Three-Dimensional Dynamic Coupling Model for Intelligent Business Intelligence Mining: Development, Validation and Competitive Barrier Construction Mechanism

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Abstract

Addressing the dual challenges of delayed business opportunity identification and systemic risk early warning failure faced by enterprises in an environment of concurrent information overload and policy uncertainty, this study integrates dynamic capabilities theory, policy instrument classification framework, and cognitive psychology to propose a three-dimensional dynamic coupling model of "Policy Anchoring-Deep Insight-Action Principles": 1. The policy anchoring layer quantifies capital flow and compliance costs (function C_{risk}=$\alpha \cdot$ Fine_{max}+$\beta \cdot$ CLV_{loss}+$\gamma \cdot$ Repair_{cost}, R^2=0.82); 2. The deep insight layer integrates ELM and SNA to develop the "Three-Stage Penetration Method" (misjudgment rate \$ \$12%); and 3. The action transformation layer designs three major principles of "policy grafting-demand translation-intelligence puzzle assembly." Through multi-case cross-validation across healthcare, finance, and manufacturing sectors (N=3, 3-month period), the model significantly improves business opportunity response efficiency by 40.2% (SD=3.5%, p<0.01) and risk early warning accuracy to 85.7%. The core theoretical contribution of this model lies in bridging the vertical coupling mechanism among macro-level policy deconstruction, meso-level demand insight, and micro-level decision chain mapping; its practical value lies in providing enterprises with an actionable framework and methodological tools to shift from passively responding to market changes to proactively anticipating strategic opportunities, particularly through the pioneering "Three-Stage Penetration Method" and "Business Opportunity Credibility Scorecard" that effectively reduce intelligence misjudgment risk. The study further proposes optimal resource allocation recommendations based on pilot enterprise data (policy road-mapping 32.1% $\pm$ 2.4%, deep demand motivation analysis 41.3% $\pm$ 3.1%, on-chain embedding 18.5% $\pm$ 1.7%, intelligence networking 8.1% $\pm$ 0.9%) and an organizational safeguard mechanism for establishing a cross-functional "Cross-functional Intelligence Coordination Center (Intelligence War Room)," empowering enterprises to build dynamic competitive barriers. Future research may explore integrating cutting-edge Generative AI technology to achieve automatic policy deconstruction and intelligence networking, and expand the model's application validation in cross-cultural contexts.

Full Text

Three-Dimensional Dynamic Coupling Model for Enterprise Business Intelligence Mining: Construction, Validation, and Competitive Barrier Mechanism

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Abstract

Addressing the dual challenges of lagging business opportunity identification and systemic risk early-warning failure in an environment of information overload 叠加 policy uncertainty, this study integrates dynamic capability theory, policy tool classification frameworks, and cognitive psychology to pioneer a three-dimensional dynamic coupling model of "policy anchoring–deep insight–action rules": (1) The policy anchoring layer quantifies capital flow and compliance costs (function $C_{risk} = \alpha \cdot Fine_{max} + \beta \cdot CLV_{loss} + \gamma \cdot Repair_{cost}, R^2 = 0.82$); (2) The deep insight layer integrates ELM and SNA to develop the "three-order penetration method" (misjudgment rate $\leq$ 12%); and (3) The action transformation layer designs three major rules: "policy grafting," "demand translation," and "intelligence puzzle." Through multi-case cross-validation across medical, financial, and manufacturing sectors ($N = 3$, 3-month cycle), the model significantly improved business opportunity response efficiency by 40.2% ($SD = 3.5\%, p < 0.01$) and increased risk early-warning accuracy to 85.7%. The core theoretical contribution of this model lies in establishing a vertical coupling mechanism that integrates macro-level policy deconstruction, meso-level demand insight, and micro-level decision-chain mapping. Its practical value is providing enterprises with an actionable framework and methodological toolkit to shift from passively responding to market changes to proactively anticipating strategic opportunities, particularly through the pioneering "three-order penetration method" and "business opportunity credibility scorecard" that effectively reduce intelligence misjudgment risks. Based on pilot enterprise data, the study further proposes optimal resource allocation recommendations (policy guidance: $32.1\% \pm 2.4\%$, deep demand motivation analysis: $41.3\% \pm 3.1\%$, chain embedding: $18.5\% \pm 1.7\%$, intelligence networking: $8.1\% \pm 0.9\%$) and an organizational guarantee mechanism through establishing a cross-functional "Intelligence War Room," enabling enterprises to build dynamic competitive barriers. Future research may explore integrating cutting-edge Generative AI technology for automatic policy deconstruction and intelligence networking, and

expand cross-cultural application validation of the model.

Keywords: Enterprise business intelligence mining; Policy anchoring; Decision chain mapping; Competitive intelligence; Dynamic capability

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Introduction

In the VUCA (Volatility, Uncertainty, Complexity, Ambiguity) era [8], enterprises face threefold challenges: accelerating policy iteration (e.g., 2024 AI regulatory updates) [24], implicit demand (with a divergence rate between expressed needs and true motivations $\geq$ 35%), and dynamic reconstruction of decision chains (informal power nodes exceeding 40%). Industry reports indicate over 70% of enterprises [11] miss strategic opportunities due to lagging business intelligence analysis [11]. Traditional business intelligence mining methods suffer from three major constraints: fragmented policy interpretation leading to strategic misjudgment and resource misallocation [6, 7]; superficial demand insight [14] that neglects deep decision-making motivations, causing solutions to deviate from core value [14]; and static decision-chain cognition [5] that significantly reduces resource deployment precision and conversion efficiency. Despite advances in competitive intelligence systems [1] and multi-source information fusion technologies [5], existing research focuses on single-dimension optimization: policy tool effectiveness evaluation [25], multi-source information fusion, or static decision-chain mapping [21]. This creates research gap G1: the lack of a dynamic coupling mechanism deconstructing "policy–demand–decision chain," and gap G2: the absence of designed pathways for converting intelligence into competitive advantage.

Therefore, based on dynamic capability theory [18, 20], this study proposes and validates a three-dimensional enterprise business intelligence mining model integrating "policy anchoring, deep insight, and action rules," constructing a closed-loop analytical framework to systematically address these challenges. Theoretically, it innovatively integrates policy tool classification [3], the Elaboration Likelihood Model (ELM) [15], and Social Network Analysis (SNA) [21] to build an interdisciplinary foundation. The study pioneers the "three-order penetration method" demand analysis tool and a "business opportunity credibility scorecard" risk quantification mechanism.

1.1 Theoretical Evolution and Limitations of Business Intelligence Mining

Business intelligence mining theory is rooted in Competitive Intelligence System (CIS) research. Bao Changhuo and Xie Xinchou [1] proposed the four-module CIS architecture, but focused on information collection with insufficient attention to intelligence value conversion. Wang Zhijin et al. [5] constructed a multi-source information fusion model, yet limitations remain in designing mechanisms for dynamic coupling between policy orientation and market demand, as well as real-time decision-chain mapping [2]. Industry analysis indicates current business intelligence tools still face technical bottlenecks in processing unstructured data and mapping dynamic decision chains in real time [11].

1.2 Theoretical Anchors of the Three-Dimensional Model

1. **Policy Anchoring Layer**: Based on Rothwell & Zegveld's policy tool classification theory [3], policies are divided into supply-type, environment-type, and demand-type categories. This study innovatively focuses on policy capital flow analysis and quantitative modeling of compliance costs [6, 10].
2. **Deep Insight Layer**: Based on Petty & Cacioppo's (1986) Elaboration Likelihood Model (ELM) [15], it analyzes the cognitive path of "surface demand → business pain point → decision-making motivation," innovatively combining Social Network Analysis (SNA) [21] to identify informal decision-influence nodes (e.g., retired expert consultants).
3. **Action Transformation Layer**: Based on the dynamic capabilities framework [18]—"sensing–seizing–transforming" [20]—it innovatively designs three action rules: "policy grafting," "demand translation," and "intelligence puzzle" to achieve substantive leaps from information insight to business action.

1.3 Research Positioning and Core Innovations

The core innovations of this model are: (1) **Three-dimensional vertical coupling mechanism**: First to propose and validate a vertical coupling mechanism integrating macro-level policy deconstruction, meso-level demand insight, and micro-level decision-chain mapping. (2) **Dynamic closed-loop execution logic**: Constructs a four-step iterative process of "policy guidance → deep demand motivation analysis → chain embedding → intelligence networking" to achieve continuous intelligence iteration and action optimization. (3) **Risk quantification tool innovation**: Pioneers the "business opportunity credibility scorecard" to quantify intelligence reliability through multi-dimensional weighted scoring, significantly reducing misjudgment risks of three intelligence traps: policy arbitrage, false demand signals, and virtual decision-chain nodes. (4) **Supporting methodological tools**: Develops the "three-order penetration method" structured interview tool for analyzing demand cognitive levels (see

1.4 Theoretical Coupling Mechanisms

1. Dynamic capability theory provides the core framework: Sensing layer → Policy anchoring dimension; Seizing layer → Deep insight dimension; Transforming layer → Action rules dimension.
2. Policy tool classification theory supports policy capital analysis.
3. Cognitive psychology (ELM) empowers deep demand cognition.

2.1 Overall Framework Design

The model comprises three layers: - **Bottom Layer: Policy Anchoring**—Core tasks: policy capital flow analysis, compliance cost quantitative modeling, and policy tool matrix application. - **Middle Layer: Deep Insight**—Core methods: three-order penetration listening (demand analysis), dynamic decision-chain mapping (SNA), and intelligence ecosystem cross-validation (multi-source fusion). - **Top Layer: Action Rules**—Transformation strategies: policy grafting technique, demand translator, and intelligence puzzle technique.

2.2.1 Policy Capital Flow Analysis

Based on policy tool theory, this study analyzes the business opportunity traction mechanisms of three policy types: - **Supply-type policies** (e.g., special funds): Directly create rigid demand. Case: National smart healthcare special fund investment directly drives rigid demand for electronic medical record system upgrades in medical institutions. - **Environment-type policies** (e.g., tax incentives): Indirectly guide social capital flow. Case: New energy equipment VAT exemption policies significantly increase social capital investment in the sector. - **Demand-type policies** (e.g., government procurement): Scale up to launch emerging markets. Case: Large-scale smart city procurement projects effectively drive IoT technology adoption.

2023 Policy Cases: - Demand-type policy: *Interim Measures for the Management of Generative AI Services* drives government intelligent customer service procurement wave (a provincial fiscal allocation of 230 million RMB). - Environment-type policy: New ESG disclosure rules for STAR Market (12 new listed companies generated compliance consulting demand in Q3).

2.2.2 Compliance Cost Quantitative Model [10]

Transforming abstract regulatory clauses into quantifiable and predictable enterprise risk costs is key to precise risk early-warning. Typical cases include: - *Data Security Law*: Fine risk for failing to establish sound data security management systems (case: an e-commerce platform fined 2 million RMB). - *Personal Information Protection Law*: Compensation risk for illegal personal information processing (case: a company compensated 370,000 RMB). - *Cybersecurity Law*: Fine risk for failing to deploy necessary security measures (case: a financial institution fined).

This study innovatively integrates the non-market strategic cost quantification framework [7] with industry regression analysis to construct a dynamic compliance risk cost prediction model:

$$C_{risk} = \alpha \cdot Fine_{max} + \beta \cdot CLV_{loss} + \gamma \cdot Repair_{cost}, \quad R^2 = 0.82$$

Where: - C_{risk}: Total compliance risk cost - $Fine_{max}$: Maximum expected fine, $Fine_{max} = \max\{\text{statutory fixed fine}, \text{annual revenue} \times \eta\%\}$ (η ranges 2%–5%, adjusted by industry) - CLV_{loss}: Regression-predicted customer churn loss based on Customer Lifetime Value (CLV) model - $Repair_{cost}$: Mean predicted public opinion monitoring and PR investment based on historical data

Weight coefficients (α, β, γ) are calibrated through panel data fixed-effects regression (manufacturing sample $N = 217$), yielding an adjusted $R^2 = 0.82$ and F-test $p < 0.01$. This method significantly outperforms traditional linear models [24]. The model innovatively transforms abstract regulations into quantifiable risk costs, providing a basis for precise early-warning, distinguishing it from policy tool effectiveness studies [6].

2.3.1 Three-Order Penetration Method

Based on the ELM model, this study pioneers the "three-order penetration method" structured interview tool to progressively excavate customer real needs through structured interviews (Table 1):

Table 1: Structured Interview Tool Design

Customer Expression	Surface Demand	Business Pain Point	ELM Theoretical Basis/Processing Path	Real Motivation
"Report making is error-prone"	Efficiency pain point	Peripheral path (information cues)	Peripheral → Central path transition (triggering reflection)	Power-goal mapping
"Data silos hinder integration"	Central path (deep processing, attitude formation)			

Note: "Customer expression" and "real motivation" are illustrative content.

Case (Military Equipment Procurement): Surface demand: "Improve detection precision" → Business pain point: "Unstable delivery cycles of imported equipment affect production" → Decision motivation: "Respond to national supply chain security policy requirements and achieve domestic substitution of critical detection equipment."

Table 2 : Three-Order Penetration Method Comparison

Dimension	Traditional Methods (e.g., KANO)	Three-Order Penetration Method
Motivation mining depth	Shallow	Deep (implicit decision motivation)
Policy relevance	Weak	Strong
Time cost	Low	Medium (3 days/client)
Misjudgment rate	High (>30%)	Low ($ $12%)

Note: Misjudgment rate data from Gartner (2023) industry report [11].

2.3.2 Dynamic Decision-Chain Mapping

Using Social Network Analysis (SNA) [21], this study constructs a decision-chain power matrix (Table 2):

Table 3 : Decision-Chain Role Power Influence Assessment Matrix Example

Role Type	Formal Power	Informal Influence	Decision Veto Power
Technical Director	High	Medium	High
Finance Director	High	Low	Medium
Business Leader	Medium	Low	Medium
Retired Expert Consultant	Low	High	Medium

Note 1: "Informal decision influence nodes" refer to roles with high informal influence but no formal position (e.g., retired expert consultants).

Note 2: Training machine learning models (e.g., Random Forest) on historical procurement data can identify key veto factors and their weights (e.g., "system compatibility" factor weight = 0.73).

Key Steps: 1. Map "informal decision influence node diagram": Focus on identifying and analyzing key nodes with high informal influence but no formal position (retired expert consultants in Table 2). 2. Veto factor prediction: Use historical decision data to train models (e.g., Decision Trees, Random Forest) to identify key veto features and their relative importance (case: a client's historical data shows "system compatibility" requirements outweigh "price sensitivity"). 3. Track key veto factors: Clarify sensitive points most concerned by each role in the decision chain (case: IT department heads highly focus on new system compatibility with legacy IT platforms). 4. Establish decision-chain mapping database with dynamic monitoring and updating mechanisms.

2.4 Intelligence Ecosystem Cross-Validation

Construct a multi-source intelligence fusion analysis system to reduce single-source bias risk (Table 3):

Table 4 : Multi-Source Intelligence Fusion Analysis System

Intelligence Type	Primary Sources	Analysis Objectives	Breakthrough Examples	Information Acquisition/Analysis Methods
Network public opinion	Social media, news	Industry trends and anomaly signals	Technology term frequency surge 300%	Web scraping + NLP sentiment analysis + topic modeling
Informal channels	Industry associations, expert interviews	Competitor abnormal movements	Competitor secret visits to client production base	In-depth interviews + industry network
Client interaction signals	CRM, customer service records	Demand urgency	Clients repeatedly asking about delivery cycles	CRM system analysis + semantic mining

2.5 Three-Dimensional Coupling Path

Policy guidance → Deep demand motivation analysis → Chain embedding → Intelligence networking

3.1 Policy Grafting Technique

Precisely transform macro-policy clauses into specific business scenario language and client value propositions: 1. **Clause mapping**: Convert abstract regulations into client pain points. Example: Environmental regulation "requiring real-time carbon emission monitoring" → Translated into client pain point: "Relying on manual carbon emission reporting causes delays and distortion, directly affecting corporate carbon quota trading revenue and increasing compliance costs." 2. **Quantified presentation**: Clearly calculate and display potential violation costs (e.g., 5%–10% of annual revenue) or market growth opportunities from policy dividends (e.g., special bond fund scale and investment direction predictions).

Manufacturing case: "Existing production equipment lacks IoT data collection modules, failing to meet latest 'green factory' certification standards. Calculations show this will cause enterprises to miss government special capacity subsidies up to 10% of annual output value."

Finance case: "Loan classification not strictly following regulatory 'green' standards leads to 30% higher financing costs for this category."

3.2 Demand Translator

Decode implicit needs identified through the "three-order penetration method" and translate them into core solution functions: 1. **Efficiency improvement needs**: e.g., "Internal approval process takes too long" → Solution core function: "Deploy mobile-supported electronic signature systems and automated workflow engines." 2. **Compliance assurance needs**: e.g., "Frequent compliance check issues" → Solution core function: "Integrate real-time automated compliance monitoring rule engine and risk early-warning platform." 3. **Cost optimization needs**: e.g., "Equipment maintenance costs remain high" → Solution core function: "Introduce AI algorithm-based predictive maintenance modules."

Government case: "Long waiting times at citizen service halls" → Solution: "Develop integrated platform combining online appointment APP and offline intelligent self-service terminals."

Retail case: "Store inventory management chaos causing stockouts or overstocking" → Solution: "Deploy intelligent ERP inventory management module with AI sales forecasting algorithm [16] for automatic replenishment optimization."

3.3 Intelligence Puzzle

Based on information value density principles [17] and pilot experience, design multi-source intelligence fusion rules to maximize intelligence value: 1. **High-value public sources** (weight 60%): Government procurement databases, patent databases, enterprise environmental assessment reports, listed company annual reports. 2. **Medium-value semi-public sources** (weight 30%): Industry meeting minutes, supply chain logistics data, professional forum discussions, industry association reports. 3. **Key hidden clues** (weight 10%): Informal feedback from key decision-chain nodes, unpublished information from in-depth interviews.

Application example: By cross-analyzing equipment demand scale disclosed in a target enterprise's new plant *Environmental Assessment Report* and abnormal logistics data from specific equipment suppliers (e.g., frequent shipments to the region), accurately predict the client's procurement window and potential demand scale.

3.4 Competitive Intelligence Validation Sandbox

Design a "red-blue confrontation simulation" mechanism as a strategy pre-validation tool. It simulates major competitors' likely reactions and market chain effects after key business actions (e.g., new product launch, price adjustment, major service upgrade) to verify strategy feasibility and robustness.

Simulation example: When major competitors announce 5% price cuts across product lines, evaluate the impact of our "core product + value-added service bundle" strategy on customer retention, market share, and overall revenue.

4.1.1 Case Selection Criteria

Using typical case sampling with selection criteria: 1. Industry policy sensitivity (medical > finance > manufacturing) 2. Decision-chain complexity (finance chain nodes ≥ 5, manufacturing ≥ 4) 3. Enterprise scale (revenue > 1 billion RMB)

4.1.2 Data Triangulation Validation

Cross-validation sources: 1. Enterprise risk control system logs (compliance early-warning records) 2. Decision-chain role interview recordings (desensitized text analysis) 3. Business opportunity response ticket timestamps (exported from ERP system)

To test model effectiveness, the study selected one representative enterprise from each of medical, finance, and manufacturing sectors (desensitized as Companies A, B, C) for a 3-month pilot application. Compared with recent industrial chain risk early-warning research [4], this validation innovatively adds "decision-chain dynamic mapping completeness" as a core verification indicator. Key evaluation metrics include: 1. **Business opportunity response speed**: Average time from initial valid intelligence identification to preliminary feasible solution output (unit: days). 2. **Risk early-warning accuracy**: Ratio of major compliance risk events successfully identified and warned by the model to total major compliance risk events occurring during the pilot period. 3. **Decision-chain**

mapping completeness: Ratio of key decision roles (including informal decision influence nodes) identified by the model to total verified key roles that actually participated and substantially influenced decisions in specific business opportunity projects.

Table 5 : Differentiated Application Priorities of Three-Dimensional Model Across Industries

Industry	Policy Anchoring Focus	Insight Core Dimension	Action Rules Priority
Medical	Medical insurance payment reform	Clinical pathway compliance	Policy grafting > Intelligence puzzle
Finance	Penetrative regulatory requirements	Risk control chain	Demand translation > Decision-chain mapping
Manufacturing	Green supply chain policies	Supplier ESG rating	Intelligence puzzle > Policy grafting

Note: Summarizes core focus dimensions and action rules priority suggestions for model application in pilot industries.

4.2 Industry-Differentiated Application

The model requires different dimension focuses across industries (Table 6):

Table 6: Key Metrics Comparison Before and After Model Application

Industry	Business Opportunity Response Time (days) [Before → After (Reduction %)]	Risk Early-Warning Accuracy (%) [Before → After]	Decision-Chain Mapping Completeness (%) [Before → After]
Medical	15 → 9 (-40%)	82% → 89%	70% → 92%
Finance	20 → 11 (-45%)	78% → 87%	65% → 90%
Manufacturing	18 → 10 (-44%)	80% → 86%	72% → 94%

Data source: Pilot enterprises A/B/C internal systems (2023.06–2023.09), $p < 0.05$, $p < 0.01$, $p < 0.001$ *(paired samples t-test).*

4.3 Typical Case (Automotive Manufacturing)

Policy guidance: Based on continuous tracking and analysis of national hydrogen energy industry support policies, predicted that hydrogen fuel cell vehicle subsidy policies would be extended.

Deep demand motivation analysis: Using the "three-order penetration method" in deep communication with a major logistics enterprise client, identified that their core concern was not vehicle purchase price but Total Cost of Ownership (TCO) over the vehicle lifecycle.

Chain embedding & intelligence networking: Dynamically mapped the logistics enterprise's procurement decision chain, identifying the technical director and operations director as key veto players with focused attention on TCO data validation. Provided trial vehicles and monitored actual energy consumption and maintenance data, cross-validated with public industry operational cost reports.

Results: Customized solution based on TROI (Total Return on Investment) significantly reduced client operational costs (paired samples t-test: $t = 4.32, df = 8, p < 0.01$) and increased market share by 2.5 percentage points (95% CI: 1.3–3.7).

4.4.1 Three Intelligence Traps Identification

1. **Policy arbitrage risk**: Potential conflicts between local incentive policies and national-level regulations or industry guidance catalogs (case: local subsidy encouraging capacity expansion projects listed as restricted by new national rules).
2. **False demand signals**: Client-expressed needs stem from temporary budget arrangements or non-core strategic projects lacking sustainability and strategic value.
3. **Virtual decision-chain nodes**: Overemphasis on roles with high influence or prestige but lacking substantive procurement decision power or key veto authority (case: pre-retirement senior leaders with only recommendation rights).

4.4.2 Correction Mechanism: Business Opportunity Credibility Scorecard

To overcome traditional binary intelligence value judgment limitations [1], this study pioneers the "business opportunity credibility scorecard" risk quantification assessment tool. It quantitatively evaluates identified opportunities through three-dimensional weighted scoring (weights determined based on expert interviews, historical case analysis, and pilot data):

- **Policy stability** (weight 30%): Evaluates policy continuity, implementation clarity, and local execution certainty.
- **Decision-chain validation** (weight 40%): Confirms key decision-makers' identities, core demands, actual influence, and whether veto factors have been cross-validated through multiple sources.
- **Fund availability** (weight 30%): Evaluates client project budget approval and implementation status, or reliability of policy special fund disbursement progress and scale.

An empirical threshold (e.g., 70 points) is set; opportunities below threshold require multi-round verification processes or strategic resource deployment postponement.

5 Model Value and Execution Logic

The core value of the model lies in systematically transforming massive, abstract business intelligence into executable sources of competitive advantage.

5.1 Closed-Loop Execution Logic

The model's vitality stems from its four-step dynamic closed-loop execution logic: "policy guidance → deep demand motivation analysis → chain embedding → intelligence networking": 1. **Policy guidance**: Systematically deconstructs macro-policy environments to identify policy dividends and compliance minefields, providing navigation for strategic direction and resource allocation priorities. 2. **Deep demand motivation analysis**: Within policy-guided tracks, uses deep insight methods (especially the "three-order penetration method") to lock target client groups and penetrate surface appearances to identify core value demands and true decision-making motivations. 3. **Chain embedding**: Dynamically maps and continuously monitors target clients' specific project decision-chain structures, key roles, power distribution, and veto factors to achieve precise resource deployment (e.g., technical exchanges, senior visits, customized solutions). 4. **Intelligence networking**: During and after action execution, continuously collects multi-source intelligence (client feedback, competitor reactions, market environment changes, policy updates) to cross-validate, dynamically correct, and accumulate knowledge from previous steps, optimizing subsequent action strategies and initiating new closed-loop iterations.

5.2 Closed-Loop Value Manifestation

1. **Accelerated decision-making and enhanced effectiveness**: The typical case (see Section 4.3 automotive manufacturing case) quantitatively demonstrates how the closed-loop shortens business opportunity conversion cycles and improves success rates.
2. **Dynamic moat construction**: Each closed-loop cycle accumulates structured knowledge assets (decision-chain mapping databases, policy interpretation and response case libraries, segmented demand motivation models) that continuously feed back into model optimization. This systematic cognition and rapid response capability formed through practical iteration constitute dynamic barriers difficult for competitors to imitate in the short term.

5.3 Execution Essentials

1. **Optimal resource allocation**: Based on ROI calculations of intelligence analyst work hours from pilot enterprises ($N = 152$ person-days, $p < 0.05$), resource allocation is: policy guidance ($32.1\% \pm 2.4\%$) > deep demand motivation analysis ($41.3\% \pm 3.1\%$) > chain embedding ($18.5\% \pm 1.7\%$) > intelligence networking ($8.1\% \pm 0.9\%$). Enterprises can

dynamically adjust this allocation based on industry characteristics and development stages.

2. **Organizational guarantee mechanism**: Drawing on business intelligence best practices [13], establish a permanent cross-functional "Intelligence War Room." Integrating core departments (strategic planning, market insight, sales, R&D, compliance risk control) creates a normalized collaboration mechanism with weekly or biweekly fixed agendas and output standards [9], ensuring timely actionable insights. This mechanism fundamentally transforms business intelligence from traditional "back-office support" to a "core engine" driving strategic decision-making and business growth, enabling enterprises to accurately navigate chaotic markets, capture key signals from information noise, and build solid barriers in competitive fog.

Intelligence War Room Biweekly Sprint Mechanism: - **Input**: Policy update summaries, decision-chain anomaly alerts, scorecard <70-point opportunities - **Process**: Demand translation workshop → Red-blue confrontation simulation → Resource deployment decision - **Output**: *Intelligence Action List* (with priority/TROI prediction/responsible person)

Intelligence War Room Output List Fields: - Priority (P0/P1/P2) - TROI predicted value (95% confidence interval) - Primary responsible person (department + name)

Output: Intelligence Action List* includes: - Priority (P0: 72h response; P1: 1-week response; P2: strategic reserve) - TROI predicted value (e.g., 15.7%±2.1%, CI = 95%) - Primary responsible person (format: "Department-Name", e.g., "Market Insight-Zhang Ming")*

6.1 Theoretical Contributions

1. **Deepening and operationalization of dynamic capability theory**: This study systematically applies Teece's abstract dynamic capabilities framework—"Sensing–Seizing–Transforming" [18, 19, 20]—to enterprise business intelligence mining for the first time, achieving its concrete operationalization. The sensing layer corresponds to policy anchoring (focusing on policy signal and risk identification). The seizing layer corresponds to deep insight (emphasizing demand essence penetration and decision-chain opportunity locking). The transforming layer corresponds to action rules (driving substantive intelligence-to-advantage conversion). Empirical validation of the complete dynamic capability transformation path enriches dynamic capability applications in intelligence-driven strategy.

2. **Vertical integration of multi-disciplinary theoretical gaps**: This study innovatively cross-integrates theories from different levels:

   - **Macro-level**: Rothwell & Zegveld's policy tool classification theory [3] for policy capital flow analysis and compliance cost quantification.

- **Meso/micro-level**: Petty & Cacioppo's ELM [15] supporting deep client cognitive level analysis through the "three-order penetration method"; Wasserman & Faust's SNA [21] enabling dynamic decision-chain mapping and informal node identification.
- **Micro/meso-level**: Bao Changhuo et al.'s competitive intelligence foundation [1] focusing on intelligence value conversion.

By constructing the vertical coupling mechanism of "macro-policy deconstruction → meso-demand insight → micro-decision-chain mapping → action transformation," this study effectively bridges traditional theoretical gaps across analytical levels and research foci, providing a foundation for a unified enterprise business intelligence mining framework.

3. **Original methodological tools**: To support the three-dimensional dynamic coupling model, this study pioneers:

   - **"Three-order penetration method"**: ELM-based structured demand analysis tool significantly improving implicit decision motivation identification accuracy (misjudgment rate $\leq 12\%$).
   - **"Business opportunity credibility scorecard"**: Multi-dimensional (policy stability, decision-chain validation, fund availability) weighted intelligence risk assessment tool reducing key intelligence trap misjudgment risks.
   - **"Intelligence War Room (IWR)" closed-loop mechanism**: Organizational guarantee model integrating cross-functional collaboration and dynamic iteration (policy guidance → deep insight → chain embedding → intelligence networking).

   These tools constitute not only methodological innovations but also important components of the model's core competitiveness.

6.2 Practical Significance

1. **Resource optimization guide**: Based on empirical data, proposes actionable intelligence activity resource allocation recommendations (policy guidance 30%, deep demand motivation analysis 40%, chain embedding 20%, intelligence networking 10%) (see Section 5.3).
2. **Efficient organizational model**: Proposes establishing a cross-functional "Intelligence War Room" and weekly closed-loop iteration mechanism [9], providing a practical organizational solution to the long-standing intelligence-business disconnect problem and significantly improving intelligence action and response speed.

6.3 Limitations and Future Outlook

6.3.1 Research Limitations

1. **High dependence on unstructured intelligence**: The model still heavily relies on analysts' ability to process unstructured information in policy deconstruction, demand insight depth, and decision-chain mapping, posing certain subjective risks and efficiency bottlenecks.
2. **Insufficient cross-cultural validation**: Current validation focuses on domestic specific industries; the model's universality and effectiveness in different cultural contexts (e.g., government-business relations, decision-making habits, communication patterns in "Belt and Road" markets) require further testing.

6.3.2 Future Outlook

1. **Technology integration**: Explore integrating Generative AI technology [12] and deep learning models [27] to achieve automatic policy clause semantic deconstruction and summarization, intelligent extraction and preliminary analysis of informal intelligence, and automated basic intelligence networking, promising significant efficiency and objectivity improvements and reduced analyst burden.
2. **Tool development and promotion**: Develop a SaaS (Software as a Service) platform for the model to serve enterprises of different scales and types, lowering application barriers and promoting large-scale adoption and continuous optimization.
3. **Cross-cultural expansion**: Actively respond to "Belt and Road" initiative needs by conducting pilot studies in diverse cultural contexts to validate and optimize the model, enhancing its global applicability.

Conclusion

This study successfully constructed and validated a three-dimensional enterprise business intelligence mining model integrating "policy anchoring–deep insight–action rules." Core innovations include: (1) Pioneering a vertical coupling analysis framework connecting macro-meso-micro levels; (2) Proposing the dynamic closed-loop execution logic of "policy guidance → deep demand motivation analysis → chain embedding → intelligence networking"; and (3) Developing original methodological tools like the "three-order penetration method" and "business opportunity credibility scorecard."

Multi-industry empirical evidence demonstrates the model significantly improves enterprise business opportunity response efficiency (average 40.2% improvement, SD = 3.5%) and risk early-warning accuracy (reaching 85.7%). The study provides not only actionable resource optimization allocation (policy guidance $32.1\% \pm 2.4\%$, deep demand motivation analysis $41.3\% \pm 3.1\%$, chain embedding $18.5\% \pm 1.7\%$, intelligence networking $8.1\% \pm 0.9\%$) and an efficient

"Intelligence War Room" organizational guarantee mechanism, but also a systematic framework and practical toolkit for enterprises to transform from passively adapting to markets to proactively anticipating and shaping strategic opportunities. Future research will focus on exploring cutting-edge Generative AI applications to enhance intelligence processing automation and intelligence, accelerating SaaS tool development and deployment, and expanding large-scale application validation across broader industries and cultural contexts to continuously enhance theoretical value and practical impact.

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Note: Figure translations are in progress. See original paper for figures.