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ARTICLE

COMPETITIVE INTELLIGENCE-DRIVEN FINANCIAL ANALYTICS: A STRATEGIC FRAMEWORK FOR ENVIRONMENTAL SCANNING AND SUSTAINABLE DECISION SUPPORT IN FINANCIAL SOFTWARE

ANÁLISE FINANCEIRA ORIENTADA POR INTELIGÊNCIA COMPETITIVA: UM FRAMEWORK ESTRATÉGICO PARA MONITORAMENTO AMBIENTAL E SUPORTE À TOMADA DE DECISÃO SUSTENTÁVEL EM SOFTWARE FINANCEIRO

[1]**Pengchong Chen:** Southwestern University of Finance and Economics Tianfu College, Sichuan, China. ORCID: https://orcid.org/0009-0004-8656-8226

[2*]**Tao Huang:** Southwestern University of Finance and Economics Tianfu College, Sichuan, China. ORCID: https://orcid.org/0009-0007-8302-8197

Corresponding Author:
Tao Huang
E-mail: tommyh@vip.163.com

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ABSTRACT

Purpose: To examine how Competitive Intelligence (CI) can be operationalized within financial software to support environmental scanning, strategic signal identification, and sustainable decision-making under volatile conditions.

Methodology/Approach: A quantitative, design-oriented approach was applied to OpenFinData, comprising 1,500 records across 19 financial tasks mapped into 12 CI dimensions. The analysis combined data preprocessing, TF-IDF, dimensionality reduction, clustering, and exploratory indicators of information density, responsiveness, and strategic fit.

Originality/Relevance: The study integrates Competitive Intelligence, Financial Analytics, and Dynamic Capabilities, positioning financial software as enabling infrastructure for organizational intelligence processes while distinguishing computational capability from organizational CI capability.

Key Findings: The findings reveal different levels of coverage and alignment between analytical workloads and CI dimensions, with greater concentration in investment intelligence and risk and compliance intelligence. Workload structure shows potential to support organizational sensing and strategic decision support but should not be interpreted as a direct measure of organizational CI maturity.

Theoretical/Methodological Contributions: The study extends the interface among CI, Environmental Scanning, Financial Analytics, and Dynamic Capabilities and proposes a reproducible procedure for mapping analytical demands into CI dimensions and assessing their strategic alignment.

Keywords: Competitive Intelligence. Environmental Scanning. Strategic Decision Support. Financial Software. Sustainable Competitive Advantage. Dynamic Capabilities. Financial Analytics

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RESUMO

Objetivo: Analisar como a Inteligência Competitiva (CI) pode ser operacionalizada em softwares financeiros para apoiar o monitoramento ambiental, a identificação de sinais estratégicos e a tomada de decisão sustentável em ambientes de elevada volatilidade.

Metodologia/abordagem: Adotou-se uma abordagem quantitativa e orientada ao design, utilizando o OpenFinData, composto por 1.500 registros distribuídos em 19 tarefas financeiras. As tarefas foram mapeadas em 12 dimensões de CI. A análise combinou pré-processamento de dados, TF-IDF, redução de dimensionalidade, clustering e indicadores exploratórios de densidade informacional, responsividade e alinhamento estratégico.

Originalidade/Relevância: O estudo integra Competitive Intelligence, Financial Analytics e Dynamic Capabilities, posicionando softwares financeiros como infraestrutura habilitadora de processos de inteligência organizacional e distinguindo capacidade computacional de capacidade organizacional de CI.

Principais resultados: Os resultados identificam diferentes níveis de cobertura e alinhamento entre as cargas analíticas e as dimensões de CI, com maior concentração em inteligência de investimento, risco e compliance. A estrutura das cargas analíticas apresenta potencial para apoiar o organizational sensing e o suporte à decisão, sem representar, contudo, uma medida direta de maturidade organizacional em CI.

Contribuições teóricas/metodológicas: O estudo amplia a interface entre CI, Environmental Scanning, Financial Analytics e Dynamic Capabilities e propõe um procedimento reproduzível para mapear demandas analíticas em dimensões de CI e avaliar seu alinhamento estratégico.

Palavras-chave: Inteligência Competitiva. Monitoramento Ambiental. Suporte à Decisão Estratégica. Software Financeiro. Vantagem Competitiva Sustentável. Capacidades Dinâmicas. Análise Financeira.

1. INTRODUCTION

Regulatory change, technological innovation, competitor actions, and shifts in consumer and investor behaviour continually reshape financial markets. Contemporary Competitive Intelligence (CI) research emphasizes the systematic collection, interpretation, and communication of external information to support strategy implementation, innovation, resilience, and organizational adaptation (Bao, 2020; Cavallo et al., 2021; Harris & Brooker, 2025; Hassani & Mosconi, 2022; Ibrahim et al., 2025; Ledi, 2024; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023; Ranjan & Foropon, 2021; Tsuchimoto & Kajikawa, 2022; Wu et al., 2023). In finance, the central challenge is therefore not simply the volume of available data, but the timely conversion of diverse signals into decision-relevant intelligence.

Financial software has become more than a reporting interface; it is a decision-support environment capable of processing and storing filings, market data, news, customer interactions, and regulatory information. Although artificial intelligence and analytics can increase the speed and scale of this work, technical performance alone does not guarantee intelligence value (Černevičienė & Kabašinskas, 2024;

Goodell et al., 2021; Hassani & Mosconi, 2022; Nagarathinam et al., 2024; Ranjan & Foropon, 2021). From a CI perspective, analysis becomes strategically useful only when it responds to a defined intelligence requirement, preserves source traceability, supports interpretation, and communicates assessable implications to decision makers (Cavallo et al., 2021; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024; Ranjan & Foropon, 2021). Accordingly, benchmark accuracy or coverage cannot substitute for an organizational intelligence process.

To fill this gap, this study proposes a CI dimensional model, based on which the OpenFinData, which is a financial evaluation dataset open and released in China and contains 1,500 data records in nineteen task files (East Money Information Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024), is analyzed in a reproducible manner. The corpus is considered evidence of the questions which financial software is expected to address, not as direct evidence of the maturity of organizations in terms of CI. The research question is formulated as follows: How much does the distribution of analytical workloads in financial software correspond to the known dimensions of the CI, and in what respects does the distribution show a lack in the development of the strategic support?

The study has four contributions. First, it aligns nineteen financial tasks with twelve CI dimensions, providing a common vocabulary for connecting financial tasks to intelligence requirements. Second, it uses workload composition as a proxy for the potential of analytical infrastructures to support organizational sensing. Third, it integrates current CI and dynamic-capability research to distinguish information processing from organizational sensing, seizing, and reconfiguration (Hassani & Mosconi, 2022; Madureira et al., 2021; Maungwa & Laughton, 2023; Soluk et al., 2021; Wu et al., 2023). Fourth, it proposes a transparent strategic-fit score for workload auditing and software procurement without implying that the score measures firm performance or organizational CI maturity.

The rest of the paper is laid out as follows. In Section 2, the theoretical framework is developed by synthesizing the latest and fundamental research on Competitive Intelligence, environmental scanning, strategic analysis, Dynamic Capabilities and financial analytics. In Section 3, the dataset, preprocessing pipeline, analytical framework and organizational-validation boundary will be described. Results and interpretation of descriptive, clustering, information-density, responsiveness, and strategic-fit tests are reported and interpreted in Section 4 from the perspective of organizational decision support. Section 5 outlines the conclusions and constraints as well as further research and future directions.

2. THEORETICAL FRAMEWORK

2.1 Competitive Intelligence and Strategic Response

Competitive Intelligence is a systematic management effort to transform internal and external information into useful intelligence for decision making. Contemporary research describes CI as a managerial process that connects intelligence requirements, ethical information gathering, analysis, interpretation, communication, and feedback with strategy and organizational action (Cavallo et al., 2021; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024; Tsuchimoto & Kajikawa, 2022). The decision requirement, rather than data availability alone, therefore determines what information should be collected and how it should be interpreted. Recent studies extend this managerial perspective to digital resources, innovation, resilience, strategy implementation, and organizational capabilities (Bao, 2020; Hassani & Mosconi, 2022; Ibrahim et al., 2025; Ledi, 2024; Ranjan & Foropon, 2021; Wu et al., 2023).

CI is inherently forward-looking because environmental scanning enables organizations to detect weak signals, emerging threats, and opportunities before they become fully visible. Contemporary research connects scanning with futures-oriented evaluation, digital information environments, strategy formulation, and dynamic capabilities (Cavallo et al., 2021; Harris & Brooker, 2025; Hassani & Mosconi, 2022). Scanning becomes strategically meaningful when signals are interpreted against a defined intelligence requirement and incorporated into planning, discussion, and organizational response rather than stored as undifferentiated information (Madureira et al., 2021; Maungwa & Laughton, 2023, 2024).

Contemporary CI scholarship defines the field as both an organizational process and a strategic capability. It connects intelligence work with strategy implementation, cross-functional coordination, intermediary roles, resilience, sustainable competitiveness, and innovation (Bao, 2020; Cavallo et al., 2021; Ibrahim et al., 2025; Ledi, 2024; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024; Tsuchimoto & Kajikawa, 2022; Wu et al., 2023). Across these studies, CI is not treated as data collection alone; its value depends on connecting evidence with a decision context, analytical interpretation, and organizational action.

Dynamic-capability research explains how intelligence can support adaptation by helping organizations recognize changes, mobilize responses, and adjust resources and routines. Recent studies show that these adaptive processes become more valuable when digital resources and analytical capabilities are integrated into organizational practice (Hassani & Mosconi, 2022; Moreira et al., 2025; Soluk et al., 2021; Van Hoang et al., 2025; Wu et al., 2023). The present study concentrates on analytical support for sensing by examining whether financial workloads represent strategically relevant information demands. The analysis may inform, but cannot demonstrate, seizing, reconfiguration, or sustained competitive advantage.

2.2 Big Data Analytics, Business Intelligence and Competitive Advantage

Business Intelligence (BI) and big-data analytics provide important infrastructure for CI, but they are not equivalent to CI. Their strategic integration begins with a defined intelligence requirement and ends with interpreted implications communicated for action (Cavallo et al., 2021; Hassani & Mosconi, 2022; Korayim et al., 2024; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024; Nagarathinam et al., 2024; Ragazou et al., 2023; Ranjan & Foropon, 2021; Rixin et al., 2025). Empirical research suggests that analytical capabilities generate greater value when supported by governance, data culture, organizational innovation, and managerial interpretation (Korayim et al., 2024; Rixin et al., 2025). Strategic contribution therefore depends on the intelligence process surrounding the technology, not only on computational capacity.

2.3 Financial Software, FinTech, and Decision Support

Financial software now serves as a multilayered decision-support environment in which statements and filings, prices and news, transactions, and regulatory information converge. Its organizational value is defined not only by speed, but also by the provision of provenance, explainability, data-quality controls, and a clear relationship between analytical output and the decision being supported (Černevičienė & Kabašinskas, 2024; Goodell et al., 2021; Nagarathinam et al., 2024). These requirements are consistent with contemporary CI research emphasizing strategic relevance, source quality, contextual interpretation, and decision-focused communication (Cavallo et al., 2021; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024).

The same as with green finance and environmental, social and governance analysis. The managerial effect necessarily relies on the interpretation of, and the way, the signals are integrated into the governance process, as this could extend the range of signals that are taken into account in the capital-allocation and compliance decision (Almaqtari et al., 2025; Chenguel & Mansour, 2024; Lim, 2024; Wang et al., 2024). The use of financial software should thus be considered an intelligence infrastructure as a complement to, not a substitute for, the judgment of the organization.

2.4 Financial Artificial Intelligence as an Enabling Layer

In financial decision processes, AI tools can support document review, sentiment analysis, anomaly detection, forecasting, and question answering (Černevičienė & Kabašinskas, 2024; Davenport et al., 2020; Goodell et al., 2021). Their relevance to CI does not arise automatically from automation; rather, they expand the speed and scale at which evidence can be screened. Strategic use still requires a defined intelligence need, reliable sources, transparent interpretation, and accountable human judgment (Ashal & Morshed, 2024; Cavallo et al., 2021; Černevičienė & Kabašinskas, 2024; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024; Ranjan & Foropon, 2021).

Financial benchmarks are used here only to delimit the types of analytical demand faced by current systems, not as sources defining CI theory. FinBen and CFinBench cover financial text analysis, reasoning, risk, and professional knowledge tasks (Nie et al., 2025; Xie et al., 2024), while OpenFinData provides the documentary workload examined in this study (East Money Information Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024). These benchmarks describe task coverage, but they neither define CI nor demonstrate organizational maturity or decision quality. The theoretical discussion therefore remains focused on environmental scanning, intelligence requirements, analysis, dissemination, and organizational adaptation as addressed in current CI research (Bao, 2020; Cavallo et al., 2021; Harris & Brooker, 2025; Hassani & Mosconi, 2022; Ibrahim et al., 2025; Ledi, 2024; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024; Ranjan & Foropon, 2021; Tsuchimoto & Kajikawa, 2022; Wu et al., 2023).

2.5 Sentiment, Entity, and Compliance Intelligence

Dictionary-based scoring approaches for financial sentiment analysis have been replaced by domain-adapted machine-learning and transformer-based methods (Du et al., 2024; Todd et al., 2024). Sentiment should be considered as a preliminary indicator for CI as a reliable gauge of market expectations, stakeholder responses and reputational shifts but should be used in conjunction with source credibility, context and materiality. Sentiment analysis, however, is not a stand-alone decision rule; it is a tool to assist a manager in interpretation, as supported by the literature.

Compliance classifications can connect a signal to a specific firm, instrument, regulator, customer, or jurisdiction, improving traceability and reducing ambiguity during interpretation. Explainable-AI research indicates that automated classifications used in financial decision making require transparent evidence and accountable governance (Černevičienė & Kabašinskas, 2024; Lim, 2024). These functions support information collection and analysis, but managerial interpretation and communication remain necessary before action is taken (Cavallo et al., 2021; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024).

2.6 Market, Sector, and Compliance Analytics as Intelligence Inputs

Market, sector, and compliance analytics contribute to CI by informing decision makers about competitive position, emerging risks, and changes in the external environment. The decisive issue is not algorithmic novelty, but whether the analytical product is reliable, explainable, timely, and connected to a specific intelligence objective (Cavallo et al., 2021; Černevičienė & Kabašinskas, 2024; Goodell et al., 2021; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2024; Nagarathinam et al., 2024). Accordingly, stock-prediction model comparisons are not treated as the theoretical core of financial intelligence; analytical methods are positioned as tools within a broader organizational process.

This organizational perspective also limits the interpretation of technical performance evidence. Prediction, classification, and extraction can inform a decision, but they cannot replace contextual interpretation, accountability, uncertainty assessment, or communication with the responsible manager. These requirements align with contemporary CI research, which emphasizes decision-defined needs, disciplined analysis, and purposeful communication (Cavallo et al., 2021; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024).

2.7 Dynamic Capabilities, Digital Maturity, and Sustainable Advantage

Dynamic capabilities provide the organizational context in which market, sector, and compliance analytics become strategically useful. Analytical outputs contribute when they help decision makers recognize environmental change, evaluate response options, and adjust resources or routines (Hassani & Mosconi, 2022; Soluk et al., 2021; Van Hoang et al., 2025; Wu et al., 2023). Their value therefore depends less on algorithmic novelty than on reliability, explainability, timeliness, and alignment with a defined intelligence need (Černevičienė & Kabašinskas, 2024; Goodell et al., 2021; Nagarathinam et al., 2024).

Technical performance alone cannot demonstrate sustainable advantage. Prediction, classification, and extraction may strengthen sensing, but they do not replace contextual interpretation, accountability, uncertainty assessment, or communication with responsible managers. Sustainable value arises when analytical outputs are embedded in organizational processes that connect evidence with coordinated action (Cavallo et al., 2021; Hassani & Mosconi, 2022; Soluk et al., 2021; Van Hoang et al., 2025; Wu et al., 2023).

2.8 Comparative Synthesis of Contemporary Literature

Table 1 synthesizes twenty-one contemporary sources selected for their direct relevance to environmental scanning, intelligence needs, CI processes, organizational sensing, dynamic capabilities, analytics, and managerial decision support. The selected studies show how CI principles operate in digital and data-intensive settings while maintaining an organizational emphasis. Only one financial-AI review is retained in the synthesis table, preventing technical model studies from overshadowing the strategic literature.

Year	Author(s)	**Topical Focus**	**Method**	**CI Relevance**
2023	Maluleka & Chummun	CI and strategy implementation	Critical literature review	High
2022	Tsuchimoto & Kajikawa	CI practices in Japanese firms	Multiple-case study	High
2024	Ledi	CI, resilience, and frugal innovation	Survey and SEM	High
2021	Ranjan & Foropon	Big-data analytics for CI	Conceptual framework	High
2025	Harris & Brooker	Environmental scanning and futures	Methodological review	High
2021	Cavallo et al.	CI and strategy formulation	Multiple-case study	High
2023	Ragazou et al.	BI for SME decision support	Bibliometric and conceptual study	High
2025	Rixin et al.	Analytics capability in Chinese SMEs	PLS-SEM survey	High
2024	Korayim et al.	Analytics and organizational innovation	Quantitative study	High
2022	Hassani & Mosconi	CI, analytics, and dynamic capabilities	SME survey	High
2024	Nagarathinam et al.	Strategic data analytics	Conceptual chapter	High
2021	Soluk et al.	Dynamic capabilities and digital innovation	Large-sample survey	High
2024	Maungwa & Laughton	Eliciting intelligence needs	Grounded-theory interviews	High
2025	Moreira et al.	SME digital transformation	Multidimensional measurement	High
2025	Van Hoang et al.	Digital capabilities and sustainable advantage	PLS-SEM study	High
2025	Ibrahim et al.	CI and sustainable competitiveness	Empirical mediation model	High
2021	Madureira et al.	Unified definition of CI	Mixed-method theory building	High
2023	Maungwa & Laughton	Theory use in CI research	Systematic literature review	High
2023	Wu et al.	CI and dynamic capabilities in SMEs	Empirical model	High
2020	Bao	CI and service innovation	Empirical study	High
2024	Černevičienė & Kabašinskas	Explainable AI in finance	Systematic review	Medium

Table 1. Comparative synthesis of twenty-one contemporary sources on competitive intelligence, organizational capabilities, and financial decision support.

2.9 Conceptual Framework of Competitive Intelligence Operationalization

Figure A presents the conceptual architecture proposed in this study. Competitive Intelligence is positioned as an organizational sensing capability supported, but not replaced, by financial software. Regulatory volatility, market uncertainty, technological disruption, competitor behaviour, and ESG pressures generate signals that enter the system as analytical workloads. Environmental scanning, analytical computation, sentiment interpretation, entity resolution, and market analysis organize those signals for managerial review. The framework begins with decision-defined intelligence needs (Maungwa & Laughton, 2024), draws on current scanning and strategic-analysis research (Cavallo et al., 2021; Harris & Brooker, 2025; Madureira et al., 2021; Maungwa & Laughton, 2023), and links sensing to decision support while reserving seizing and reconfiguration for subsequent organizational action (Hassani & Mosconi, 2022; Soluk et al., 2021; Wu et al., 2023).

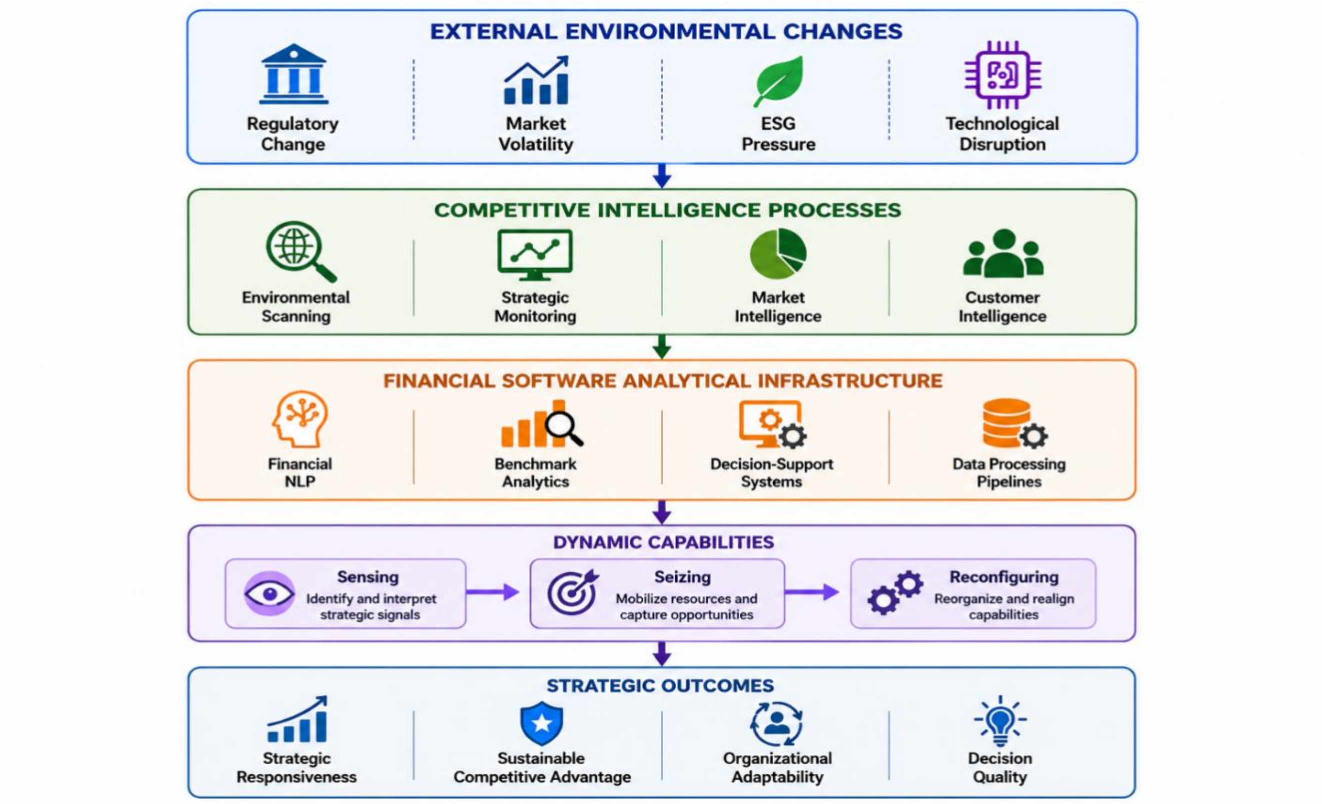

Figure A. Conceptual Framework Linking Competitive Intelligence, Financial Software, and Strategic Decision Support

3. METHOD

3.1 Research Design and Analytical Stance

The research design is quantitative and design-oriented. It treats the OpenFinData corpus as a structured representation of analytical demand and examines the distribution, density, and latent similarity of those demands (East Money Information Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024). The unit of computation is the record, whereas the unit of interpretation is the organizational intelligence requirement represented by the record. The study does not evaluate the predictive accuracy of a specific model and does not claim to measure a complete CI cycle.

3.1.1 Organizational Interpretation of the Analytical Framework

Although the empirical analysis is computational, the interpretive question is organizational: what kinds of intelligence demands are represented in the software workload? OpenFinData is therefore treated as a documentary artefact of analytical demand, not as a sample of firms or managers (East Money Information

Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024). The study evaluates corpus structure and construct alignment only. It does not claim that a benchmark score demonstrates CI maturity, decision quality, or financial performance. This boundary follows contemporary CI research by separating analytical inputs from organizational interpretation and action (Madureira et al., 2021; Maungwa & Laughton, 2023, 2024).

3.1.2 Organizational Validation Boundary and Triangulation Protocol

Three evidentiary levels are kept separate. Level 1 is corpus evidence: record counts, prompt structure, rubric concentration, and latent similarity. Level 2 is construct interpretation: the transparent mapping of tasks to CI dimensions using contemporary CI literature (Bao, 2020; Cavallo et al., 2021; Harris & Brooker, 2025; Hassani & Mosconi, 2022; Ibrahim et al., 2025; Ledi, 2024; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024; Ranjan & Foropon, 2021; Tsuchimoto & Kajikawa, 2022; Wu et al., 2023). Level 3 is organizational validation: practitioner agreement, observation of real decisions, and evidence that workload gaps correspond to delayed or inferior responses. Only Levels 1 and 2 are examined here. A complete validation study should combine independent practitioner coding, inter-rater agreement, interviews with analysts and procurement managers, and longitudinal case evidence. This protocol addresses the benchmark-orientation concern without inventing organizational data that were not collected.

3.2 Dataset Description

The empirical basis is OpenFinData, an openly released Chinese financial evaluation dataset developed by East Money Information and Shanghai Artificial Intelligence Laboratory (East Money Information Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024). The version analysed contains 1,500 records distributed across nineteen JSON task files. Each record includes an identifier, a Chinese-language question, and a schema-dependent answer payload. The corpus contains 575 multiple-choice items, 700 rubric-scored items, and 225 open-ended question-answering items. The question texts have a mean length of 490.38 characters (SD = 901.32).

The nineteen task files were mapped to twelve CI dimensions: investment intelligence, environmental scanning, sentiment intelligence, risk and compliance intelligence, entity intelligence, knowledge intelligence, customer intelligence, sector intelligence, market intelligence, macro intelligence, data-quality audit, and analytical computation. The mapping was developed from task definitions and interpreted against environmental-scanning research, intelligence-needs literature, CI process models, and recent empirical CI applications (Bao, 2020; Cavallo et al., 2021; Harris & Brooker, 2025; Hassani & Mosconi, 2022; Ibrahim et al., 2025; Ledi, 2024; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024; Ranjan & Foropon, 2021; Tsuchimoto & Kajikawa, 2022; Wu et al., 2023). Investment intelligence is the largest dimension, with 375 records, while risk and compliance intelligence and entity intelligence each contain 150 records.

3.3 Computational Environment

All preprocessing and analyses were performed in a Kaggle-compatible Python 3.11 environment. pandas 2.2 and NumPy 2.0 were used for data handling, scikit-learn 1.5 for vectorization, dimensionality reduction, clustering, and diagnostics, and Matplotlib 3.9 for figure generation. The 1,500-record corpus can be processed on a standard CPU; optional CUDA-enabled libraries were retained only to support larger replications.

3.4 Preprocessing Pipeline

The schema-aware loading was the first feature in the pre-processing pipeline. Multiple-choice, rubric-scored and open-question records were identified using field names and then each observation was mapped to a task, identifier, question, schema, number of options, answer and rubric fields (East Money Information Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024). Normalization: whitespace was normalized, tokenization: Han characters, Latin words and numeric groups were separated with a Unicode-aware regular expression. The answers in cases where the responses were missing or empty were given the explicit label unanswerable, and 150 of these cases appeared in the business-compliance subset and were retained with an imputation flag.

1500 records were analysed and no records were discarded after checking for exact question duplication. Question-length z scores were calculated to identify observations more than 3 SDs from the mean; however, flagged observations were not excluded because they are part of the workload intended to be conducted on the questions. The four numeric variables - question characters, token count, answer characters, and option count - were standardized, with task, schema, and CI dimension being encoded as categorical features. Then the character bigram and trigram TF-IDF features were extracted, which resulted in a 1,500 x 2,000 sparse matrix with the minimum document frequency set as three and the maximum vocabulary set as 2,000 features.

3.5 Analytical Framework

The analytical framework contains five operations that transform the cleaned workload into descriptive strategic signals. These measures are author-defined analytical devices and should not be interpreted as established organizational scales. Equation 1 specifies TF-IDF weighting for text representation.

$$w(t, d) = tf(t, d) \cdot \log((|D| + 1) / (df(t) + 1)) + 1 \quad (1)$$

In Equation 1, tf(t, d) is the frequency of term t in document d, df(t) is the number of documents containing t, and |D| is the corpus size. Smoothing prevents division by zero and stabilizes weights for rare terms.

Equation 2 defines the information-density score I_d, an exploratory measure combining option count and token count. It is intended to describe prompt structure rather than cognitive difficulty or strategic importance.

$$I\_d(q) = (n\_opt(q) + 1) \cdot \ln(1 + n\_tok(q)) \quad (2)$$

In Equation 2, n_opt(q) is the number of explicit response options and n_tok(q) is the number of Chinese, Latin, and numeric tokens in question q. Adding one gives open and rubric-scored questions a non-zero value, while the logarithm reduces the leverage of exceptionally long prompts.

Equation 3 defines the responsiveness index rho for dimensions containing rubric-scored records. The index summarizes the mean weight of the highest-scored rubric criterion in each record. It captures rubric concentration, not observed organizational response speed.

$$rho(c) = (1 / |R\_c|) \cdot sum\_\{q \text{ in } R\_c\} \max\_k s\_k(q) \quad (3)$$

In Equation 3, R_c is the set of rubric records in CI dimension c and s_k(q) is the weight assigned to criterion k for record q. For dimensions without rubric records, the global median rho is used solely to retain a common computational scale; this imputation is reported as a limitation.

Equations 4a and 4b define the K-means objective and the silhouette coefficient used in exploratory cluster selection. Candidate values of K from four to twelve were compared, and the solution with the highest mean silhouette coefficient was retained.

$$J(K) = sum\_\{i=1..K\}\ sum\_\{x \text{ in } C\_i\}\ || x - mu\_i ||\text{^}2 \quad (4a)$$

$$s(x) = (b(x) - a(x)) / \max(a(x), b(x)) \quad (4b)$$

In Equation 4a, C_i is cluster i and mu_i is its centroid in the LSA-projected space. In Equation 4b, a(x) is the mean distance between x and points in its assigned cluster, while b(x) is the smallest mean distance between x and another cluster.

Equation 5 defines the composite strategic-fit score S(c), which summarizes workload coverage, information density, rubric concentration, and within-dimension cohesion. The score is a transparent diagnostic for this corpus and is not presented as a validated CI maturity index.

$$S(c) = 0.30 \cdot C(c) + 0.25 \cdot I(c) + 0.30 \cdot rho(c) + 0.15 \cdot K(c) \quad (5)$$

In Equation 5, C(c) is log-normalized record coverage, I(c) is min-max normalized mean information density, rho(c) is the rubric-concentration index, and K(c) is one minus the normalized within-dimension standard deviation of information density. The weights distribute influence across the four components and were selected for exploratory balance rather than estimated from organizational outcomes. Moderate weight perturbations did not change the identity of the highest- and lowest-ranked dimensions. Expert elicitation, Delphi assessment, or multicriteria validation is nevertheless required before the composite can be used for procurement or organizational capability assessment (Ibrahim et al., 2025; Madureira et al., 2021; Maungwa

& Laughton, 2023, 2024; Nagarathinam et al., 2024).

3.6 Pipeline Workflow and Algorithm

Figure 1 shows the workflow from the OpenFinData JSON files to the dimension-level strategic-fit table (East Money Information Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024). Schema-aware parsing, text processing, numeric standardization, and TF-IDF representation feed the information-density, rubric-concentration, dimensionality-reduction, and clustering stages. The final layer translates the descriptive outputs into a bounded managerial interpretation.

Figure 1. Analytical pipeline for the strategic-framework study

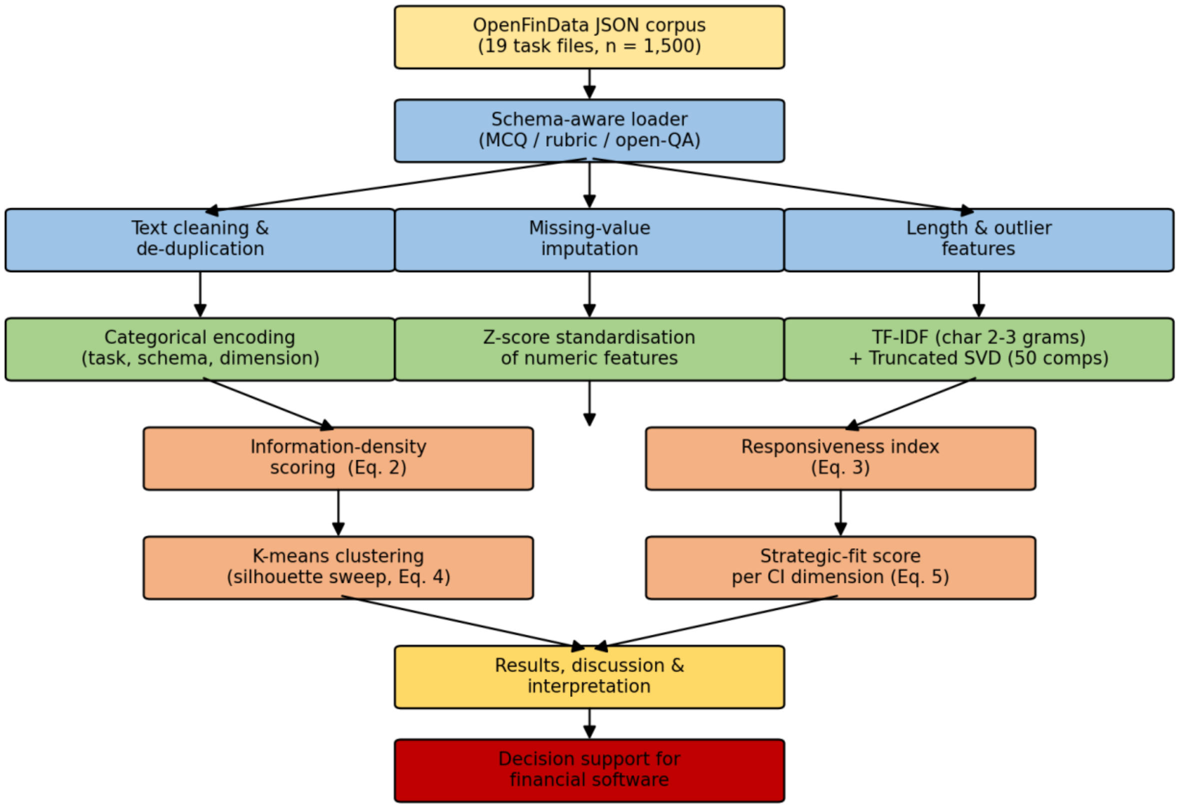

Figure 1. Analytical pipeline from raw OpenFinData JSON files to strategic-fit ranking, including the preprocessing, feature engineering, scoring and clustering stages used in this study.

Algorithm 1 summarizes the procedure for reproducibility. It loads the JSON files, detects schema, normalizes text, flags missing answers, encodes categorical variables, standardizes numeric features, creates the TF-IDF representation, performs truncated SVD and K-means selection, calculates the exploratory indices, and ranks the CI dimensions.

Algorithm 1: Strategic Fit Pipeline. Input: directory D of JSON files. Output: dataframe of records with cluster labels and a CI-dimension-level strategic-fit table.

Step 1: load each OpenFinData JSON file and detect its schema (East Money Information Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024). Step 2: normalize question and answer text and retain missing answers with an explicit imputation flag. Step 3: check exact duplicates and flag question-length outliers without deleting valid long prompts. Step 4: encode task, schema, and CI dimension. Step 5: standardize the numeric feature block. Step 6: build the character bigram and trigram TF-IDF matrix using Equation 1. Step 7: project the matrix into a 50-dimensional LSA space. Step 8: calculate information density and rubric concentration using Equations 2 and 3. Step 9: compare K values from four to twelve using Equation 4. Step 10: calculate and rank the dimension-level strategic-fit scores using Equation 5. Citations to unrelated forecasting studies were removed because these implementation steps are defined and reported directly in the present method.

4. RESULTS AND DISCUSSIONS

4.1 Descriptive Statistics and Schema Distribution

After preprocessing, the corpus contained 1,500 unique records across nineteen tasks and twelve CI dimensions. There were no exact duplicate questions. A total of 150 missing or empty answer fields, all located in the business-compliance subset, were labelled unanswerable and retained with an imputation indicator (East Money Information Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024). Question length was strongly right-skewed: the median was 211 characters, the mean was 490.38 (SD = 901.32), and the maximum was 10,278 characters.
Figure 2 shows that investment intelligence is the largest dimension, followed by risk and compliance intelligence, entity intelligence, knowledge intelligence, and analytical computation. Rubric-scored records account for 46.7% of the corpus, multiple-choice records for 38.3%, and open-ended records for 15.0%. Figure 3 presents the schema composition and the heavy-tailed question-length distribution on a logarithmic axis.

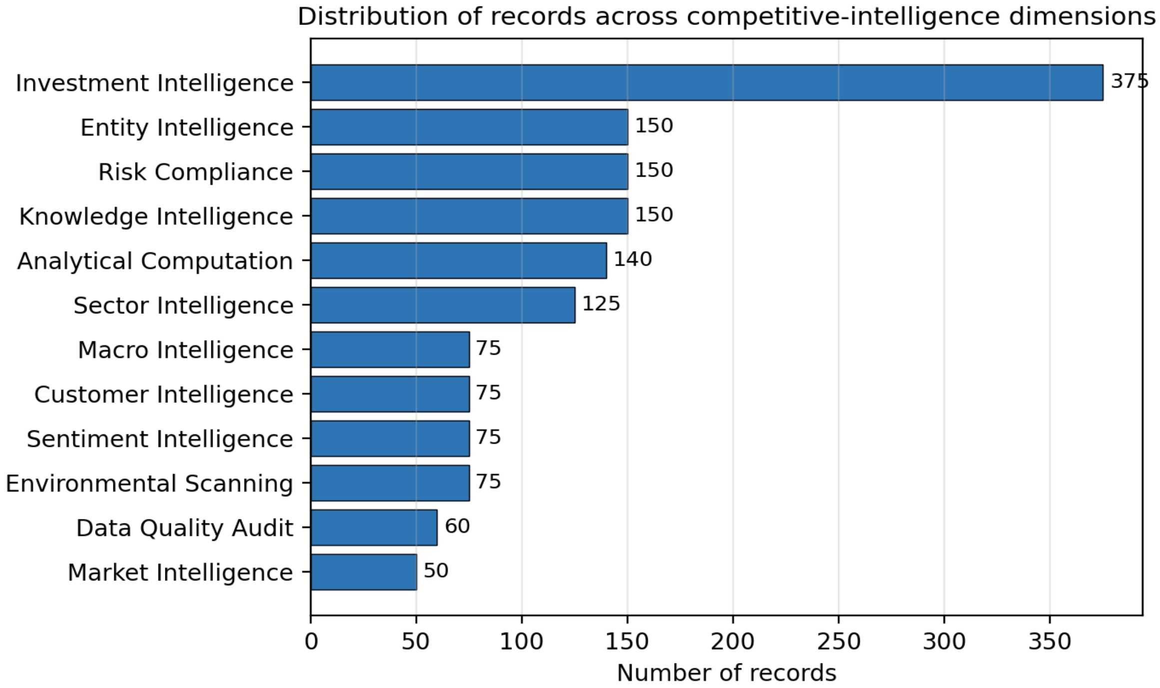

Figure 2. Distribution of records across the twelve competitive-intelligence dimensions in the cleaned OpenFinData corpus.

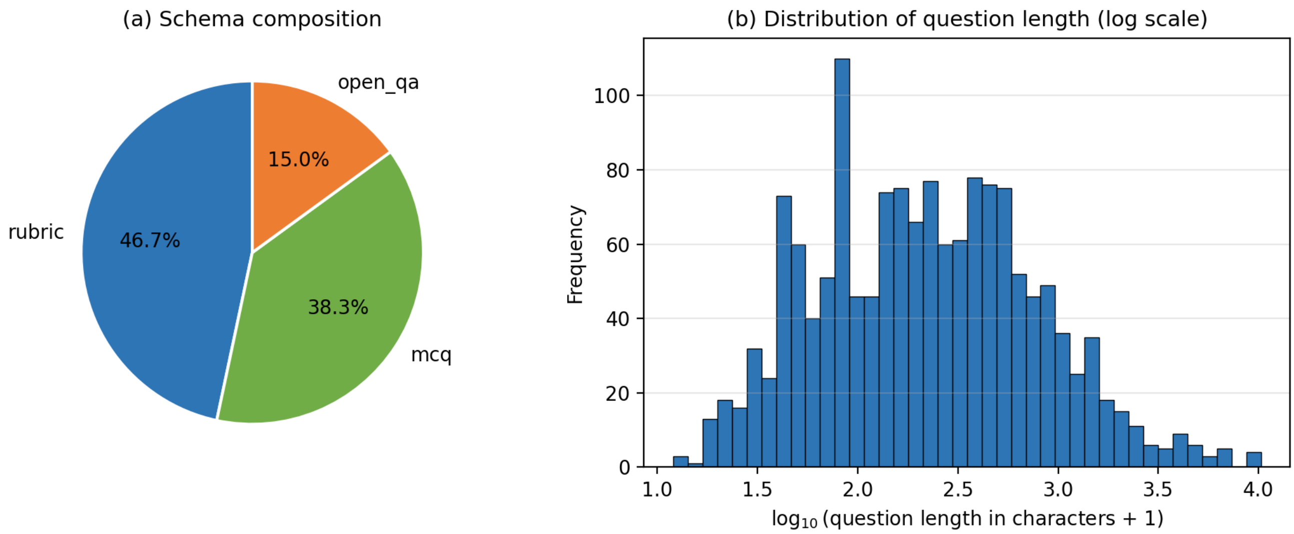

Figure 3. Schema composition (left) and log-scaled question-length distribution (right) across all 1,500 cleaned records.

Table 2 reports the descriptive statistics for the four numeric features used in standardization. The wide dispersion in question length and token count supports the logarithmic damping in Equation 2 and z-score scaling before clustering. These transformations are methodological choices reported for reproducibility rather than claims derived from external forecasting studies.

Feature	Mean	Std	Min	Median	Max
Question characters	490.38	901.32	11	211	10,278
Question tokens	177.66	185.31	11	121.5	1,974
Answer characters	59.79	74.79	1	4	534
Number of options	3.14	1.60	0	4	7

Table 2. Descriptive statistics for the four numeric features used in the preprocessing pipeline (n = 1,500).

4.2 Multiple-Choice Answer-Key Diagnostics

Within the 575 multiple-choice records, the answer-key distribution was uneven: B accounted for 33.2% of correct responses, A for 29.2%, C for 21.9%, D for 13.9%, and E for 1.7%. Figure 4 compares this distribution with a uniform 0.20 reference. Task-level answer entropy ranged from 0.678 for entity disambiguation to 1.400 for intent understanding, indicating that some task files concentrate correct answers more heavily than others.

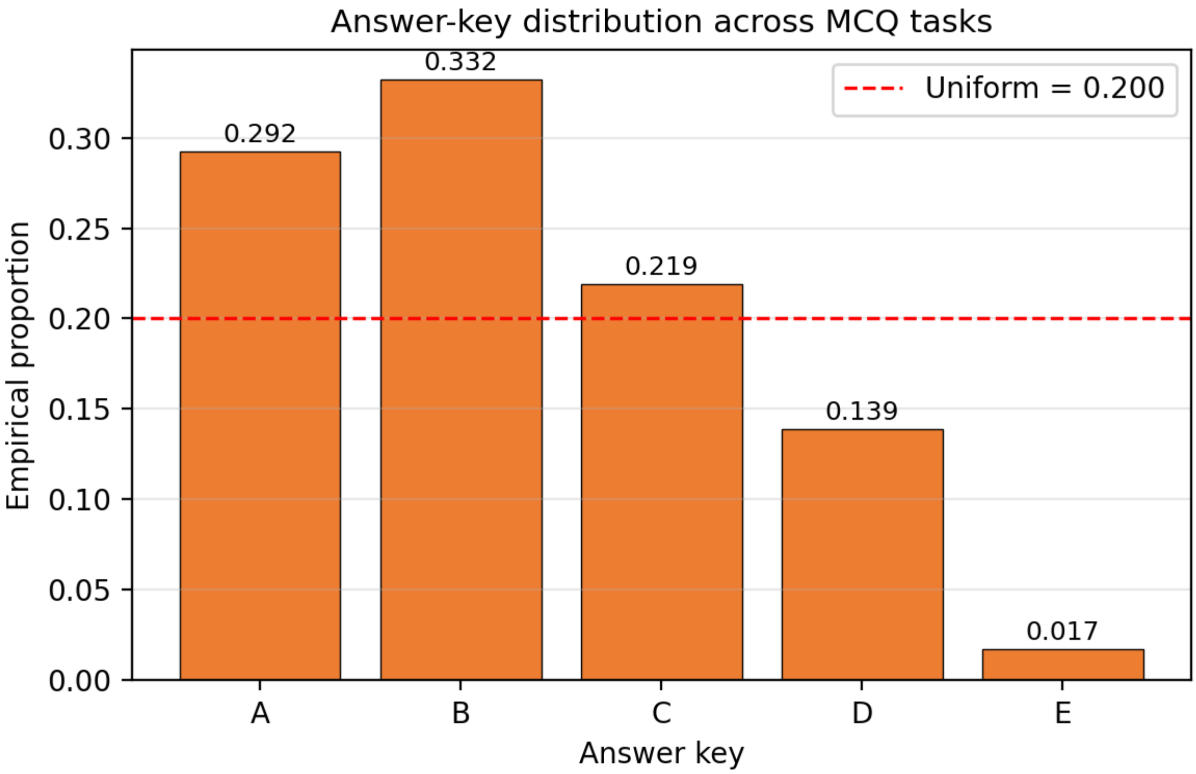

Figure 4. Empirical answer-key distribution across all multiple-choice tasks (n = 575) compared to the uniform reference line.

4.3 Information Density by CI Dimension

The exploratory information-density score shows marked differences across dimensions. Environmental scanning had the highest mean value (28.13), followed by sector intelligence (27.61), customer intelligence (25.54), and market intelligence (24.55); risk and compliance intelligence had the lowest mean (3.48). Figure 5 displays the distributions by dimension. Because the score is partly driven by prompt length, the result indicates structural workload intensity rather than superior strategic importance.

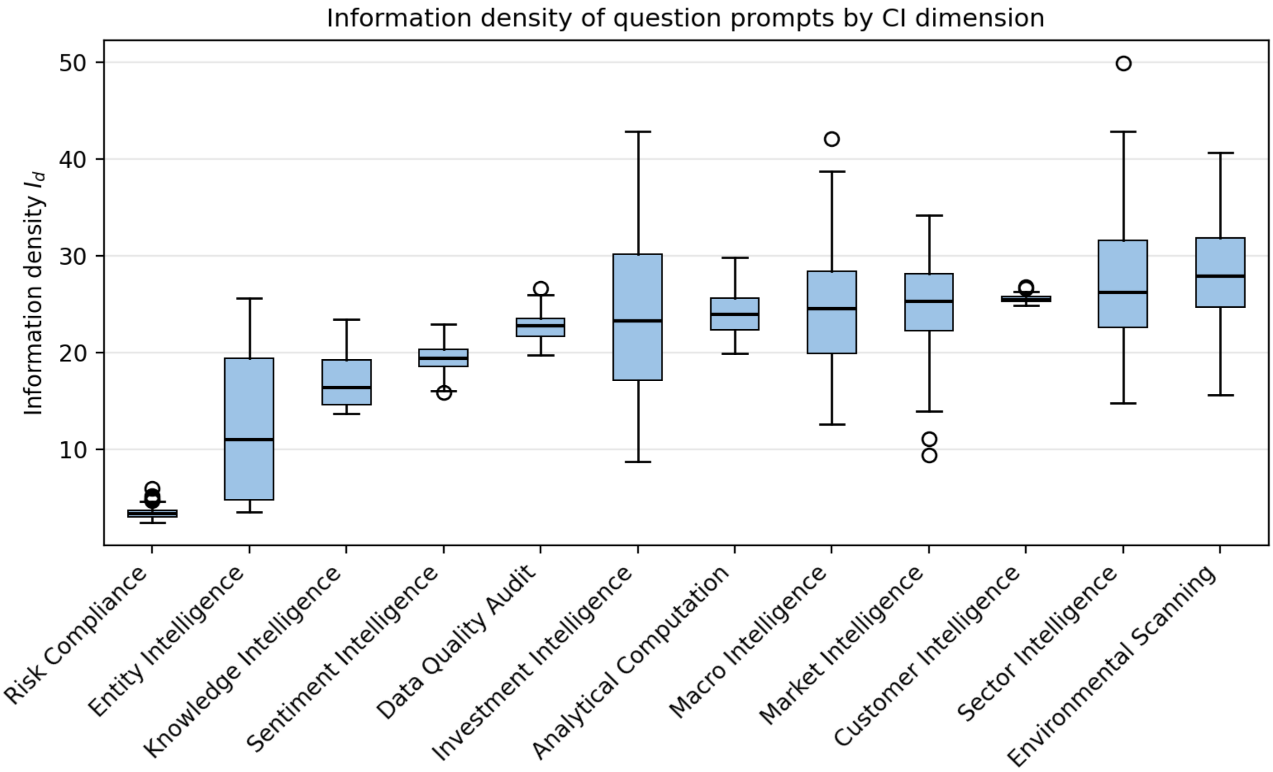

Figure 5. Information density I_d by CI dimension. The lower whisker on risk compliance reflects very short compliance prompts, while environmental scanning and sector intelligence carry long, multi-part analytical narratives.

4.4 Cluster Structure and Latent Topical Geometry

Truncated singular value decomposition with fifty components retained 66.1% of cumulative variance in the TF-IDF matrix. The K-means sweep reached its highest silhouette coefficient at K = 6 (s = 0.391). This value indicates moderate, not strong, separation. The clusters are therefore interpreted as overlapping workload patterns rather than definitive CI categories, which is consistent with the way market, customer, compliance, and analytical intelligence activities intersect in practice.

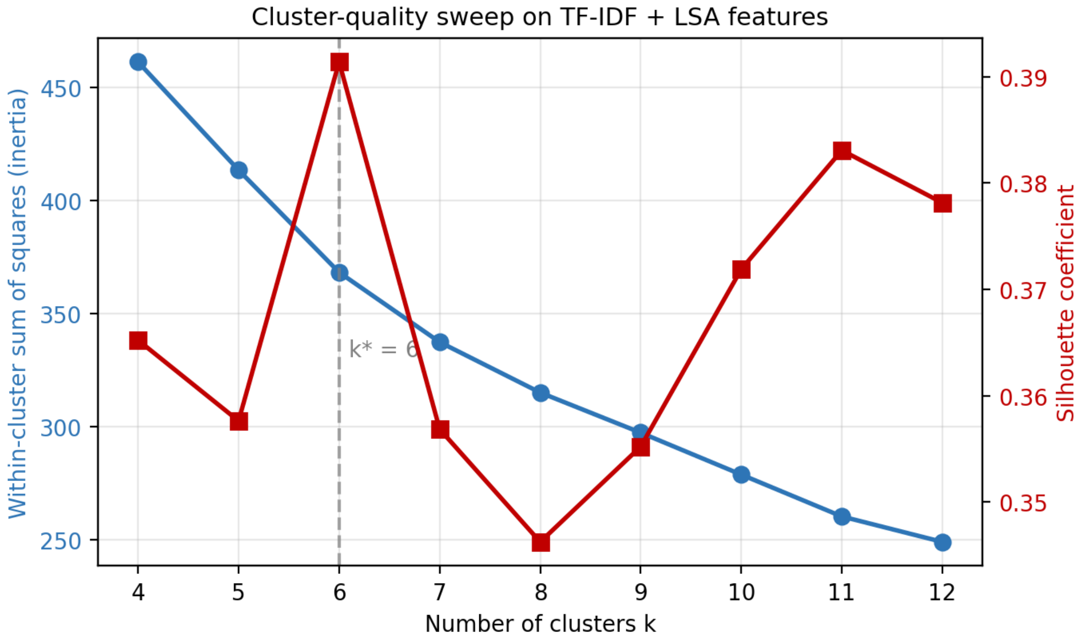

Figure 6. Cluster-quality sweep on the LSA features showing inertia (left axis) and silhouette coefficient (right axis) across candidate cluster counts.

Figure 7 cross-tabulates the six clusters and twelve CI dimensions. Several clusters concentrate on a limited set of dimensions: one is dominated by sentiment-oriented prompts, another by analytical-computation and value-extraction records, and another by long investment-intelligence narratives. The correspondence provides convergent evidence for parts of the proposed mapping, but it is not external organizational validation because both the mapping and clusters originate from the same corpus.

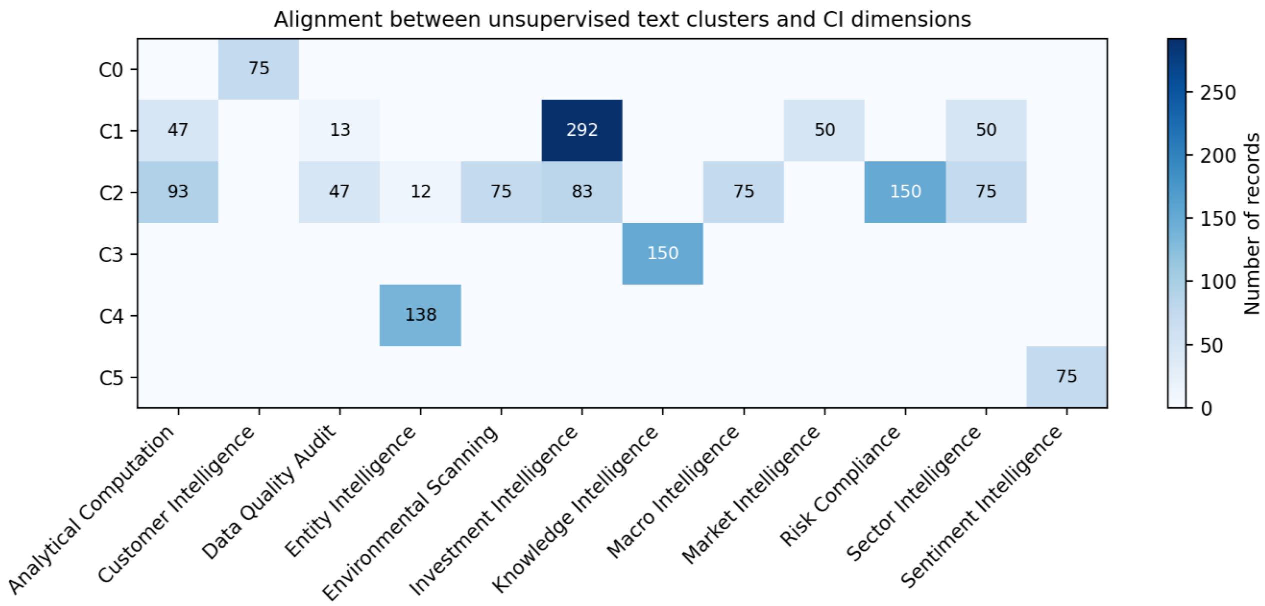

Figure 7. Heatmap of record counts across the six K-means clusters and the twelve CI dimensions, showing strong block structure consistent with the dimensional mapping.

4.5 Responsiveness and Strategic-Fit Ranking

Among dimensions containing rubric-scored records, the median responsiveness index was 0.382, ranging from 0.324 for environmental scanning to 0.409 for market intelligence. Figure 8 shows that market and investment intelligence concentrate a larger share of rubric weight in a single criterion, whereas environmental scanning and sector intelligence distribute weight more broadly. The result concerns rubric structure and should not be read as direct evidence of faster organizational response.

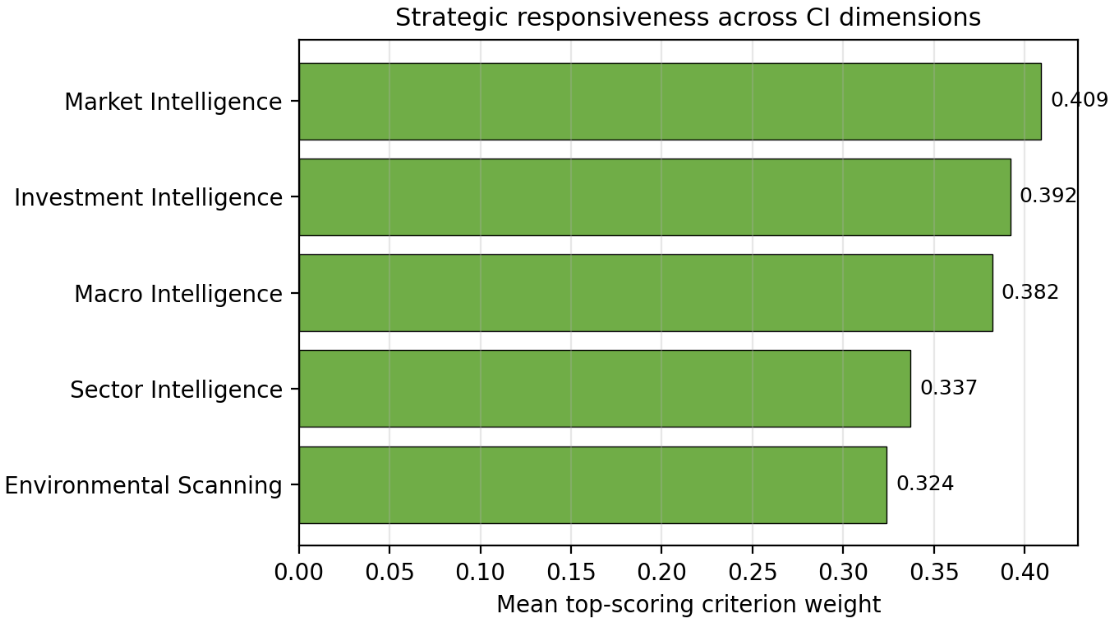

Figure 8. Responsiveness rho across CI dimensions with rubric records, computed as the mean top-criterion weight per question.

Table 3 reports the four components and composite score for each CI dimension. Customer intelligence ranked first (S = 0.700), followed by analytical computation (S = 0.678) and data-quality audit (S = 0.639). Entity intelligence (S = 0.464), risk and compliance intelligence (S = 0.508), and macro intelligence (S = 0.577) formed the lowest three. The ranking reflects the specified workload-based formula; it does not establish comparative business performance.

CI Dimension	Records	Coverage C	Density I	Responsiveness rho	Cohesion K	Strategic Fit S
Customer intelligence	75	0.730	0.895	0.382	0.950	0.700
Analytical computation	140	0.835	0.843	0.382	0.681	0.678
Data-quality audit	60	0.693	0.781	0.382	0.805	0.639
Investment intelligence	375	1.000	0.825	0.392	0.000	0.624
Environmental scanning	75	0.730	1.000	0.324	0.349	0.619
Sentiment intelligence	75	0.730	0.643	0.382	0.798	0.614
Sector intelligence	125	0.816	0.979	0.337	0.126	0.610
Knowledge intelligence	150	0.846	0.553	0.382	0.675	0.608
Market intelligence	50	0.663	0.855	0.409	0.284	0.578
Macro intelligence	75	0.730	0.869	0.382	0.176	0.577

CI Dimension	Records	Coverage C	Density I	Responsiveness rho	Cohesion K	Strategic Fit S
Risk compliance	150	0.846	0.000	0.382	0.931	0.508
Entity intelligence	150	0.846	0.349	0.382	0.058	0.464

Table 3. Strategic-fit composite scores per CI dimension, computed via Equation 5 with weights 0.30, 0.25, 0.30, 0.15 on coverage, density, responsiveness and cohesion.

4.6 Discussion

4.6.1 Alignment Between Workload and Strategic Framework

The empirical findings support the limited assertion that recurring patterns in the financial workload can be interpreted through CI dimensions. They do not validate a complete CI system or establish causation between workload composition and organizational performance. Partial correspondence between assigned dimensions and unsupervised clusters provides internal convergent evidence; external validation would require independent practitioner coding, organizational cases, and decision-outcome evidence (Bao, 2020; Ibrahim et al., 2025; Madureira et al., 2021; Maungwa & Laughton, 2023, 2024; Wu et al., 2023).

4.6.2 Strategic Implications of the Fit Ranking

The strategic-fit ranking can serve as a structured prompt for software architects and procurement teams. High scores indicate that a dimension is relatively well represented and internally consistent in this corpus, whereas low scores suggest a need for richer or more decision-relevant workloads. The diagnostics are consistent with dynamic-capability research (Hassani & Mosconi, 2022; Soluk et al., 2021; Van Hoang et al., 2025; Wu et al., 2023) and relate most directly to sensing, the first stage of organizational adaptation.

4.6.3 Comparison with Recent Literature

The study complements financial benchmarking research by shifting attention from model accuracy to the strategic composition of the workload (East Money Information Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024; Nie et al., 2025; Xie et al., 2024). Benchmark sources describe analytical coverage, while contemporary CI research explains why intelligence needs, source evaluation, interpretation, communication, and managerial integration matter (Bao, 2020; Cavallo et al., 2021; Ibrahim et al., 2025; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024; Wu et al., 2023). The contribution lies in connecting these bodies of work without treating a benchmark as a proxy for an organizational intelligence system.

4.6.4 Methodological Contribution

Methodologically, the study combines schema-aware loading, TF-IDF, latent semantic analysis, K-means clustering, and an explicit dimension-level composite in a reproducible pipeline. The contribution is not the individual algorithms, which are established, but their use in a transparent workload audit tied to a clearly bounded CI interpretation. Every component of the composite is reported separately so that users can inspect why a dimension receives a particular score.

4.6.5 Practical Implications for Financial Software

In practice, the framework can support a workload-gap review. A dimension with many records but low density or cohesion may require redesign rather than simple expansion, whereas a high-scoring dimension with limited coverage may require careful scaling. Managers should interpret the score alongside regulatory requirements, intelligence needs, source quality, qualitative review, and expert judgment. It is not a stand-alone procurement rule (Cavallo et al., 2021; Ibrahim et al., 2025; Madureira et al., 2021; Maungwa & Laughton, 2023, 2024).

4.6.6 Limitations

The conclusions were limited by a number of factors. First, the framework has not been tested via executive interviews, practitioner panels, procurement actions, or over time, through case studies. Second, it uses one Chinese language corpus containing 1500 records, and the findings may be related to the language, regulations and task designing features of this corpus (East Money Information Co., Ltd., & Shanghai Artificial Intelligence Laboratory, 2024). Thirdly, if longer prompts are given, they get more points for the information density and may not adequately value the length of a compliance question. Fourth, dimensions without rubric records have their dimensions imputed as rho. Fifth, the silhouette coefficient is 0.391, which suggests clusters that overlap. Last but not least, the composite weights are exploratory. To use the reproduction in a wider organizational context, the reproduction has to be replicated with FinBen, CFinBench, regulatory corpora and multilingual corpora, and then followed by Delphi or multicriteria validation (Nie et al., 2025; Xie et al., 2024).

4.6.7 Organizational and Managerial Relevance

Although the pipeline is computational, its intended use is organizational. The framework helps managers assess whether a financial-software workload supports a balanced set of intelligence needs or concentrates too narrowly on technically convenient tasks. It may inform software procurement, workload auditing, regulatory-adaptation reviews, and the design of environmental-scanning routines. Its use should remain diagnostic until practitioner agreement and case-based decision evidence are available (Bao, 2020; Ibrahim et al., 2025; Madureira et al., 2021; Maungwa & Laughton, 2023, 2024; Wu et al., 2023).

5. FINAL CONSIDERATIONS

This study demonstrates that Competitive Intelligence can be operationalized within financial software environments as a strategic organizational capability rather than merely a computational benchmarking exercise. By interpreting analytical workloads as representations of organizational sensing and decision-support requirements, the study connects financial analytics infrastructure with environmental scanning, strategic responsiveness, and dynamic capability development. The findings suggest that financial software systems increasingly function as organizational intelligence platforms through which firms interpret volatility, prioritize strategic signals, and support sustainable decision-making processes.

The methodological contribution is a repeatable, Kaggle-compatible pipeline that produces dimension-level scores, exploratory clusters, and record-level diagnostics across the three schema families in OpenFinData. The theoretical contribution is a bounded operational bridge between financial analytics and contemporary CI scholarship: the corpus represents analytical demand, while environmental scanning, intelligence needs, strategy, CI processes, and dynamic-capability research provide the logic for interpretation (Bao, 2020; Cavallo et al., 2021; Harris & Brooker, 2025; Hassani & Mosconi, 2022; Ibrahim et al., 2025; Ledi, 2024; Madureira et al., 2021; Maluleka & Chummun, 2023; Maungwa & Laughton, 2023, 2024; Ranjan & Foropon, 2021; Soluk et al., 2021; Tsuchimoto & Kajikawa, 2022; Wu et al., 2023). The managerial contribution is an open audit framework that can support, but not supersede, expert procurement and capability assessment.

There are three research directions that then follow. The dimensional structure should be replicated using benchmark data, in this case, multilingual with peer-reviewed data sets such as FinBen and CFinBench, to check for stability of the dimensional structure across languages and regulatory context (Nie et al., 2025; Xie et al., 2024). Second, the strategic fit of the workload must be coupled with the accuracy, calibration, reliability and traceability of the model, to form a demand/ability management assessment. Thirdly, further studies should investigate if there are changes in analytical workload that precede the changes in intelligence practice and managerial response that are observed.

Further work should estimate the composite weights with senior analysts and CI practitioners, test alternative formulations through sensitivity analysis, and incorporate multimodal evidence such as charts and earnings calls. Organizational case studies should then determine whether workload gaps contribute to decision delays, missing signals, unnecessary cross-functional analysis, or weak communication. Such evidence would extend the sensing-oriented framework supported by recent dynamic-capability studies (Hassani & Mosconi, 2022; Soluk et al., 2021; Wu et al., 2023) toward the organizational processes of seizing opportunities and reconfiguring resources.

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