$$

Here, $\frac{I_n}{n}$ is the maximally mixed state, representing complete uncertainty over all criteria. As $p \to 1$, the quantum state becomes increasingly random, losing all specific performance information. To evaluate how resilient or robust an alternative is to this noise, we compute its fidelity (Miszczak et al., 2009) with the benchmark state ρ^*:

$$F\left(\rho_i, \rho^*\right) = \left(\text{Tr}\left[\sqrt{\sqrt{\rho_i}\rho^*\sqrt{\rho_i}}\right]\right)^2 \tag{7}$$

Fidelity measures the quantum similarity between two states, with $F = 1$ indicating perfect alignment and $F = 0$ indicating complete orthogonality. When applied to noisy versions of ρ_i, fidelity can serve as a robustness metric, revealing how much the alternative's proximity to the ideal benchmark degrades under increasing noise.

This perspective allows for probabilistic benchmarking, since alternatives with high fidelity even under noise are stable and reliably close to optimal. However, alternatives with low fidelity under small noise are highly sensitive and unreliable. Such analysis helps differentiate between structural inefficiency (captured by decoherence) and measurement fragility (captured by quantum noise), guiding both diagnostic and prescriptive decision-making strategies.

3.1.2.4 Recoherence Paths and Improvement Strategy Improvement in QI-MCDM is conceptualized as a process of recoherence (Maniscalco et al., 2008) - the recovery of entanglement and alignment with the ideal benchmark ρ^*. This step addresses how alternatives can move toward optimal performance not by arbitrary adjustments but through guided, structure preserving transformations.

Let ρ_i be the current state of an alternative and let ρ_i' be a transformed version obtained through targeted improvements. The objective is to identify a ρ_i' that both dominates ρ_i in terms of performance and increases structural entanglement (coherence). Formally, we define the optimization problem as:

$$\max_{\rho_i'} EI\left(\rho_i'\right) \text{ subject to } \rho_i' \geq \rho_i \tag{8}$$

where $\geq$ denotes Pareto dominance (Deb et al., 2002) or admissible improvement across performance criteria. Recoherence trajectories are constrained by the residual entanglement in ρ_i. Alternatives with high initial entanglement can explore more coordinated paths of improvement, while alternatives with low entanglement may require sequential or isolated interventions. Mathematically, this process can be viewed as a quantum control problem, where a transformation U (unitary or non-unitary) is applied to the state ρ_i :

$$\rho_i' = U\rho_i U^+ \text{ or } \rho_i' = E(\rho_i) \quad (9)$$

with E representing a CPTP (completely positive trace-preserving) map that respects operational feasibility.

3.1.2.5 Composite QI-MCDM Score To synthesize the three-core quantum-inspired indicators - Entanglement Index (EI), Inverted Decoherence Distance ($1-D$), and Fidelity (F) (Streltsov et al., 2017) - into a single performance score, we propose a weighted geometric mean, defined as:

$$\text{QI\_Score}_i = \prod{}_{k=1}^{3} x_{ik}^{w_k}, \text{ where } x_{ik} \in \{\text{EI}, 1-D, F\}, \sum w_k = 1 \quad (10)$$

Unlike classical MCDM methods that rely on additive independence, the QI-MCDM criteria are inherently interdependent, and their synergy cannot be modeled through simple summation (Dyer & Sarin, 1979). Besides, the geometric mean penalizes alternatives with poor performance in any one dimension (Figueira et al., 2005), aligning with quantum principles where coherence or robustness loss cannot be offset linearly (Baumgratz et al., 2014). Finally, since all components are normalized to $[0,1]$, the geometric mean operates effectively without requiring transformation.

In this research we adopted weights of $w = (0.4,0.3,0.3)$, placing greater emphasis on entanglement, which signals the systemic potential for joint improvement. However, weights may be adjusted to reflect expert preferences or explored via sensitivity analysis.

3.2 Assessing the Impact of Contextual Variables on QI-MCDM Scores

While the entanglement structure among performance criteria offers insight into interdependencies, it is equally important to understand what drives these entanglements. Specifically, this section examines whether and how contextual variables - particularly those socio-economic and demographic - influence the strength and frequency of entanglement between pairs of criteria. This regression-based approach complements the previous analysis by providing a causal-explanatory interpretation: do changes in the contextual variables help explain why certain criteria become more or less entangled?

Let $P = \{p_1, p_2, \ldots, p_m\}$ denote the set of all unique entangled pairs (e.g., $p_1 =$ criterion1 + criterion2), $F(p_j) \in \mathrm{N}$ denote the frequency of each entangled pair across all alternatives A_i, $Z_i \in \mathrm{R}^q$ denote the vector of contextual variables associated with alternative i. To model the relationship between contextual variables and entanglement pair frequency, we must join each entangled pair p_j to the alternatives where it appears; compute the average value of each contextual variable Z_k across those alternatives for p_j; and merge these averages into a dataset $D \in \mathrm{R}^{m\times(q+1)}$, with columns: $D_j = \left(F(p_j), Z_j^{-1}, \ldots, Z_j^{-q}\right)$

Hence, a standard Ordinary Least Squares (OLS) regression can be performed:

$$F(P_j) = \beta_0 + \sum_{k=1}^{q} Z_j^{-k} + E_j \quad (11)$$

where $F(p_j)$ is the frequency of entanglement for pair p_j, Z_j^{-k} is the average contextual value for variable k among alternatives exhibiting p_j, and β_k is the regression coefficient reflecting the marginal effect of contextual factor k on entanglement frequency.

Eventually, given the limited number of distinct entangled pairs, the linear model may suffer from small-sample bias and heteroskedasticity. As a robustness check, we further suggest employing non-parametric models, such as Random Forests with Partial Dependence (Breiman, 2001; Friedman, 2001), to confirm and visualize the contextual influence on entanglement frequency.

Let $\mathrm{F} : \mathrm{R}^p \to \mathrm{R}$ denotes the fitted random forest model mapping the contextual variables Z to entanglement frequency f. The marginal effect of a specific variable z_k on f is examined via partial dependence (PD):

$$\mathrm{PD}(z_k) = \frac{1}{n}\sum_{i=1}^{n} \mathrm{F}\left(z_1^{(i)}, \ldots, z_k, \ldots, z_p^{(i)}\right) \quad (12)$$

This computes the expected entanglement frequency holding all other variables at their observed values while varying z_k across its range. The model outputs a permutation-based importance metric $\Delta_{MSE}(z_l)$ for each variable z_l, representing the percentage increase in mean squared error when z_l is randomly permuted. This allows ranking the most influential contextual variables driving entanglement frequency (Strobl et al., 2007). Besides, partial dependence plots also reveal whether entanglement frequency increases monotonically, non-monotonically, or exhibits phase-shift behavior with respect to each contextual variable (Goldstein et al., 2015).

4 Analysis and Discussion of Results

Table 1 reports on the descriptives for the Chinese bank criteria and their respective contextual variables. The criteria we use in the first stage MCDM analysis were collected

Table 1 Descriptive statistics for the criteria and contextual variables

Type	Direction	Variable	Mean	Median	St. Dev.	CV	Skewness	Kurtosis	Entropy
Criteria	MIN	Staff expenses	1658341.444	345413.000	3304344.682	1.993	3.351	11.463	2.322
	MIN	gross loans charged written off	1806017.742	315968.000	3147121.878	1.743	2.079	3.680	3.322
	MIN	Loan loss reserves	6955266.388	1613439.000	15309522.020	2.201	4.282	20.717	2.371
	MIN	Fixed assets	3302477.372	513799.000	7712044.773	2.335	3.268	10.016	2.922
	MAX	equity	35328105.891	7324572.000	74974145.106	2.122	3.604	13.634	2.322
	MIN	Interbank liabilities	87283703.212	20003935.000	143551334.953	1.645	2.440	6.524	2.922
	MIN	Non-performing loans	3611935.576	739864.000	7436527.677	2.059	3.548	13.515	2.922
	MAX	Profit after tax	3564913.889	677439.000	7960732.577	2.233	3.728	14.256	2.922
	MAX	Total assets	440693012.018	95806657.000	892791883.312	2.026	3.491	12.968	2.522
	MAX	deposits	381586471.840	83973059.000	769151995.771	2.016	3.500	13.080	2.522
	MAX	loans	245930944.773	45875752.000	535703392.644	2.178	3.720	14.925	2.322
	MAX	Securities and investment	131123895.780	36284915.000	225498841.587	1.720	3.058	10.526	2.846
	MAX	Net interest income	7318354.817	1602040.000	15218006.590	2.079	3.653	14.085	3.122
	MAX	Non-interest income over operating revenue ratio	21.912	21.000	9.688	0.442	0.341	1.497	2.922
	MAX	Operating revenue	9984260.196	1967467.000	20207816.312	2.024	3.364	11.740	2.922
	MAX	Non-interest income	2666005.130	411342.360	5191272.285	1.947	2.759	7.598	3.122
	MAX	Total capital adequacy ratio	13.705	14.000	1.433	0.105	0.745	1.249	3.122
	MAX	Non-interest expenses over average total assets ratio	1.295	1.000	0.456	0.353	0.898	−1.197	0.922
	MAX	Net income	3564913.889	677439.000	7960732.577	2.233	3.728	14.256	2.922
	MAX	Liquid assets	80468741.302	17555370.000	161232252.169	2.004	3.558	13.754	2.846
Contextual	value of investments into the primary AI market (billion yuan)		129.498	118.840	53.274	0.411	0.051	−0.772	1.722
	Number of investments into the primary AI market		834.667	822.000	129.290	0.155	0.741	−0.816	1.722
	size of the AI market in China (billion yuan)		11.627	9.410	5.686	0.489	0.317	−1.473	1.485
	market size of the smart city industry in China (trillion yuan)		16.378	14.900	10.344	0.632	0.153	−1.296	1.157
	market size of machine vision in China (billion yuan)		129.489	138.900	82.678	0.638	0.256	−0.969	1.485

from BankFocus. More specifically, the negative criteria we used, as indicated by "MIN", include staff expenses, gross loans charged written off, loan loss reserves, fixed assets, interbank liabilities and non-performing loans, while the positive criteria, as indicated by "MAX" include equity, profit after tax, deposits, loans, securities and investment, net interest income, the ratio between non-interest income and operating revenue, operating revenue, non-interest income, total capital adequacy ratio, the ratio between non-interest expenses and average total assets, net income and liquid assets. Except for the ratios, all the variables are in the unit of thousand USD. We have a balanced panel dataset covering 43 Chinese commercial banks between 2015 and 2024. In terms of the contextual variables, we include (1) value of investments into the primary AI market in China 2015–2024 (billion yuan); (2) Number of investments into the primary AI market in China 2015–2024; (3) size of the AI market in China 2016–2024 (billion yuan); (4) market size of the smart city industry in China 2016–2024 (trillion yuan); (5) market size of machine vision in China 2016–2024 (billion yuan).

QI MCDM results for entanglement, decoherence, fidelity, and the respective resulting QI_Scores are duly reported in Table 2, in terms of their averaged values over the years for the collected sample of Chinese banks based on the performance criteria depicted in Table 1. The top-ranked banks in the QI-MCDM evaluation—Bank of Tianjin, Industrial Bank Co. Ltd., Huishang Bank, Bank of Ningbo, and Bank of Beijing—demonstrate a consistently high level of entanglement, moderate decoherence, and superior fidelity,

Table 2 Averaged QI MCDM results over the years for the Chinese banks

Bank	Entanglement	Decoherence	Fidelity	QI_Score
BANK OF TIANJIN	4.1630	0.7419	0.2373	0.7655
INDUSTRIAL BANK CO LTD	4.1375	0.7431	0.2362	0.7614
HUISHANG BANK CO LTD	4.1339	0.7433	0.2360	0.7608
BANK OF NINGBO	4.1153	0.7442	0.2352	0.7578
BANK OF BEIJING CO LTD	4.1011	0.7449	0.2346	0.7555
BANK OF CHONGQING	4.0987	0.7451	0.2344	0.7551
BANK OF JIANGSU CO LTD	4.0491	0.7475	0.2322	0.7471
CHONGQING RURAL COMMERCIAL BANK	4.0439	0.7478	0.2320	0.7462
CHINA MINSHENG BANKING CORPORATION	4.0313	0.7484	0.2314	0.7442
XIAMEN BANK	4.0049	0.7498	0.2301	0.7398
BANK OF SUZHOU CO LTD	3.9933	0.7503	0.2297	0.7380
BANK OF NANJING	3.9663	0.7517	0.2285	0.7337
JIANGXI BANK CO LTD	3.9602	0.7520	0.2282	0.7327
BANK OF ZHENGZHOU CO., LTD.	3.9549	0.7523	0.2280	0.7318
HUA XIA BANK CO., LIMITED	3.9470	0.7527	0.2276	0.7306
CHINA EVERBRIGHT BANK COMPANY LIMITED	3.9236	0.7538	0.2266	0.7268
SHENGJING BANK	3.8997	0.7550	0.2255	0.7229
BANK OF GUIYANG CO LTD	3.8965	0.7552	0.2253	0.7224
TIANJIN RURAL COMMERCIAL BANK CO LTD	3.8926	0.7554	0.2252	0.7218
GUANGDONG SHUNDE RURAL COMMERCIAL BANK COMPANY LIMITED	3.8860	0.7557	0.2248	0.7206
SHANGHAI PUDONG DEVELOPMENT BANK	3.8475	0.7576	0.2231	0.7145
BANK OF HEBEI CO LTD	3.8397	0.7580	0.2228	0.7132
HARBIN BANK	3.8189	0.7591	0.2218	0.7098
CHINA CITIC BANK CORPORATION LIMITED	3.8095	0.7595	0.2214	0.7083
BANK OF COMMUNICATIONS CO. LTD	3.8058	0.7597	0.2213	0.7077
BANK OF CHENGDU CO LTD	3.7721	0.7614	0.2197	0.7023
BEIJING RURAL COMMERCIAL BANK CO LTD	3.7698	0.7615	0.2196	0.7019
CHENGDU RURAL COMMERCIAL BANK CO LTD	3.7665	0.7617	0.2195	0.7014
QILU BANK CO LTD	3.7653	0.7617	0.2194	0.7012
BANK OF HUNAN CO., LTD.	3.7507	0.7625	0.2188	0.6988
BANK OF RIZHAO	3.7332	0.7633	0.2180	0.6960
HANKOU BANK	3.7255	0.7637	0.2176	0.6947
BANK OF CHINA LIMITED	3.7204	0.7640	0.2174	0.6939
BANK OF XI'AN CO LTD	3.7175	0.7641	0.2173	0.6934
BANK OF JIUJIANG CO LTD	3.7154	0.7642	0.2172	0.6931
JIANGSU JIANGYIN RURAL COMMERCIAL BANK	3.7115	0.7644	0.2170	0.6925
BANK OF DONGGUAN	3.6924	0.7654	0.2162	0.6894
SHANGHAI RURAL COMMERCIAL BANK	3.6687	0.7666	0.2151	0.6855
SHENZHEN RURAL COMMERCIAL BANK CO LTD	3.6292	0.7685	0.2133	0.6792
JIANGSU SUZHOU RURAL COMMERCIAL BANK CO	3.6138	0.7693	0.2126	0.6767
BANK OF GUILIN CO LTD	3.5994	0.7700	0.2120	0.6743
CHINA CONSTRUCTION BANK CO., LTD	3.5436	0.7728	0.2095	0.6653
WUXI RURAL COMMERCIAL BANK CO.,LTD	3.4328	0.7784	0.2045	0.6474

culminating in the highest composite QI_Scores. These banks share structural characteristics that support integrated decision-making, rapid technology adoption, and operational agility (Wang et al., 2025). As joint-stock commercial banks or regionally focused institutions with flexible governance structures, they have embraced fintech and AI-driven risk assessment models, particularly in SME lending, digital payments, and green finance (Guo & Zhang, 2023). In contrast, the bottom-ranked banks—Bank of Dongguan, Jiangsu Jiangyin Rural Commercial Bank, Bank of Jiujiang, Bank of Xi'an, and Bank of China—display lower levels of entanglement and fidelity, coupled with higher decoherence, which collectively depress their QI_Scores. These institutions are often rural commercial banks or large state-owned banks encumbered by legacy systems, hierarchical governance, and slower responsiveness to technological change (Yuan et al., 2025). Their operational structures tend to be more siloed, with weaker integration between loan

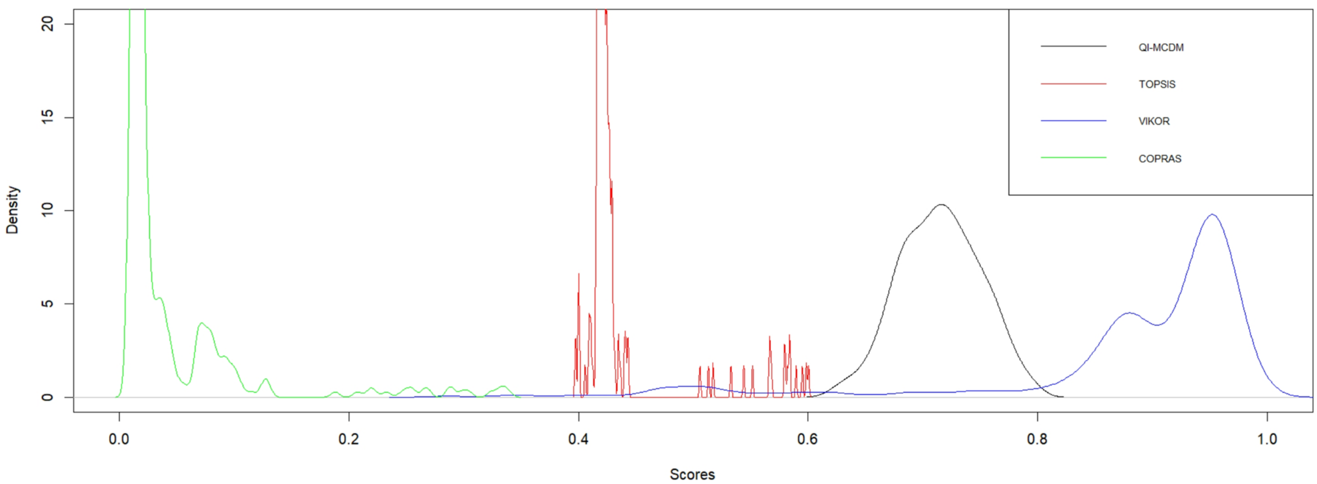

Fig. 1 Density plot comparison between QI_Scores and traditional MCDM models

portfolios, deposit mobilization, and cost control mechanisms. While stable in traditional metrics, these banks have been slower to incorporate AI in credit screening, customer management, or performance analytics, resulting in fewer synergistic linkages among their core performance criteria (Wang et al., 2024). In the case of large banks like Bank of China, the vast institutional complexity and regional fragmentation may further inhibit the coherence and alignment of strategic objectives across divisions, diminishing the capacity to exhibit the dynamic, entangled behavior observed in their higher-ranked counterparts.

A comparison of QI_Scores with the performance scores obtained using traditional MCDM models, such as TOPSIS, VIKOR, and COPRAS is shown in Fig. 1, where their respective densities are superimposed for the sake of cross-checking and additional inference insights. In TOPSIS, VIKOR, and COPRAS, we considered equal unit-weights for each criterion, while specifically in VIKOR its trade-off parameter was set at 0.5. QI MCDM scores, besides being quite symmetrical, are neither biased towards 0 (like COPRAS) or 1 (like VIKOR), ranging mostly from 0.6 to 0.8. It is also worth noting that, differently from TOPSIS scores, QI_Scores are not concentrated around few values, nor present discontinuity in their distributional profile.

These results imply the distinctive capacity of QI-MCDM to capture subtle differences in multidimensional performance of Chinese banks through quantum-influenced constructs such as fidelity, entanglement, and decoherence. In contrast, COPRAS scores are highly left-skewed, concentrated near zero, implying that most alternatives are perceived as low-performing, a pattern that may arise from the model's additive normalization structure lacking inter-criteria compensation (Podvezko, 2011). VIKOR scores, by contrast, are heavily right skewed, peaking around 0.95, indicative of score inflation and reduced discriminative power when most banks are ranked as highly desirable. TOPSIS, while theoretically more balanced, shows discrete, discontinuous clusters—a consequence of Euclidean distance calculations that can amplify small differences in normalized performance vectors, especially under equal-weight assumptions (Shyur & Shih, 2024; Ferrarini et al., 2024). This artifact introduces ranking instability and undermines interpretability.

Table 3 Performance score correlation matrix. (*)

	QI.Score	TOPSIS	VIKOR	COPRAS
QI.Score	1.000000	−0.224546	−0.022127	−0.121163
TOPSIS	−0.224546	1.000000	−0.480570	0.919418
VIKOR	−0.022127	−0.480570	1.000000	−0.631743
COPRAS	−0.121163	0.919418	−0.631743	1.000000

(*) Positive correlations in red, negative correlations in blue

Besides, the performance score correlation matrix reported in Table 3 reveals that QI_Scores are slightly and negatively decorrelated with traditional MCDM models. While the strongest positive association between TOPSIS and COPRAS merits attention, negative correlation pairs are also verified between VIKOR and TOPSIS and VIKOR and COPRAS performance scores for Chinese banks.

These results highlight the non-redundant information structure embedded in QI-MCDM, which detect multi-criteria interdependencies that are otherwise flattened or ignored in classical linear scoring models. Additionally, the correlation structure among the classical models reinforces some known methodological overlaps and divergences. The strong positive correlation (0.92) between TOPSIS and COPRAS is expected, as both rely on monotonic normalization and linear aggregation schemes (Malefaki et al., 2025), differing only in how the relative scores are expressed and scaled. Conversely, the moderate negative correlations between VIKOR and both TOPSIS (–0.48) and COPRAS (–0.63) suggest that VIKOR's compromise-oriented trade-off mechanism—especially with the decision-making coefficient set at 0.5 - drives rank reversals for alternatives evaluated poorly on any critical criterion (Sałabun et al., 2020).

Figure 2 depicts the entanglement network plot for the Chinese banks, unveiling the structural co-dependencies among a subset of performance criteria (total assets, loans, deposits, interbank liabilities, securities and investments, and liquidity). These entanglements arise when the quantum state representations of alternatives exhibit statistically significant off-diagonal correlations, often due to underlying systemic or contextual forces. They suggest that these criteria jointly influence the system's performance, meaning their combined measurement distributions cannot be factorized into independent components. This phenomenon is particularly plausible in the Chinese banking sector, where institutional structures, regulatory regimes, and economic mandates tend to promote coordinated financial behavior across balance sheet components (Feng et al., 2022; Hachem & Song, 2021).

For example, total assets are a cumulative construct inherently shaped by the volume of loans, deposits, and securities held, which are themselves influenced by regulatory capital requirements and market demand. In state-influenced banking systems like China's, liquidity positions are not managed in isolation but often in tandem with interbank liabilities to satisfy central bank guidelines on reserve adequacy and liquidity coverage ratios (Li et al., 2025). Similarly, strategic portfolio allocations into securities and investments are frequently rebalanced in response to deposit inflows, credit risk exposures in loan portfolios, and broader macroeconomic signals - factors that align temporally and behaviorally, leading to entangled measurement distributions across banks (Wang & Zhuang, 2022). Thus, the entanglement structure reflects how operational decisions, regulatory compliance, and systemic shocks induce joint variability across these criteria.

Table 4 reports on the OLS frequency regression results, revealing the significant explanatory power of contextual variables on entanglement frequency between criteria pairs. Precisely, results suggest that entanglement within this subset of banking performance criteria (cf. Figure 2) is increasing over time, that is, the Chinese banking system is becoming more structurally co-dependent. However, it is noteworthy that larger AI market size is associated with less frequent entanglement. Similarly, larger smart city markets are linked to reduced inter-criterion entanglement.

The observed patterns of reduced entanglement among Chinese banking performance criteria under certain conditions of the AI market structure can be interpreted in a three-fold fashion. First, in environments characterized by rapid growth in artificial intelligence (AI) investment or smart city infrastructure, banks tend to exhibit reduced structural coupling between core financial metrics such as loans and deposits. This decoupling may result from increasing innovation intensity, digital financial intermediation, and the emergence of differentiated business models, which foster more autonomous evolution of key balance sheet components (Tang et al., 2024; Lin et al., 2023; Liu et al., 2024;

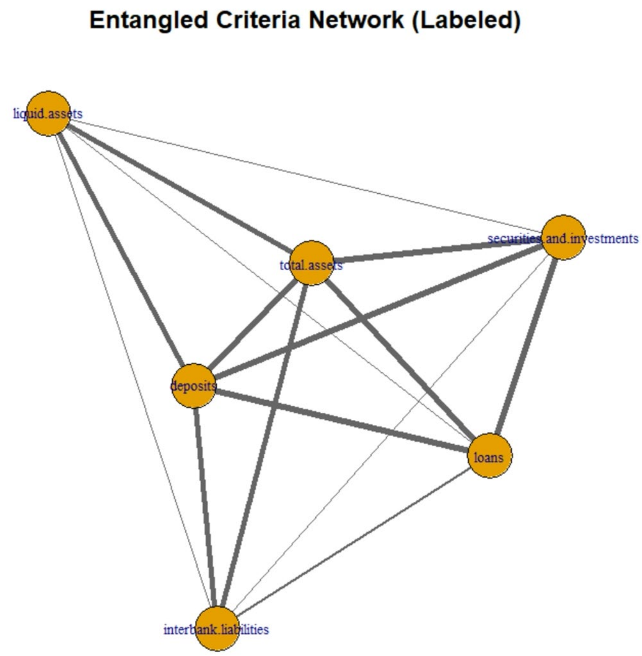

Fig. 2 Entanglement network for Chinese bank criteria

Table 4 OLS frequency regression results. (*)

Variable	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	−2.3E+07	5,246,000	−4.46	0.0016***
year	11,600	2603	4.46	0.0016**
log(Number of investments into the primary AI market)	−4.3	8.21	−0.52	0.613
log(market size of machine vision)	41.9	764.2	0.06	0.958
log(market size of the smart city industry)	−1143	391.8	−2.92	0.017*
log(size of the AI market)	−236.1	58.3	−4.05	0.0029**
Description	Value			
Residual standard error:	77.27 on 9 degrees of freedom			
Multiple R-squared:	0.8335			
Adjusted R-squared:	0.741			
F-statistic:	9.01 on 5 and 9 DF, p-value: 0.002607			

*, **, *** represent sigificance levels at 10%, 5% and 1%, respectively. Units: Number of investments into the primary AI market (count); market size of machine vision (billion yuan); market size of the smart city industry (trillion yuan); size of the AI market (billion yuan)

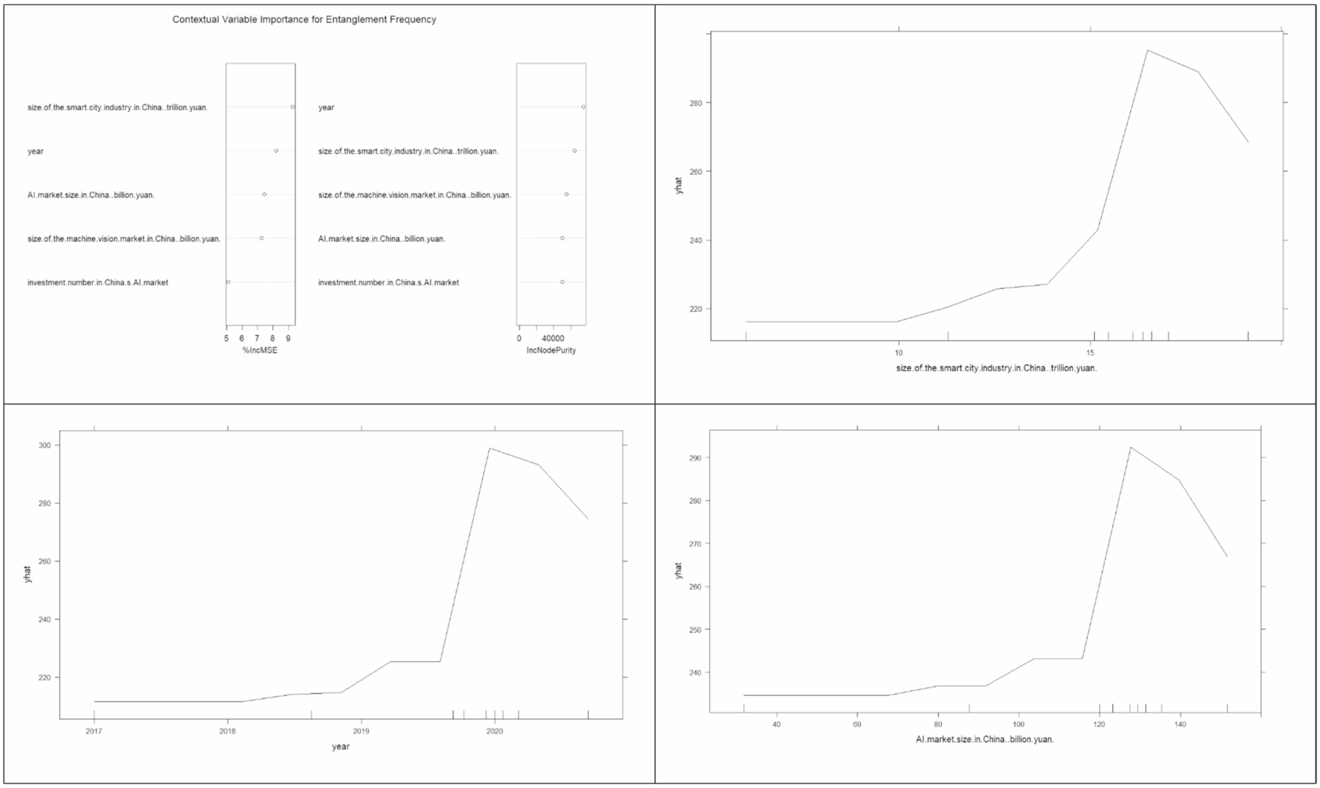

Fig. 3 Panel plot with the results of the partial dependence random forest model

Wang & Zhuang, 2022). Consequently, traditional dependencies between asset and liability structures weaken, leading to a measurable decline in systemic entanglement. Second, greater systemic complexity, often triggered by technological advancement or policy-induced diversification, promotes localized strategic interactions rather than globally entangled behaviors. In such contexts, banks adapt by pursuing specialized financial configurations, resulting in fewer criteria that co-vary significantly across institutions (Haldane & May, 2011; Gai et al., 2011; Caccioli et al., 2018; Huang and Chen., 2021). Third, this decoupling effect can also be interpreted as a form of stabilization, wherein advanced and data-rich environments mitigate volatility and reduce the propagation of shocks across financial indicators (Wu et al., 2024; Wang and Wang, 2022; Aboussalah et al., 2023). Taking together, these patterns suggest that lower entanglement may signal a more mature, resilient, and differentiated financial system, particularly in the face of emerging technological and contextual complexity.

Figure 3 depicts the panel plot for the results of the random forest with partial dependence and their respective plots with respect to trend, size of AI market, and size of smart city industry in China. The plot on the top left corner confirms that the most influential contextual variables are those found to be significant in Table 4. Their influence is measured by the permutation-based importance metric $\Delta_{MSE}(z_l)$ for each variable z_l, as discussed in the methodology (cf. Section 3.2). For example, as for the plot in the top right corner, one may see the nonlinear relationship between the size of the smart city industry in China and the frequency of entangled banking criteria pairs, reflecting a three-phase transition in systemic financial behavior under evolving technological conditions. In the first phase (approximately 7–13 trillion yuan), the relationship is characterized by a flat profile. Here, entanglement frequency remains low and stable, suggesting that banking criteria such as loans, deposits, liquidity, and asset structures operate with a high degree of independence. This phase reflects a pre-entanglement regime, where smart city investments are still in their nascent stages, dispersed across fragmented urban initiatives and lacking the systemic integration required to impose significant structural coordination on banking institutions (He et al., 2024; Song et al., 2023; Lin et al., 2023). At this point, AI and digital infrastructure are not yet sufficiently embedded within the financial ecosystem to induce co-evolution of balance sheet variables. As such, banks maintain traditional siloed operations, with minimal pressure to adapt their internal configurations in response to technological or infrastructural shifts (Fan & Liu, 2021; Xie & Wang, 2023). In the second phase (approximately 13–15.5 trillion yuan), a marked acceleration in entanglement frequency is observed, corresponding to the threshold where smart city development reaches a level of systemic integration and scale. At this juncture, banks begin to interact with a highly digitized urban environment characterized by real-time data flows, AI-managed infrastructure, and interconnected economic agents (Guo & Zhang, 2023; Lin et al., 2023). These external pressures necessitate tighter coupling among internal financial metrics— cf. Figure 2—leading to structural co-dependencies. The entanglement rise in this regime is a manifestation of strategic adaptation, where banks respond to the complexity of urban AI ecosystems by bundling services (e.g., loans linked to infrastructure investment), aligning risk management with urban analytics, and harmonizing financial operations across business lines (Liu et al., 2024; Wang & Zhuang, 2022). In the third phase (beyond ~15.5 trillion yuan), entanglement frequency declines or stabilizes, indicating a shift toward modular equilibrium. Here, the smart city system is mature, standardized, and orchestrated through AI, enabling banks to re-modularize and specialize. Decentralized architectures such as embedded finance, platform banking, and API ecosystems facilitate a return to conditional independence among metrics (Işık et al., 2025; Lin & Chang, 2019). This reflects a broader trend of intelligent autonomy, where complexity is managed through algorithmic control, allowing for selective de-risking and strategic differentiation. Results for the year and size of AI market in China can be interpreted similarly.

The trends observed for year suggest a gradual yet non-linear transformation in the structural configuration of Chinese banks over the study period. In the early years, entanglement frequency remains modest, reflecting a banking system still dominated by traditional operational linkages, regulatory mandates, and limited exposure to large-scale AI or smart city ecosystems. As time progresses—particularly in the mid-period—there is an inflection point where entanglement intensifies. This reflects the integration of digital infrastructure, fintech partnerships, and AI-enabled credit and risk systems, leading to stronger systemic coupling among key balance sheet and performance criteria. Toward the later years, however, this coupling plateaus or slightly recedes, consistent with banks developing modular operational strategies and risk buffers that reduce the propagation of shocks between criteria, in line with the recoherence and modularization mechanisms captured in the QI-MCDM framework.

For the AI market size variable, the partial dependence plot reveals a pattern that parallels but also nuances the smart city effect. At low AI market penetration, banks exhibit relatively high entanglement, often because AI adoption is concentrated among a few large institutions that integrate new systems deeply across multiple functions. As the AI market expands into a mid-range scale, the frequency of entanglement begins to decline. This reflects market diffusion: AI tools become more standardized and widespread, enabling individual banking functions (e.g., payments, credit scoring, liquidity management) to operate with greater autonomy. In QI-MCDM terms, decoherence increases slightly, but fidelity to the ideal benchmark remains stable, indicating that decoupling is a choice rather than a structural breakdown. At the highest levels of AI market size, entanglement is lowest—banks have diversified their AI applications into specialized verticals, resulting in modular configurations that are resilient to localized disturbances and that require less system-wide coordination.

From a QI-MCDM perspective, these trajectories illustrate that rising technological maturity (via AI or smart city development) can drive the system through phases of coherence gain (more entanglement) and coherence release (strategic decoupling). The three quantum-inspired indicators—entanglement, decoherence, and fidelity—allow us to distinguish between beneficial decoupling (high fidelity under low entanglement) and harmful fragmentation (low fidelity with low entanglement), which is a distinction conventional MCDM rankings cannot make.

5 Conclusions

This study proposed a quantum-inspired multi-criteria decision-making (QI-MCDM) framework for evaluating the structural performance of Chinese banks in the context of rapid AI market expansion and smart city development. By embedding classical banking performance indicators into a quantum probability space, the model quantified three structural properties—entanglement among criteria, decoherence from an ideal benchmark, and robustness under noise—that are not captured by traditional MCDM methods.

Empirical analysis revealed substantial variation in QI-MCDM scores across bank types. Joint-stock commercial and agile regional banks exhibited high entanglement, moderate decoherence, and strong fidelity, reflecting integrated decision-making and technological adaptability. In contrast, large state-owned and rural commercial banks showed weaker coherence and greater structural fragmentation, often linked to legacy systems and hierarchical governance.

Comparisons with TOPSIS, VIKOR, and COPRAS demonstrated that QI-MCDM provides non-redundant and more discriminative performance insights, avoiding score inflation, discontinuities, or compression effects common in classical models. Network-based entanglement analysis further showed that certain performance dimensions—such as assets, deposits, liquidity, and securities—are structurally co-dependent, and that the strength of these dependencies is sensitive to contextual factors.

Regression and random forest analyses identified year, AI market size, and smart city industry size as the most influential contextual drivers of entanglement. Partial dependence plots revealed three-phase transitions: from low, stable entanglement in early technological stages, to heightened systemic coupling during intermediate integration, to a modular equilibrium in mature markets. These patterns underscore the dynamic nature of structural performance in technologically evolving financial systems.

From a practical standpoint, the findings suggest several concrete actions for bank managers. In the early stages of technological integration, managers should actively build synergies across units—for example, by establishing cross-functional AI task forces that align credit, liquidity, and risk management functions. During intermediate phases, when systemic entanglement is heightened, managers can mitigate vulnerability by redesigning IT systems into modular architectures, adopting AI-driven risk dashboards, and introducing capital buffers that dampen the transmission of shocks across business lines. In mature AI and smart city contexts, strategic flexibility can be preserved by selectively coupling functions (e.g., linking lending with smart city infrastructure projects) while maintaining operational independence in areas like liquidity management to avoid over-concentration.

For policymakers, the results point to the need for regulation that adapts as banks adopt new technologies. In the early stages, regulators could issue step-by-step guidelines for AI use and encourage banks to keep risks contained within separate units. As adoption expands, stress tests should be updated to capture how problems in one area (such as credit) might spread to others (like liquidity or capital). Tools such as regulatory sandboxes can allow banks to test AI-based solutions in a controlled environment, while targeted incentives can reward banks that build flexible and well-governed structures. These measures would help ensure that technological progress makes the system more resilient, not more fragile.

Despite its contributions, this study is not without limitations. First, the analysis focuses solely on Chinese banks, which may restrict the generalizability of the findings to other banking systems operating under different regulatory regimes and technological conditions. Second, although the dataset incorporates a wide range of financial and contextual indicators, it remains constrained by reliance on publicly available information, which may not fully capture internal strategic or operational dimensions of bank performance. Third, the quantum-inspired constructs applied here—such as entanglement and decoherence—depend on specific methodological assumptions, and alternative formulations or parameterizations could yield different results. Finally, while the study emphasizes AI and smart city markets as contextual drivers, other structural forces (e.g., regulatory shocks, cultural factors, or global financial interdependencies) may also influence performance patterns but were beyond the scope of this paper.

Building on these limitations, future research could extend the QI-MCDM model to cross-country settings—for example, applying it to other emerging markets such as India or Brazil, or to advanced economies like the U.S. or EU—to test whether the entanglement–decoupling dynamics observed in China generalize across different institutional and regulatory contexts. At the methodological level, incorporating higher-frequency or transaction-level data would allow the framework to capture more granular dynamics of systemic coherence. In addition, integrating QI-MCDM with network contagion models or agent-based simulations could provide richer insights into how structural interdependencies propagate under stress scenarios. Finally, exploring hybrid quantum–machine learning or explainable AI approaches could not only improve predictive power but also enhance the interpretability of entanglement patterns for both managers and policymakers.

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Declarations

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