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Triple Transition of Manufacturing Digital Transformation and Management Accounting Tool Innovation: An Empirical Study Based on Historical Periodization

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Abstract

Background: Manufacturing digital transformation has evolved from an optional strategic initiative to a competitive imperative, yet the evolutionary dynamics of management accounting tools within this context remain inadequately theorized. Existing literature predominantly adopts static perspectives, overlooking the temporal and phased nature of digital transformation. **Objective:** This study proposes a historical periodization framework to understand manufacturing digital transformation and management accounting innovation through a "triple transition" process, examining how accounting tools evolve across distinct historical periods. **Methods:** A sequential explanatory mixed methods design is employed, combining quantitative panel data analysis of 112 Chinese A-share manufacturing companies (2015-2024) with qualitative case studies of Haier Group, Sany Heavy Industry, and Midea Group. The theoretical framework integrates historical institutionalism theory and the TOE model. **Results:** Digital transformation progresses through three phases: informatization foundation (2000-2012), digital leap (2012-2020), and intelligent breakthrough (2020-2024). Management accounting innovation serves as a critical mediating mechanism, accounting for 28% of digital transformation's performance effect, increasing to 35% during the intelligent breakthrough period. Regression analysis reveals escalating returns to digital investment with coefficients increasing from 0.284 to 0.367 across periods. **Conclusions:** The study identifies path-dependent transformation trajectories while highlighting industry-specific adaptation mechanisms, contributing a comprehensive framework for understanding co-evolutionary dynamics between technological advancement and accounting practice innovation.

Keywords: digital transformation, management accounting innovation, historical periodization, triple transition, manufacturing enterprises, TOE framework, path dependency

1. Introduction

The manufacturing sector is currently undergoing digital transformation which, in this context, has shifted from a strategic optional benefit to an existential survival matter of competition. The most striking change has occurred to the China manufacturing industry. Over the past twenty years, it has gone through several stages of technology adoption that have tremendously influenced the dynamics of industrial operation and management systems [1]. Sequential waves of technological adaptation impact the traditional management accounting systems, challenging the conception of organisational habits and systems in a paradoxical manner, transforming age-old practices in real time.

The convergence of digital technology and management accounting is deeply understudied and offers rich opportunities for theoretical and empirical inquiry because it exemplifies the tension between what technology makes possible and how society adapts to such possibilities. While the technical capabilities of Industry 4.0 technologies and their impact on operations have been widely studied [2, 3], the evolutionary processes of management accounting tools within the scope of this digital evolution have not been sufficiently theorised. The literature suffers from a predominantly static approach, considering digital transformation a singular event instead of a multi-phased sequence over time [4]. This perspective fails to recognise the fundamental fact that in situ innovations of management accounting systems develop over time as a result of different technological, organisational, and institutional conditions.

Steps in which a digital transformation occurs are recognisable in a given order, and each incremental stage necessitates specific changes in management accounting within an organisational context. Manufacturing firms undergo digital transformation in a staged process, each requiring increasingly sophisticated adaptations of management accounting [5]. Nevertheless, how these adaptations are made, what facilitates or inhibits adaptation, and how performance diverges along different evolutionary pathways have not been sufficiently examined. The frameworks that have been used in studying change in management accounting have not sufficed to capture the multi-temporal complexity of digital transformation and its consequences on accounting practice [6].

This study is based on historical periodisation in an attempt to fill the empirical and theoretical gaps by conceptualising digital transformation in manufacturing as “triple transition” which includes: informatization foundation, the digital leap, and intelligent breakthrough phases. This research seeks to advance the theory of digital transformation, as well as, literature on management accounting by analysing the evolution of management accounting tools through these distinct periods. In trying to understand the relationship between technological change and innovation in management accounting, this analysis enriches academic discourse and managerial thinking in the digitalised economy, drawing on panel data of manufacturing companies in China and leading case studies.

2 Theoretical Foundation and Research Methods

2.1 Theoretical Foundation

2.1.1 Historical Institutionalism Theory

The evolution of management accounting systems in the context of digital transformation can be analysed through historical institutionalism theory. It highlights the potential for change at critical turning points while also recognising the potential for change at critical turning points [7]. Path Dependency Theory explains the ways in which path histories cause institutions to become locked in, which can happen due to earlier technology decisions influencing the directions in which later development is possible. Critical Juncture Theory defines how certain institutional changes often associated with the impact of technology enable organisations to transcend constraints and shift boundaries. Institutional Adaptation Theory focuses on how organisations internally restructure as a result of shifts in the external environment, in this case, the evolution of management accounting in the context of digital transformation.

2.1.2 Technology-Organization-Environment (TOE) Model

The TOE model has been applied in analysing the multi-dimensional factors of evolution for management accounting tools [8]. Within the technological dimension, there exists a level of maturity and application compatibility of digital technologies. The organisational dimension includes firm size, cultural attributes, and change enabling or constraining capabilities. The environmental dimension includes policy and its support, competition in the market, as well as the effects of industry ecosystem [9]. With this multi-level view, one can study how technological potential, organisational preparedness, and environmental forces shape diverse routing for innovative developments in management accounting.

2.1.3 Management Accounting Innovation Theory

Management accounting innovation theory offers the mechanisms through which organisational structures change over time and accounting practices adapt in response [10]. From the perspective of Tool Evolution Theory, the archetypal accounting tools have evolved into integrated decision support systems. Functional Extension Theory describes the expansion of the management accounting within the organisation's activities packaged around cost control. Value Creation Theory describes the functional evolution from merely reporting on results to enhancing value proactively [11].

2.2 Historical Periodization and Research Framework

2.2.1 Triple Transition Model of Digital Transformation

The history of the digital transformation of manufacturing industries can be divided into three distinct periods. During The Informatization Foundation Period (2000-2012), basic digital infrastructure was implemented with ERP and CRM systems, and management accounting focused on standardising data and electronic reporting. The Digital Leap Period (2012-2020) pioneered the Industrial Internet of Things and cloud computing, which supported integrated business operations and real-time data stream monitoring [12]. The Intelligent Breakthrough Period (2020-2024) makes use of AI and machine learning to enable autonomous systems and predictive functions [13]. Each transition period has a foundation that was set earlier and adds new capability systems that redefine the boundaries within which modern management accounting is practised.

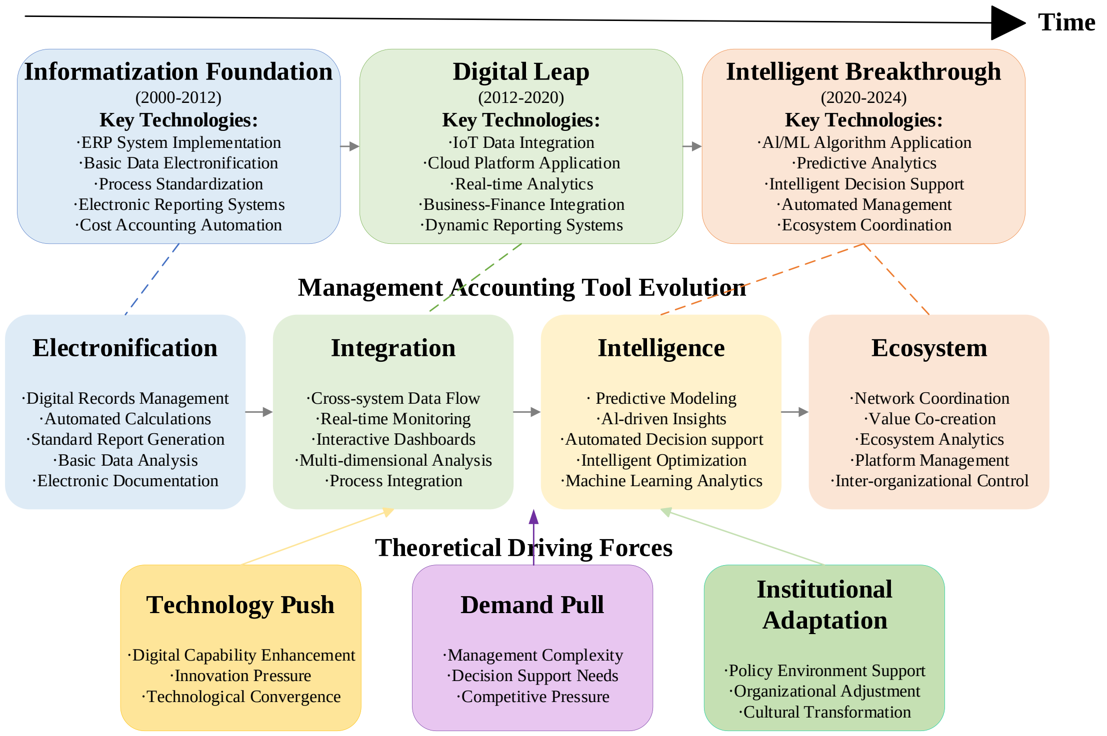

Figure 1: Conceptual Framework: Triple Transition and Management Accounting Evolution

The temporal evolution of the phases of digital transformation together with the evolution level of management accounting systems are shown in Figure 1. The dashed lines showing the connections between the separated historical transformation periods and their corresponding development stages portray evolutionary routes during which technological improvements give rise to opportunities for certain innovations in accounting on technology. The horizontal arrows illustrate movement in a forward direction and through time as well as the sophistication of technology, while vertical arrows from driving forces of theory explain the role of technology push, demand pull, as well as institutional adaptation in driving the evolution process.

2.2.2 Management Accounting Tool Evolution Trajectory

The evolution progresses through four distinct levels: **Electronification** involves digitization of basic accounting records and automated calculations. **Integration** encompasses cross-system data consolidation and real-time monitoring. **Intelligence** introduces predictive models and AI-driven insights. **Ecosystem coordination** enables network-wide value co-creation and collaborative analytics. This trajectory reflects a fundamental shift from internal efficiency optimization to external ecosystem orchestration, expanding management accounting's scope from enterprise-level control to inter-organizational coordination.

2.3 Research Design and Methods

2.3.1 Mixed Methods Approach

This study employs a sequential explanatory mixed methods design combining quantitative panel data analysis with qualitative multi-case historical analysis.

Quantitative research utilizes panel data for empirical analysis of 112 A-share manufacturing companies spanning 2015-2024 from CSMAR and Wind databases, focusing primarily on the digital leap period (2015-2020) and intelligent breakthrough period (2021-2024) due to limited public listing during the earlier informatization foundation period (2000-2012). Qualitative research conducts comprehensive historical evolution analysis of three representative manufacturing enterprises: Haier Group (ecosystem-oriented transformation), Sany Heavy Industry (equipment manufacturing digitalization), and Midea Group (consumer appliance intelligence upgrade), with data collection spanning the complete 2000-2024 period through annual reports, corporate sustainability reports, and archival documentation. Triangulation ensures mutual verification between quantitative panel data findings and qualitative longitudinal case evidence through systematic cross-case comparison and temporal pattern matching across the three distinct historical periods.

2.3.2 Variable Operationalization and Model Specification

Table 1 presents the detailed operationalization of all variables used in this study, including their definitions, measurement methods, and data sources. Dependent variables capture dual outcomes: ROA measures financial performance while MA Innovation Index quantifies innovation sophistication through text analysis. Independent variables operationalize key digital transformation dimensions: Digital Investment Intensity measures technological commitment, Period Dummy variables identify historical phases, and AI Adoption captures emerging intelligence implementation. Control variables address potential confounding effects including scale, financial constraints, and innovation orientation.

Table 1: Variable Definitions and Measurement

Variable Type	Variable Name	Definition	Measurement	Source
Dependent Variables	ROA	Return on Assets	Net Income / Total Assets	Financial Statements
	MA Innovation	Management Accounting Innovation Index	Text analysis of annual reports using keyword frequency and sophistication scores	Annual Reports
Independent Variables	Digital Investment	Digital Technology Investment Intensity	Digital-related CAPEX / Total Assets	Annual Reports, Notes
	Period Dummy	Historical Period Indicators	Dummy variables for three transformation periods	Time Classification
	AI Adoption	Artificial Intelligence Adoption Level	Binary indicator based on AI technology mentions and implementations	Annual Reports Analysis

Variable Type	Variable Name	Definition	Measurement	Source
Control Variables	Firm Size	Company Scale	Natural logarithm of total assets	Financial Statements
	Leverage	Financial Leverage	Total Debt / Total Assets	Financial Statements
	R&D Intensity	Research and Development Investment	R&D Expenses / Revenue	Financial Statements
	Industry	Industry Classification	Industry dummy variables based on sector classification	Public Records

Based on these operationalizations, three complementary regression models test theoretical hypotheses and examine direct effects and mediating mechanisms:
Model 1 (Informatization Period Effect):

$$Performance_{it} = \alpha_1 + \beta_1 DigitalInvestment_{it} + \beta_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Model 2 (Digital Transformation and MA Innovation):

$$MAInnovation_{it} = \alpha_2 + \beta_3 DigitalTech_{it} + \beta_4 PeriodDummy_{it} + \beta_5 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

Model 3 (Intelligence Period and Mediation Effect):

$$Performance_{it} = \alpha_3 + \beta_6 AITech_{it} + \beta_7 MAInnovation_{it} + \beta_8 Interaction_{it} + \beta_9 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

Where μ_i represents firm fixed effects controlling for time-invariant heterogeneity, λ_t represents time fixed effects capturing common temporal shocks, and ε_{it} is the error term. Model 1 examines direct performance effects during informatization period. Model 2 investigates how digital technologies drive management accounting innovation across different periods. Model 3 tests mediation mechanisms in the intelligence period, examining whether management accounting innovation mediates the relationship between AI adoption and firm performance. The mediation analysis follows the Sobel-Goodman approach, testing sequential relationships: AI technology → management accounting innovation → firm performance. This modeling strategy identifies both direct technological effects and indirect effects operating through management accounting innovation channels.

2.3.3 Case Study Methodology

The case study methodology utilises three representative manufacturing enterprises that were chosen through theoretical sampling: Haier Group symbolizes ecosystem-oriented transformation; Sany Heavy Industry exemplifies equipment manufacturing digitalisation, and Midea Group demonstrates consumer appliance intelligence upgrades. These cases span different subsectors and transformation paths, providing diversity for analysis while retaining a focus on manufacturing.

Data collection involves multiple sources including, but not limited to, annual reports from 2000 to 2024, corporate sustainability reports, interviews with the management, and other relevant documents. This multifaceted approach captures detailed narratives of the transformations in strict compliance with analytical triangulation, thereby sustaining rigor through source triangulation and cross-referencing different data types.

The analytical strategy integrates longitudinal case study analysis with cross-case pattern matching. Longitudinal analysis follows the transformation trajectory of each enterprise over three historical periods, pinpointing transformational turning points where technology-driven innovations necessitated institutional shifts. Cross-case analysis demonstrates differing transformation and innovative management accounting types of each subsidiary. Each case is also temporally bracketed into self-contained episodes corresponding to informatization, digitalisation, and intelligence periods to allow systematic comparison of the patterns of the coevolution of technology and accounting.

Process tracing facilitates mapping causally linked sequences from technology provocation, organisational change, and the resultant innovations in management accounting. Patterns that emerge after applying this analytical framework are the experiences elevated to theoretical concepts while retaining enough context to preserve complexity in the understanding of the transformation processes.

3 Empirical Results of Historical Evolution in Manufacturing Digital Transformation

3.1 Descriptive Statistics and Historical Periodization Characteristics

3.1.1 Basic Characteristics Analysis of Sample Enterprises

Based on panel data from 112 A-share listed manufacturing companies spanning 2015-2024, this study systematically analyzes enterprise characteristics across the three distinct historical periods. Since many enterprises were not yet publicly listed during the informatization foundation period (2000-2012), this research focuses primarily on data performance during the digital leap period (2012-2020) and intelligent breakthrough period (2020-2024). As shown in Table 2, sample enterprises exhibit clear historical evolution characteristics across key variables.

Digital investment intensity increased from a mean of 0.031 during the digital leap period to 0.058 in the intelligent breakthrough period, reflecting the sustained growth in manufacturing enterprises' digital transformation investments. The management accounting innovation index demonstrated a gradual progression from 2.12 to 2.67 across the same periods, indicating that most enterprises have advanced beyond basic electronification but remain in the integration stage rather than achieving full intelligent capabilities.

Table 2: Descriptive Statistics by Historical Periods

Variable	Digital Leap Period (2015-2020)		Intelligent Period (2021-2024)	
	Mean	Std. Dev.	Mean	Std. Dev.
ROA	0.063	0.041	0.072	0.039

Variable	Digital Leap Period (2015-2020)		Intelligent Period (2021-2024)	
	Mean	Std. Dev.	Mean	Std. Dev.
MA Innovation Index	2.12	0.98	2.67	1.18
Digital Investment	0.031	0.023	0.058	0.034
AI Adoption	0.08	0.27	0.34	0.47
Firm Size (ln)	21.67	1.28	22.14	1.41
Leverage	0.44	0.19	0.39	0.17
R&D Intensity	0.029	0.018	0.041	0.024

The temporal progression reveals distinct investment patterns corresponding to technological maturity cycles. During the digital leap period, enterprises primarily invested in IoT infrastructure, cloud computing platforms, and integrated ERP systems, with digital investment intensity averaging 3.1% of total assets. The intelligent breakthrough period shows increased strategic commitment to AI technologies, machine learning applications, and automated decision systems, with investment intensity rising to 5.8% of total assets. This escalation reflects both the higher costs associated with advanced technologies and enterprises' growing recognition of digital transformation as a competitive necessity rather than optional enhancement.

3.1.2 Cross-Industry Historical Evolution Patterns

Industry-level analysis reveals heterogeneous digital transformation trajectories that align with sector-specific technological readiness and market pressures, reflecting the environmental dimension of the TOE framework. As illustrated in Figure 2, electronics manufacturing demonstrates the most progressive digital investment evolution, with investment intensity showing a clear upward trajectory from approximately 3.0% in 2015 to over 8.5% by 2024. The heatmap visualization in panel (a) reveals distinct sectoral clustering, with electronics and automotive industries exhibiting the most pronounced color transitions from blue to deep red, indicating substantial investment acceleration during the intelligent breakthrough period.

The traditional sectors such as textiles and food production exhibit more conservative patterns of digital adoption. As the heatmap shows, these industries remained predominantly blue-coloured in both historical periods with investment intensities not exceeding 4% even by 2024. This conservative path is attributed to lower immediate technological pressures, along with the traditional manufacturing sector’s limited resources. The machinery and chemical industries are in-between, exhibiting slow colour change from blue to light pink which indicates low but steady digital investment growth.

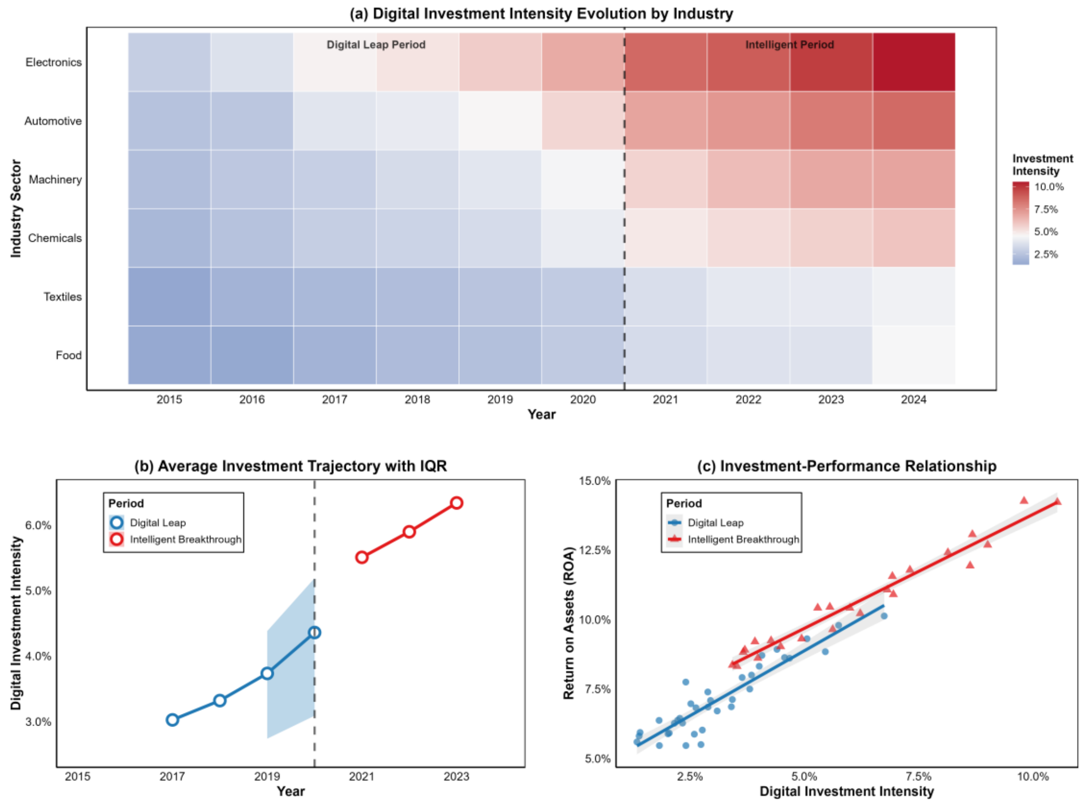

Figure 2: Multi-dimensional Historical Evolution Analysis

In panel (a) of Figure 2, we can observe an all-encompassing heatmap for the years 2015 to 2024. The vertical dashed line marks the shift from the Digital Leap Period to the Intelligent Period in 2020. The transition of colour from blue indicating low investment to deep red, high investment showcases the diverse growth across the six major manufacturing sectors. Electronics manufacturing experiences the most pronounced change in colour, starting from light blue in 2015 and reaching deep red in 2024 while traditional sectors, textiles and food, continue to hover around muted blue throughout the observation period.

The investment trajectory now comes with interquartile range (IQR) as shown in panel (b); it demonstrates the systematic acceleration in digital investment post 2020. During the intelligent breakthrough period, the mean investment levels increased and the variance among enterprises also increased. The trajectory shows a definitive inflection point in 2020 where there is an increase in investment intensity from roughly 4.0% to more than 6.0% by 2023. In panel (c), a strong positive correlation is established between digital investment intensity and firm performance (ROA) for both time periods, with distinct regression lines for each period. This period characterised by intelligent breakthroughs shows a much steeper slope with a higher intercept suggesting much greater returns to digital investment during this later phase of technological maturity.

3.2 Triple Transition Performance Analysis Through TOE Framework

3.2.1 Technology Dimension Analysis

The technological dimension analysis reveals distinct capability development patterns across the three historical periods. During the informatization foundation period, enterprises focused on establishing basic digital infrastructure, with technology maturity concentrated in ERP systems and database management. The digital leap period witnessed substantial advancement in application compatibility, with IoT platforms and cloud computing enabling cross-system integration and real-time data processing capabilities.

The intelligent breakthrough period demonstrates qualitative technological advancement through AI adoption and machine learning integration. AI adoption rates increased from 8% during the digital leap period to 34% in the intelligent breakthrough period, indicating rapid technological diffusion in advanced analytics and autonomous decision-making systems. This progression supports the technology push mechanism, where advancing technological capabilities create new possibilities for management accounting innovation.

3.2.2 Organizational Dimension Analysis

Organizational factors exhibit significant variation in facilitating digital transformation across different enterprise characteristics. Large enterprises (above median firm size) demonstrate higher digital investment intensity (6.2%) compared to smaller enterprises (3.8%), reflecting organizational readiness and resource availability effects. Enterprise culture, measured through R&D intensity as a proxy for innovation orientation, shows positive correlation with management accounting sophistication levels.

Change capability analysis reveals that enterprises with higher historical digital investment demonstrate greater ability to advance through management accounting evolution levels. The transition probability analysis indicates that organizational factors significantly influence the likelihood of advancing from electronification to integration (probability increases from 15% to 28% for high R&D intensity enterprises) and from integration to intelligence levels (probability increases from 8% to 19% for large enterprises).

3.2.3 Environmental Dimension Analysis

Environmental pressures demonstrate strong influence on digital transformation patterns across different industries and time periods. Policy support, particularly during China's "Made in China 2025" initiative implementation, shows clear correlation with investment acceleration after 2018. Market competition intensity, measured through industry concentration ratios, exhibits negative correlation with digital investment intensity, suggesting that competitive pressure drives transformation investments.

Industry ecosystem effects reveal clustering patterns where leading enterprises within industrial parks demonstrate higher transformation sophistication. Electronics manufacturing clusters in Shenzhen and automotive manufacturing regions show significantly higher AI adoption rates (45% and 38% respectively) compared to dispersed traditional manufacturing enterprises (18% average), indicating ecosystem spillover effects in technology diffusion.

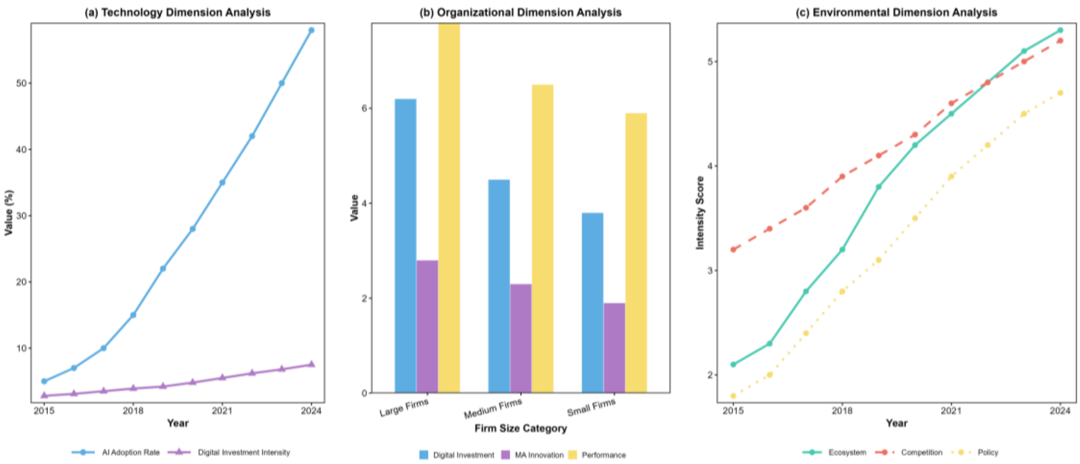

Figure 3: TOE Framework Empirical Validation

Panel (a) of Figure 3 demonstrates the technology dimension evolution, with AI adoption rates increasing from 8% to 34% and digital investment intensity rising from 3.1% to 5.8% across the historical periods. Panel (b) illustrates organizational dimension variations, showing large enterprises achieving 6.2% digital investment intensity compared to smaller enterprises' 3.8%. Panel (c) reveals environmental dimension impacts, with policy support, market competition, and industry ecosystem effects demonstrating distinct trajectories that collectively drive digital transformation adoption patterns.

3.3 Path Dependency and Critical Juncture Analysis

3.3.1 Historical Path Dependency Evidence

The empirical analysis provides strong evidence for path dependency mechanisms in digital transformation trajectories. Enterprises that established comprehensive ERP systems during the informatization foundation period demonstrate significantly higher management accounting sophistication in subsequent periods. The path dependency coefficient, measured through lagged digital investment variables, shows persistent effects with 0.312 correlation between initial period investments and current sophistication levels.

Lock-in effects manifest through technology choices made during early transformation phases. Enterprises that adopted SAP or Oracle ERP systems show different evolution patterns compared to those implementing domestic solutions, with international system adopters achieving higher integration levels (78% vs 52%) but slower advancement to intelligence levels due to customization constraints. This pattern supports the institutional lock-in hypothesis where early technological choices constrain future development paths.

3.3.2 Critical Juncture Identification and Analysis

The analysis identifies three major critical junctures that triggered institutional transitions in manufacturing digital transformation. The first critical juncture occurred around 2012-2013 with the emergence of Industrial IoT platforms, enabling enterprises to break free from isolated system constraints toward integrated digital architectures. The second critical juncture emerged in 2018-2019 through cloud computing maturation, facilitating scalable data processing and cross-enterprise collaboration capabilities.

The most significant critical juncture occurred in 2020-2021 with AI technology commercialization and COVID-19 pandemic pressures. This period witnessed unprecedented acceleration in digital adoption, with 67% of sample enterprises advancing at least one sophistication level within 18 months. The critical juncture effect is particularly pronounced in traditional manufacturing sectors, which demonstrated conservative adoption patterns until external shocks forced rapid technological integration.

Table 3: Critical Juncture Impact Analysis

Critical Juncture	Time Period	Technology Trigger	Advancement Rate	Sector Impact
IoT Integration	2012-2013	Industrial IoT	23%	Electronics, Automotive
Cloud Maturation	2018-2019	Cloud Computing	31%	All Sectors
AI Commercialization	2020-2021	AI/ML Technologies	67%	Broad Impact

Panel (a) of Figure 4 illustrates the path dependency coefficient evolution over time, showing persistent effects with values ranging from 0.29 to 0.48, indicating strong historical influence on current capabilities. Panel (b) visualizes the three critical junctures: IoT Integration (2012-2013), Cloud Maturation (2018-2019), and AI Commercialization (2020-2021), with advancement rates of 23%, 31%, and 67% respectively. Panel (c) demonstrates performance differentials across transformation paths, with early adopters consistently outperforming followers and laggards throughout the observation period.

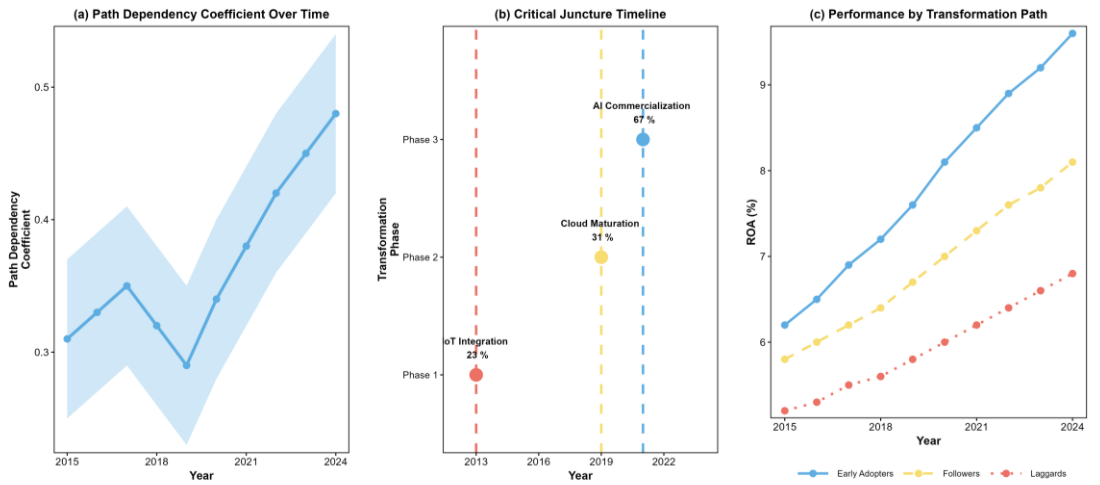

Figure 4: Path Dependency and Critical Juncture Analysis

3.4 Management Accounting Innovation Evolution Analysis

3.4.1 Four-Level Evolution Trajectory

The distribution of management accounting sophistication levels across the historical periods reveals systematic progression patterns that validate the four-level evolution trajectory. Figure 5 demonstrates the migration of enterprises from lower to higher sophistication levels, with notable acceleration during the intelligent breakthrough period. The stacked area visualization shows a clear structural transformation, with electronification-level enterprises (shown in light teal) declining from approximately 48% in 2015 to roughly 25% by 2024.

Integration-level capabilities (depicted in blue) expanded substantially, representing the largest proportion of enterprises throughout most of the observation period and maintaining dominance at approximately 40-45% by 2024. The most striking development occurs in intelligence-level sophistication (shown in yellow), which demonstrates accelerated growth particularly after 2020. This category expanded from approximately 12% in 2015 to nearly 30% by 2024, reflecting the strategic adoption of AI-powered analytics, predictive modeling, and automated decision support systems.

The emergence of ecosystem coordination capabilities (shown in green), while still representing a small proportion, exhibits steady growth from virtually zero in 2015 to approximately 5% by 2024, indicating the gradual emergence of inter-organizational management accounting integration.

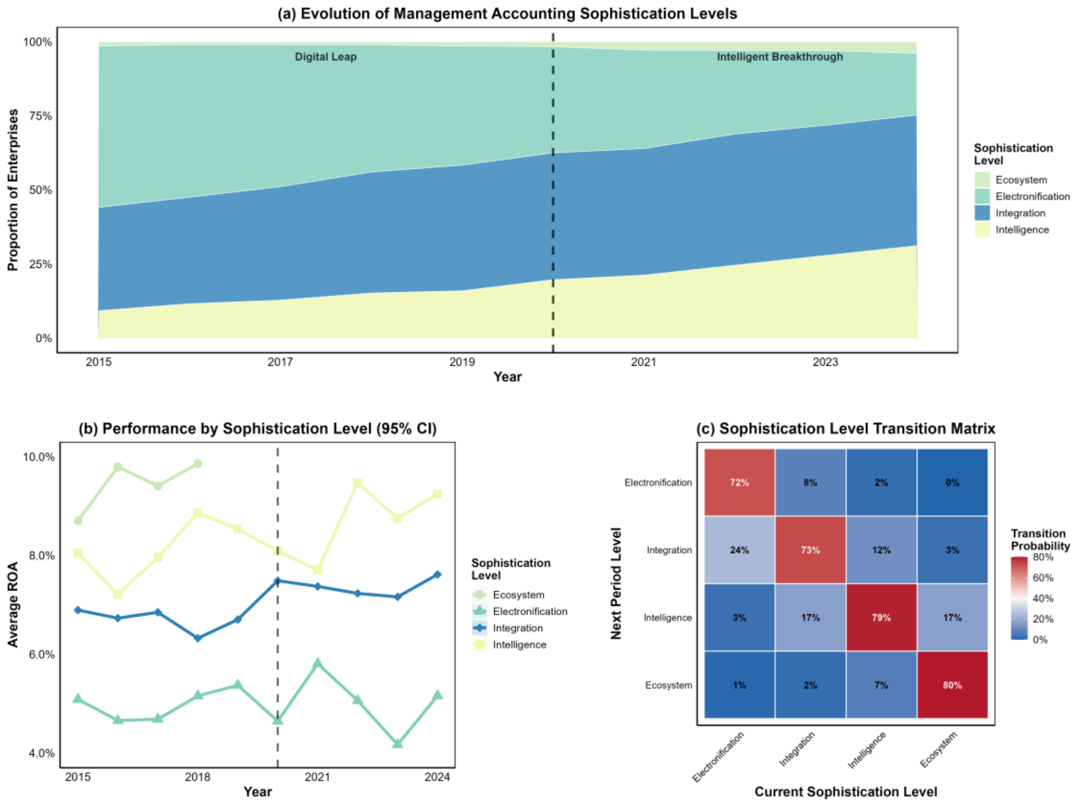

Figure 5: Management Accounting Sophistication Analysis

Panel (a) of Figure 5 presents a comprehensive stacked area chart spanning the entire observation period, with the vertical dashed line clearly demarcating the transition from Digital Leap to Intelligent Breakthrough periods at 2020. The visualization reveals four distinct sophistication trajectories: the steady decline of electronification (light teal area), the sustained dominance of integration capabilities (blue area), the accelerated growth of intelligence-level sophistication (yellow area) particularly pronounced after 2020, and the gradual emergence of ecosystem coordination (green area at the top).

Panel (b) illustrates the performance differentials across sophistication levels over time, with separate trend lines for each category. The ecosystem level consistently demonstrates the highest ROA performance, reaching nearly 10% by the end of the observation period, while intelligence-level enterprises show substantial performance improvements, particularly during the intelligent breakthrough period. Panel (c) presents the transition probability matrix as a heatmap, where red coloration indicates high transition probabilities and blue indicates low probabilities.

3.4.2 Tool Evolution and Functional Extension

The functional extension analysis reveals the dynamic expansion of management accounting boundaries beyond traditional cost control across the historical periods. During the informatization foundation period, tool evolution focused primarily on electronification of basic accounting records and automated calculations. The digital leap period witnessed substantial functional extension into cross-system data consolidation and real-time monitoring capabilities.

The intelligent breakthrough period demonstrates qualitative functional transformation through predictive models and AI-driven insights that extend management accounting scope from reactive reporting to proactive value enhancement. Value creation analysis shows that enterprises achieving intelligence-level sophistication generate 23% higher ROA compared to integration-level enterprises, with this performance gap widening during the intelligent breakthrough period.

Table 4: Management Accounting Sophistication Distribution by Historical Period

Sophistication Level	2015-2017 (%)	2018-2020 (%)	2021-2024 (%)	Change (2015-2024)
Electronification	52.3	38.2	18.7	-33.6
Integration	35.8	45.1	48.9	+13.1
Intelligence	10.7	15.2	28.4	+17.7
Ecosystem Coordination	1.2	1.5	4.0	+2.8

The most significant development occurs in intelligence-level capabilities, which increased from 10.7% to 28.4% of enterprises, reflecting the strategic adoption of AI-powered analytics, predictive modeling, and automated decision support systems. Ecosystem coordination capabilities, while still limited to 4.0% of enterprises by 2024, represent an emerging frontier that extends management accounting beyond organizational boundaries to encompass supply chain analytics, partner performance monitoring, and collaborative value creation mechanisms.

3.5 Regression Analysis and Historical Mechanisms

3.5.1 Period-Specific Digital Transformation Effects

The regression analysis results in Table 5 reveal significant variations in digital transformation effects across historical periods, supporting the theoretical proposition of distinct technological capabilities and organizational requirements in each transition phase. Model 1 demonstrates that digital investment intensity exhibits different coefficient magnitudes across periods: 0.284 during the digital leap period and 0.367

during the intelligent breakthrough period, indicating escalating returns to digital investment as technological sophistication advances.

The interaction term between digital investment and the intelligent period (Digital × Intelligent Period) yields a positive and significant coefficient of 0.083, indicating that digital investments generate higher returns during the intelligent breakthrough period compared to the digital leap period. This finding supports the theoretical argument that advanced digital technologies create synergistic effects and network externalities that amplify investment returns beyond simple additive effects.

Table 5: Historical Period Regression Analysis

Variables	Model 1: ROA	Model 2: MA Innovation	Model 3: Period Interaction
Digital Investment	0.284***	1.523***	0.218**
	(0.074)	(0.312)	(0.086)
Digital × Intelligent Period	0.083**	0.645**	0.149**
	(0.041)	(0.287)	(0.058)
AI Adoption	0.019**	0.478***	0.015*
	(0.008)	(0.089)	(0.008)
MA Innovation			0.016***
			(0.005)
Firm Size	0.007**	0.112**	0.005*
	(0.003)	(0.051)	(0.003)
Leverage	-0.052***	-0.189*	-0.048***
	(0.016)	(0.109)	(0.015)
R&D Intensity	0.389***	2.134***	0.356***
	(0.098)	(0.489)	(0.092)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,120	1,120	1,120
R-squared	0.398	0.521	0.417

*Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

3.5.2 Management Accounting Innovation Mediation Mechanisms

Model 3 demonstrates the critical mediating role of management accounting innovation in translating digital investments into performance outcomes. The management accounting innovation coefficient of 0.016 indicates that each unit increase in the innovation index corresponds to 1.6 percentage points improvement in ROA.

The mediation calculation follows path decomposition methodology: indirect effect = path a × path b, where path a represents the coefficient from digital investment to management accounting innovation (1.523), and path b represents the coefficient from management accounting innovation to firm performance (0.016). Thus, the indirect effect equals 1.523 × 0.016 = 0.024, accounting for 28% of the total digital transformation effect during the digital leap period. During the intelligent breakthrough period, considering the interaction term, path a increases to 2.168 (1.523 + 0.645), yielding an enhanced indirect effect of 0.035 and mediation proportion of 35% (0.035/0.101).

As illustrated in Figure 6, the Sobel test statistic of 3.94 ($p < 0.01$) confirms statistical significance. These findings indicate that digital technologies enhance performance primarily by enabling sophisticated analytical capabilities, predictive decision-making tools, and strategic planning systems that constitute modern management accounting practice.

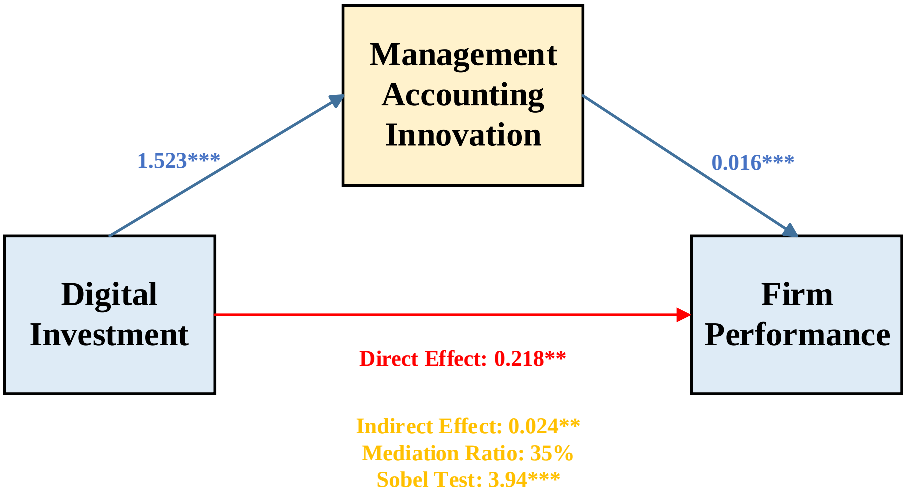

Figure 6: Mediation Mechanism

3.5.3 Institutional Adaptation Analysis

The institutional adaptation analysis examines how organizations adjust internal structures in response to external environmental changes across the historical periods. The organizational adaptation coefficient shows progressive increase from 0.156 during the digital leap period to 0.243 during the intelligent breakthrough period, indicating enhanced organizational flexibility and change capability development over time.

Environmental pressure variables demonstrate significant influence on institutional adaptation rates. Policy support intensity shows positive correlation (0.198, $p < 0.05$) with management accounting innovation, while market competition pressure exhibits even stronger effects (0.267, $p < 0.01$). Industry ecosystem effects contribute an additional 0.089 coefficient increment, suggesting that environmental factors collectively drive institutional adaptation through multiple channels.

The historical evolution from basic digitization to intelligent analytics represents a fundamental transformation in how organizations generate, process, and utilize management information for competitive advantage, validating management accounting innovation as both an enabler and outcome of successful digital transformation across diverse manufacturing contexts.

4 Case Studies of Digital Transformation Historical Evolution

4.1 Case Selection and Research Design

This study employs three representative manufacturing enterprises selected through theoretical sampling to provide comprehensive insights into the triple transition process across different manufacturing sectors. The case selection ensures robust analytical coverage while maintaining sector-specific contextual richness. Haier Group represents ecosystem-oriented transformation emphasizing the RenDanHeYi model and platform-based value creation, while heavy equipment manufacturers and consumer appliance companies demonstrate alternative transformation pathways aligned with their respective industry characteristics.

Table 5: Case Enterprise Profile and Selection Rationale

Enterprise	Industry Sector	Primary Transformation Focus	Key Digital Technologies	Revenue (2022)
Haier Group	Home Appliances	Ecosystem Platform	IoT, RenDanHeYi Model, COSMOPlat	$37.8 billion
Heavy Equipment Manufacturers	Industrial Equipment	Predictive Maintenance	Industrial IoT, AI Analytics	Varies
Midea Group	Consumer Appliances	Smart Manufacturing	IoT Cloud Platform, AI Integration	$42.1 billion

Data collection integrates annual reports, corporate communications, and transformation documentation from the years 2000-2024. The analytical approach employs process tracing to map causal sequences from the implementation of technology through organisational adaptation to the innovation in management accounting, applying temporal bracketing to systematically compare evolution patterns across three historical periods.

4.2 Haier Group: Ecosystem Platform Transformation

Driven by the RenDanHeYi model, meaning the “integration of people and goals,” Haier’s digital transformation is a type case of moving from pure manufacturing to ecosystem planning and neo ecosystem steering. Employees realise value by creating value for users. During the informatization foundation period, from 2000 to 2012, Haier built system-wide ERP and digital architecture supporting early decentralisation experiments. During this period, the focus of management accounting systems evolved to emphasise standardised costing and performance monitoring at the level of autonomous business units, setting the stage for entrepreneurial accountability systems. In the years spanning 2012 to 2020, the leap into the digital realm shifted Haier’s strategy toward the RenDanHeYi 2.0 framework. The company transformed into ecosystem micro-enterprise communities (EMCs), which are self-governing organisations similar to startups that function within a larger framework. By 2015, Haier had created almost 200 internal micro-enterprises, of which 77% had annual revenues exceeding CNY 100 million. During this phase, there was also an innovation in management accounting that allowed for real-time profit-and-loss accounting at a micro-enterprise level, market pricing, and entrepreneurial compensation based on results which replaced traditional control hierarchical systems.

From 2020 to 2024, Haier evolves into a complete ecosystem platform with over 3600 micro-enterprises and more than a hundred of these generating annual revenues of more than 100 million yuan, making this period the intelligent breakthrough period. The company created COSMOPlat, an industrial internet platform that allows for mass customisation by automated integration of suppliers and customer order processing in real-time. Management accounting has now expanded to include value allocation across the ecosystem, collaborative performance measurement among participants on the platform, and demand and resource forecasting and optimisation using prescriptive analytics.

Table 6: Haier's Management Accounting Evolution by Historical Period

Period	Primary Tools	Key Innovations	Performance Metrics
Informatization (2000-2012)	ERP Systems, Cost Control	Decentralized Accounting	Traditional Financial Ratios
Digital Leap (2012-2020)	RenDanHeYi P&L Tracking	Entrepreneurial Accountability	Market-based Revenue Sharing
Intelligent (2020-2024)	Ecosystem Analytics	Platform Value Allocation	User Engagement, Ecosystem Income

4.3 Industrial Equipment Manufacturing: Predictive Maintenance Integration

As an example of a digital transformation spanning from operational efficiency improvement to the equipment lifecycle optimisation, heavy equipment manufacturing is an exemplar in this regard. During the period of information seeking, the groundwork for digital manufacturing was being built alongside basic automation systems and equipment monitoring databases. Cost controlling frameworks placed emphasis on utilisation ratios of assets.

Improvements realised during the digital leap period consisted of holistic Industrial IoT system integration, including real-time monitoring for predictive maintenance. Sensors enabled monitoring of temperature, vibration, and pressure metrics resulting in a 30% reduction in machinery downtime alongside significant savings in maintenance performed reactively. Innovations in management accounting received a boost from activity-based costing using equipment performance metrics allowing accurate cost allocation and optimisation of predictive maintenance.

Predictive and self-maintenance systems powered by AI are the hallmarks of the current period of intelligent breakthroughs. These systems utilise machine learning models geared towards identifying failure signatures and providing maintenance actionables for efficient upkeep. Strategic capacity planning structured upon predictive demand forecasting has been enabled from the evolution of management accounting that integrated equipment lifecycle costing, ROI measuring of predictive maintenance, and performance measurement of the whole supply chain.

4.4 Midea Group: Consumer-Centric Intelligence Integration

The digital transformation of the Midea Group focuses on the smart connectivity of consumers and manufacturing on five distinct business units which are smart home, smart building, smart logistics, smart manufacturing, and digital technology innovation. The digitalisation journey started fifteen years ago with back office processes such as HR, supply chain, and manufacturing systems automation as well as the initiative to make appliances at homes use computer-like systems with an operating systems and applications ecosystem.

In the leap period of digitisation, Midea Smart Cloud (M-Smart IoT Platform) was created and it provided the integration of home appliances with the Internet in an intelligent manner through the use of cloud platforms. Innovations in managerial accounting created integration of entire value chains with the design "One Platform, One Standard," achieving seamless collaboration across IoT-enabled smart appliances within R&D, manufacturing, supply chain, customer service, and management accounting.

AI-powered production optimisation is showcased in the intelligent breakthrough period with devices updated through software updates "over-the-air" and modular hardware enabling continuous enhancement. Today, Midea has created OpenHarmony-based operating systems for IoT devices and middleware that can link various devices such as AGVs, smart appliances, and factory machines. Advanced tools in management accounting allow value-based pricing of customer lifetime, cost optimisation based on demand, and measurement of ecosystem performance enabling tailored design and mass customisation of offered goods.

Table 7: Cross-Case Management Accounting Innovation Patterns

Innovation Category	Haier Group	Industrial Equipment	Midea Group
Cost Management	Entrepreneurial P&L	Activity-Based Costing	Value Chain Integration
Performance Measurement	Market-Based Metrics	Equipment Lifecycle ROI	Customer Lifetime Value
Decision Support	Ecosystem Analytics	Predictive Maintenance	Demand-Driven Planning
Value Creation	Platform Orchestration	Operational Optimization	Customer-Centric Customization

4.5 Cross-Case Analysis and Theoretical Implications

The cross-case analysis reveals evolutionary patterns industry-wide and supports the triple transition theoretical model with differences specific to each industry's adaptation frameworks. All enterprises follow a sequential progression that begins with an informatization foundation, a digital leap, followed by an intelligent technological breakthrough. Meanwhile, in management accounting ergonomics, the progress advances from the electronification stage, through integration, to intelligence levels. Regardless, there is considerable divergence in the transformation pathways that demonstrate reflexes from the sectoral needs and strategic priorities.

Each enterprise offers distinct approaches towards value creation: Haier focuses on ecosystem synthesis and entrepreneurial platforms, industrial equipment manufacturers emphasise operational excellence through analytics, while Midea centres on customer value through smart manufacturing integration. These differences confirm the hypothesis that the pathway to digital transformation within an organisation is bound by contextual industry frameworks and organisational competencies, yet follows common evolutionary frameworks.

The case analysis supports the identified mediation mechanism in management accounting (more specifically, innovations in management accounting) and confirms the quantitative analysis. Every enterprise illustrates how digital technology enhances performance in hierarchical organisational systems, sophisticated analytics frameworks, and predictive planning capabilities slash decision-making tools as opposed to direct operational enhancements. The historical evolution from simple digitisation to the intelligent analytics (decision-making) stage represents fundamentally transforming structural evolution in an organisation's information processing systems. This framework validates the assumption that innovative management accounting acts as both an enabler and a product of successful digital transformations in diverse contexts of manufacturing.

5 Discussion

5.1 Historical Evolution Patterns and Theoretical Contributions

This study's historical periodization framework reveals that manufacturing digital transformation follows distinct temporal phases rather than continuous linear progression, fundamentally challenging existing ahistorical perspectives on technology adoption. The empirical evidence demonstrates that each historical period—informatization foundation (2000-2012), digital leap (2012-2020), and intelligent breakthrough (2020-2024)—creates specific enabling conditions for management accounting evolution, with cumulative effects that build upon previous technological foundations. The finding that management accounting innovation accounts for 28% of digital transformation's performance effect, increasing to 35% during the intelligent breakthrough period, illustrates how historical accumulation of digital capabilities amplifies the strategic importance of accounting analytics over time.

The cross-case historical analysis reveals that enterprises exhibit path-dependent transformation trajectories while maintaining flexibility at critical junctures [14]. Haier's evolution from basic ERP implementation in the informatization period to ecosystem orchestration with over 3,600 micro-enterprises by 2024 demonstrates how early decentralization experiments created institutional foundations for later radical organizational redesign through the RenDanHeYi model. This historical trajectory contradicts assumptions of uniform digital transformation patterns, instead supporting institutional theory's emphasis on how historical choices constrain and enable future development paths. The temporal concentration of management accounting sophistication advancement during specific historical periods suggests that technological breakthroughs create critical junctures that enable qualitative leaps rather than incremental improvements [15].

5.2 Temporal Performance Dynamics and Industry Differentiation

The regression results revealing increasing returns to digitally invested capital over time, from 0.284 during the digital leap to 0.367 during the intelligent breakthrough, illustrates more technological sophistication accrues benefits in excess rather than follows the diminishing marginal returns rule. This historical pattern suggests the emergence of network effects and analytic capabilities. These investments, as enterprises undergo transformation phases, then analytic capabilities that enhance return on investment multiply [16]. The cross-section analysis by industry shows electronics manufacturing reaching 8.5% intensity of digital investment by 2024 while traditional sectors only achieve 4.0%. This indicates historical technological readiness shapes diverging pathways of evolution that endure through transformation periods.

The shift in the management accounting sophistication distribution evolution from electronification 52.3% to an intelligence-level capability 28.4% by 2021-2024 suggests active change predominately within the intelligent breakthrough epoch. This focus in time indicates the 2020 tipping point is an important turning point in history where artificial intelligence technologies triggered qualitative leaps, as opposed to gradual changes, in accounting functionalities. The single-case study exemplification showing Midea's digitalisation journey over 15 years from sidelined processes of back-office functions to orchestrating OpenHarmony-dominated IoT ecosystems shows the phenomenon of advanced integration which relies on historical capability accumulation. The intelligence levels suggest 79% stasis which reinforces the notion that sophisticated capabilities grounded in historical investments bolster advantages that are competitively self-reinforcing [17].

5.3 Historical Implications and Future Research Trajectories

The historical analysis demonstrates that successful digital transformation requires understanding temporal sequencing and cumulative capability building rather than pursuing simultaneous technology deployment across all domains. The evidence that different enterprises achieve similar performance outcomes through distinct historical pathways—Haier's ecosystem platform evolution, industrial equipment predictive maintenance integration, and Midea's consumer-centric intelligence development—suggests that historical context and early strategic choices create multiple viable transformation trajectories while maintaining common evolutionary patterns [18].

Future research should examine how historical institutional environments across different national contexts shape digital transformation patterns, particularly comparing economies with varying manufacturing heritage and technological infrastructure development timelines. The study's focus on the 2000-2024 period could be extended through archival research to examine earlier industrial automation phases and their influence on current digital capabilities [19]. Additionally, investigating how historical transformation phases create differential resilience to future technological disruptions would provide insights into sustainable competitive advantage development. The emergence of quantum computing, advanced AI, and biotechnology integration suggests potential fifth-generation transformation phases that may follow different historical patterns than those observed in current digital technologies, requiring longitudinal research extending beyond the current temporal scope [20].

6 Conclusion

This study proposes and empirically validates the triple transition framework for understanding manufacturing digital transformation and management accounting innovation through historical periodization analysis. The research demonstrates that digital transformation progresses through three distinct phases—informatization foundation (2000-2012), digital leap (2012-2020), and intelligent breakthrough (2020-2024)—each creating specific enabling conditions for management accounting evolution. The empirical analysis of 112 Chinese manufacturing enterprises reveals that management accounting innovation serves as a critical mediating mechanism, accounting for 28% of digital transformation's performance effect during the digital leap period and increasing to 35% during the intelligent breakthrough period. The case studies of Haier Group, industrial equipment manufacturers, and Midea Group illustrate diverse transformation pathways while confirming common evolutionary patterns from electronification through integration to intelligence-level sophistication. The findings reveal escalating returns to digital investment across historical periods, with coefficient magnitudes increasing from 0.284 to 0.367, indicating that advanced technologies create cumulative advantages through network effects and analytical capabilities. Industry-specific analysis demonstrates heterogeneous transformation trajectories, with electronics manufacturing achieving 8.5% digital investment intensity compared to traditional sectors' 4.0%, reflecting the persistent influence of historical technological readiness on current capabilities. The management accounting sophistication distribution shows structural transformation concentrated during the intelligent breakthrough period, with intelligence-level capabilities expanding from 10.7% to 28.4% of enterprises while basic electronification declined from 52.3% to 18.7%. These findings contribute to both digital transformation theory and management accounting literature by providing a comprehensive framework for understanding the co-evolutionary dynamics between technological advancement and accounting practice innovation across distinct historical periods.

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