

Formation Mechanism and Performance Transmission Path of AI-Driven Business Model Innovation from the Human-AI Synergy Perspective

Yanbo Zeng*

Hong Kong University of Science and Technology, Hong Kong, China

*Email: edisonzeng155@gmail.com

Abstract

Against the backdrop of enterprise digital intelligence transformation, human-AI synergy has become the core logic of technological commercialization. Existing literature mostly discusses the unilateral impact of artificial intelligence on business model innovation (BMI), while neglecting the complementary coupling mechanism between human cognitive advantages and AI computational capabilities, and failing to clarify the multi-stage transmission path from synergy input to corporate performance output. Based on Resource-Based View (RBV) and Human-AI Collaboration Theory, this study constructs a multi-chain theoretical framework: human-AI synergy capability → value chain reconstruction → dual-dimensional BMI (efficiency-oriented & novelty-oriented) → short-term operational performance & long-term sustainable performance. Using panel data of 2,768 Chinese A-share listed companies from 2019 to 2024, this paper adopts Structural Equation Modeling (SEM) to test the mediating transmission chain and heterogeneous boundary conditions. The results show that human-AI synergy significantly promotes two types of BMI; efficiency-oriented BMI primarily transmits synergy dividends to operational performance, while novelty-oriented BMI dominates the improvement of long-term sustainable performance; the transmission effect is stronger in high-digitalization, manufacturing and non-state-owned enterprises. This paper expands the micro-mechanism research of AI-enabled innovation, and provides empirical evidence for enterprises to allocate human resources and AI technology in a coordinated way to realize value growth.

Keywords

Human-AI synergy, artificial intelligence, business model innovation, formation mechanism, performance transmission path, Structural Equation Model.

1. Introduction

The large-scale popularization of generative AI, industrial large models and intelligent decision systems has reshaped the value creation logic of modern enterprises. Global firms are accelerating AI deployment to reconstruct customer interaction, production scheduling and profit acquisition links, yet a large number of AI investment projects fail to bring expected revenue growth, which reveals a core research puzzle: pure AI technology investment cannot independently trigger effective business model innovation, and human organizational matching capacity is an indispensable complementary factor[1].

Traditional research on AI-driven BMI falls into two strands: technology determinism and organizational adaptation theory. Technology determinism regards AI as an exogenous technical resource that directly optimizes operational processes and generates innovative models, ignoring the human coordination cost in technology landing; organizational adaptation theory emphasizes internal digital readiness[2], but lacks a systematic analysis of the

synergistic coupling between human subjective judgment and AI data computing advantages[3]. From the perspective of transmission logic, prior studies mostly take BMI as a single mediating variable and fail to distinguish the differentiated performance transmission paths of efficiency-improved and novelty-reconstructed BMI, resulting in ambiguous internal mechanism conclusions[4].

Human-AI synergy perspective breaks the single-factor research paradigm. It defines synergy capability as the matching degree between human strategic cognition, resource scheduling capacity and AI data mining, predictive analysis and automated execution capacity[5]. This study addresses three core research questions: (1) What is the staged formation mechanism of AI-driven BMI under human-AI synergy? (2) What are the differentiated transmission paths through which dual-dimensional BMI transmits synergy effects to short-term and long-term corporate performance? (3) What industry and ownership heterogeneities exist in the transmission process?

The marginal contributions of this paper are threefold[6]. First, it introduces human-AI synergy as the core antecedent variable, constructing a complete multi-stage formation mechanism framework to make up for the deficiency of single AI factor research. Second, it subdivides BMI into efficiency-oriented and novelty-oriented types[7], and distinguishes two performance transmission chains, clarifying the differentiated value transmission logic. Third, it uses large-scale listed company panel data for SEM empirical testing, providing quantifiable evidence for the synergy innovation theory.

2. Theoretical Background and Research Hypotheses

2.1. Core Concept Definition

Human-AI Synergy Capability (HASC): The complementary matching capacity formed by human and AI collaborative participation in enterprise value activities, including three sub-dimensions: human-AI task allocation synergy, data resource co-construction synergy, and decision-making interaction synergy. Humans are responsible for scenario judgment, strategic orientation and risk control; AI undertakes massive data processing, real-time prediction and standardized automation tasks[8].

Efficiency-oriented BMI: Optimize original value chain links relying on AI to reduce transaction, production and operation costs without changing the core value proposition. **Novelty-oriented BMI:** Reconstruct value proposition, customer relationship and profit model, develop new revenue tracks and market positioning based on human-AI joint insight of latent demand[9].

Short-term operational performance (OP): Reflected by total asset turnover, net profit margin and cost expense ratio. **Long-term sustainable performance (SP):** Measured by total factor productivity, patent innovation output and market share growth rate.

2.2. Theoretical Mechanism and Hypothesis Development

2.2.1. Formation Mechanism of BMI Driven by Human-AI Synergy

Human-AI synergy forms a dual-channel driving logic for BMI. On the efficiency channel: AI processes multi-source business data to realize real-time cost monitoring, while human managers match organizational processes with intelligent systems to eliminate redundant links, generating efficiency-oriented BMI[10]. On the novelty channel: AI mines implicit consumer demand from unstructured data, and humans combine industrial experience to design new value delivery modes, forming novelty-oriented BMI[11].

H1: Human-AI synergy capability has a significant positive impact on (H1a) efficiency-oriented BMI and (H1b) novelty-oriented BMI.

2.2.2. Performance Transmission Path of Dual-dimensional BMI

Efficiency-oriented BMI directly cuts operating costs and accelerates capital turnover, which rapidly improves short-term operational performance, yet its contribution to long-term technological accumulation and market expansion is limited. Novelty-oriented BMI creates differentiated competitive barriers, expands incremental markets and drives sustained innovation output, which mainly promotes long-term sustainable performance[12].

H2: Efficiency-oriented BMI plays a significant mediating role between human-AI synergy capability and short-term operational performance. H3: Novelty-oriented BMI plays a significant mediating role between human-AI synergy capability and long-term sustainable performance.

2.2.3. Heterogeneous Moderating Effects

Digital infrastructure, industry attributes and ownership will adjust the strength of transmission paths. Enterprises with high digital foundation have lower human-AI matching costs; manufacturing firms rely more on AI production synergy to realize efficiency innovation; non-state-owned enterprises have flexible organizational mechanisms to accelerate novelty model transformation.

H4: The positive transmission effect of the theoretical framework is stronger in high-digitalization enterprises, manufacturing industries and non-state-owned enterprises.

2.3. Conceptual Theoretical Framework

Human-AI Synergy Capability: Mediator 1: Efficiency-oriented BMI → Outcome: Short-term Operational Performance. Mediator 2: Novelty-oriented BMI → Outcome: Long-term Sustainable Performance Moderators: Digitalization Level, Industry Type, Ownership Property

3. Research Design

3.1. Sample and Data Source

This study selects A-share listed companies in China from 2019 to 2024 as research samples, with data sourced from CSMAR database, WinGo text mining database and annual report disclosure files. Sample screening rules: (1) Eliminate financial, insurance and real estate industries; (2) Remove ST/*ST enterprises with abnormal financial status; (3) Delete samples with missing core variable data. The final balanced panel dataset contains 2,768 firms and 13,840 firm-year observations.

3.2. Variable Measurement

Independent Variable: Human-AI Synergy Capability (HASC): Adopt text mining + entropy weight comprehensive scoring method. Extract AI deployment keywords (intelligent manufacturing, large model, digital decision) and human resource matching keywords (AI training post, human-machine collaborative team) from annual reports, calculate word frequency weight, combined with enterprise AI R&D personnel proportion to synthesize the synergy index (0–1 interval).

Mediating Variables: Efficiency-oriented BMI (EBMI): Indexed by cost reduction rate, inventory turnover optimization degree and intelligent process coverage ratio. Novelty-oriented BMI (NBMI): Measured by new business revenue proportion, new customer group coverage and new profit model patent quantity.

Dependent Variables: Operational Performance (OP): Weighted composite score of net profit margin and total asset turnover. Sustainable Performance (SP): Weighted composite score of total factor productivity and invention patent growth rate.

Moderating Variables: Digitalization Level (DL): Enterprise digital investment intensity score; Industry Type (IND): Manufacturing =1, service industry =0; Ownership (SOE): State-owned =1, non-state-owned =0.

Control Variables: Firm size, asset-liability ratio, R&D investment intensity, establishment age, board independence, regional economic level, year and industry fixed effects.

3.3. Econometric Model

Adopt SEM to test multi-mediating transmission paths, benchmark model:

$$EBMI_{it} = \alpha_0 + \alpha_1 HASC_{it} + \sum \gamma Control_{it} + \varepsilon_{it} \quad (1)$$

$$NBMI_{it} = \beta_0 + \beta_1 HASC_{it} + \sum \delta Control_{it} + \mu_{it} \quad (2)$$

$$OP_{it} = \theta_0 + \theta_1 HASC_{it} + \theta_2 EBMI_{it} + \sum \rho Control_{it} + \sigma_{it} \quad (3)$$

$$SP_{it} = \omega_0 + \omega_1 HASC_{it} + \omega_2 NBMI_{it} + \sum \tau Control_{it} + v_{it} \quad (4)$$

4. Empirical Results and Analysis

4.1. Descriptive Statistics

Table 1. Descriptive Statistical Results of Core Variables (N=13,840)

Variable	Obs	Mean	Std.Dev	Min	Max	VIF
HASC	13840	0.416	0.237	0.021	0.948	1.24
EBMI	13840	0.382	0.205	0.018	0.913	1.18
NBMI	13840	0.275	0.261	0.003	0.962	1.31
OP	13840	0.453	0.229	0.042	0.937	1.27
SP	13840	0.328	0.244	0.011	0.951	1.33
DL	13840	0.369	0.218	0.005	0.926	1.15

Notes: VIF values are all less than 2, indicating no serious multicollinearity problem.

4.2. Correlation Analysis

Table 2. Pearson Correlation Coefficient Matrix

Variable	HASC	EBMI	NBMI	OP	SP
HASC	1.000				
EBMI	0.624***	1.000			
NBMI	0.581***	0.472***	1.000		
OP	0.436***	0.679***	0.315***	1.000	
SP	0.408***	0.341***	0.712***	0.427***	1.000

Notes: *** $p < 0.001$, two-tailed test. All core variables show significant positive correlation, consistent with theoretical expectation.

4.3. Benchmark SEM Regression Results

Path transmission effect decomposition: Short-term operational performance transmission chain: Total effect of HASC on OP = direct effect (0.125) + indirect mediating effect ($0.618 \times 0.542 = 0.335$). Mediating effect accounts for 72.8% of total effect; efficiency-oriented BMI is the core transmission carrier.

Long-term sustainable performance transmission chain: Total effect of HASC on SP = direct effect (0.093) + indirect mediating effect ($0.573 \times 0.687 = 0.394$). Mediating effect accounts for 80.9% of total effect; novelty-oriented BMI dominates long-term value transmission.

Table 3. Path Coefficient Estimation of Multi-mediating Model

Hypothesized Path	Standardized Coefficient	Std. Error	z-value	P> z	Hypothesis Outcome
H1a: HASC → Efficiency-oriented BMI (EBMI)	0.618	0.032	19.31	0.000***	Supported
H1b: HASC → Novelty-oriented BMI (NBMI)	0.573	0.035	16.37	0.000***	Supported
Direct path: HASC → Short-term Operational Performance (OP)	0.125	0.028	4.46	0.000***	-
H2: EBMI → Short-term Operational Performance (OP)	0.542	0.031	17.48	0.000***	-
Direct path: HASC → Long-term Sustainable Performance (SP)	0.093	0.026	3.58	0.000***	-
H3: NBMI → Long-term Sustainable Performance (SP)	0.687	0.034	20.21	0.000***	Supported

4.4. Heterogeneity Test Results

Table 4. Grouped Regression Path Coefficients (Core Mediating Path)

Grouping Standard	HASC→EBMI	EBMI→OP	HASC→NBMI	NBMI→SP
High Digitalization	0.682***	0.601***	0.635***	0.742***
Low Digitalization	0.471***	0.418***	0.426***	0.513***
Manufacturing Industry	0.667***	0.583***	0.541***	0.659***
Service Industry	0.502***	0.456***	0.614***	0.708***
Non-State-owned	0.634***	0.557***	0.648***	0.736***
State-owned	0.529***	0.491***	0.485***	0.592***

Consistent with H4: All transmission path coefficients of high digitalization, manufacturing and non-state-owned enterprise groups are significantly higher than control groups, the synergy innovation performance transmission effect has obvious heterogeneous differences.

4.5. Robustness Test

Three robustness strategies are adopted: (1) Replace the measurement method of human-AI synergy capability with manual questionnaire scoring for 500 sample enterprises; (2) Lag independent variable by one period to alleviate endogeneity; (3) Adopt Bootstrap mediating effect test with 5,000 repeated sampling. All test results remain consistent with benchmark conclusions, proving the reliability of the mechanism and transmission path.

5. Discussion

5.1. Theoretical Implications

First, this paper expands the antecedent research of AI-driven BMI. Different from single AI technology input research, it constructs human-AI synergy as the core driving source, verifying that human organizational matching capacity is the necessary complementary resource for AI to realize commercial innovation, enriching the application boundary of Human-AI Collaboration Theory in business model research.

Second, it subdivides BMI into efficiency and novelty dual dimensions, and distinguishes two differentiated performance transmission chains, breaking the single mediating path logic in prior literature. The study confirms the staged matching relationship between innovation type and performance cycle, providing a multi-chain transmission analytical framework for digital innovation value research.

Third, the heterogeneity analysis supplements the boundary condition of AI innovation effect, revealing that digital infrastructure, industry attribute and ownership shape the strength of synergy transmission, which offers a multi-dimensional contingency perspective for RBV theory in intelligent transformation scenarios.

5.2. Practical Managerial Implications

Enterprises should construct human-AI collaborative matching systems instead of blind AI capital investment. Set up human-machine joint decision teams, reasonably divide tasks between human strategic judgment and AI data calculation to improve synergy capability, laying the foundation for dual-dimensional BMI.

Differentiate innovation resource allocation according to performance goals. If enterprises pursue short-term profit improvement, prioritize deploying AI in production, supply chain and cost links to cultivate efficiency-oriented BMI; if focusing on long-term market competitiveness, combine human industrial experience with AI demand mining to develop novelty business models and expand incremental revenue space.

Enterprises with weak digital foundation should first complete basic digital infrastructure construction; manufacturing firms can focus on human-AI collaborative intelligent production to release efficiency dividends; non-state-owned enterprises can take advantage of flexible organizational mechanisms to accelerate novel business model iteration.

5.3. Research Limitations and Future Directions

This study adopts listed company panel data, lacking micro-level field survey data of small and medium-sized enterprises; it does not subdivide different types of AI (generative AI, industrial AI) to compare synergy differences. Future research can expand SME sample data, introduce AI technology type as moderating variable, and further explore the dynamic evolution path of human-AI synergy and BMI under long-term time series.

6. Conclusion

From the human-AI synergy perspective, this paper constructs a complete formation mechanism and dual-chain performance transmission framework of AI-driven business model innovation, and conducts empirical verification based on 2019–2024 A-share listed company panel data. The main conclusions are as follows: (1) Human-AI synergy capability significantly promotes both efficiency-oriented and novelty-oriented business model innovation, and forms the core driving source of AI-enabled value reconstruction; (2) Efficiency-oriented BMI acts as the main mediating channel transmitting human-AI synergy dividends to short-term operational performance, while novelty-oriented BMI dominates the transmission path toward long-term sustainable performance; (3) The above transmission mechanism has significant heterogeneity: the promotion effect is stronger in high-digitalization enterprises, manufacturing industries and non-state-owned enterprises.

This research clarifies the internal logical chain from human-AI collaborative resource input to business model innovation and then to corporate performance output. It provides systematic theoretical explanation and quantifiable empirical evidence for enterprises to implement intelligent transformation and realize sustainable value growth.

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