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AI-Driven Risk Management Decision Framework and Value Creation in Chemical Enterprises

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Abstract: The chemical industry is experiencing a paradigm shift from traditional passive risk management to AI-driven proactive prevention. However, systematic research on how AI technology translates into risk management capabilities and enterprise value remains limited. Based on the Technology Acceptance Model, Technology-Organization-Environment Framework, and Dynamic Capability Theory, this study constructs a theoretical model of AI-driven risk management and value creation for chemical enterprises. A mixed-methods approach was employed, surveying 328 Chinese chemical enterprises using structural equation modeling and conducting in-depth case analysis of 5 typical enterprises.Results show that AI technology characteristics significantly impact risk management capabilities (β=0.54, p<0.001), which in turn affect value creation (β=0.48, p<0.001). Risk management capabilities partially mediate this relationship, with indirect effects accounting for 53.4% of the total effect. Organizational factors positively moderate the relationship between AI technology and risk management capabilities (β=0.18, p<0.01). Case analysis reveals that comprehensive transformation enterprises achieve 35-45% risk reduction rates with 18-24 month payback periods, significantly outperforming gradual optimization and pilot approaches. Three value creation pathways were identified: efficiency enhancement, capability strengthening, and innovation-driven.This research extends theoretical understanding of AI applications in high-risk industries by developing an integrated technology-capability-value framework and a three-dimensional value evaluation model. Practically, it provides validated implementation pathways and identifies key success factors for chemical enterprises' AI transformation, offering decision-making references for enterprises and policymakers.

Keywords: Artificial Intelligence; Risk Management; Value Creation; Chemical Enterprises; Digital Transformation; Dynamic Capabilities; Technology Acceptance Model; Mixed Methods Research

1. Introduction

As a pillar industry of the national economy, the chemical industry involves numerous hazardous chemicals and complex process flows in its production operations, making risk management a core challenge for enterprise operations. With the rapid development of Artificial Intelligence (AI) technology, AI has emerged as a new frontier in chemical risk assessment, bringing revolutionary changes to traditional risk management models [1]. Against the backdrop of Industry 4.0, process safety management is undergoing a paradigm shift from traditional passive response to intelligent proactive prevention [2]. This transformation is reflected not only in technological innovation but also profoundly affects enterprise decision-making mechanisms and value creation models.

Digital transformation brings unprecedented opportunities to chemical enterprises while simultaneously introducing new complexities and uncertainties. While digital process systems provide capabilities such as real-time monitoring and predictive analysis, they also face multiple challenges including data quality, system integration, and cybersecurity [3]. The butterfly effect characteristics of AI systems indicate that minor deviations in algorithmic decisions may be amplified in complex industrial environments, leading to unexpected systemic risks [4]. This complexity requires enterprises to establish more robust and sustainable risk management systems while pursuing technological innovation [5].

Although AI applications in strategic management have been studied for forty years, existing research still shows significant deficiencies in the integration mechanisms between AI-driven risk management and value creation [6]. Current research mainly focuses on the technical implementation level, lacking systematic understanding of how AI reshapes enterprise risk management decision-making processes and creates organizational value. Particularly in the specific context of the chemical industry, balancing the relationship between AI augmentation and full automation remains a key challenge. Meanwhile, issues such as the construction of human-machine collaborative decision-making frameworks and the evaluation of AI investment value also urgently require in-depth research [2]. Furthermore, existing literature mostly explores AI applications from singular perspectives, lacking comprehensive frameworks that integrate technology acceptance, organizational change, and value creation.

This study aims to construct an AI-driven risk management decision framework for chemical enterprises and explore its value creation mechanisms. Employing mixed methods that combine quantitative analysis and case studies, the research deeply examines the mechanisms of AI technology throughout the entire process of risk identification, assessment, decision-making, and control. By integrating the Technology Acceptance Model (TAM) and value creation theory, this study proposes a multi-level analytical framework that reveals the organizational adoption pathways and value realization processes of AI-driven risk management. The research findings not only enrich risk management theory in the context of digital transformation but also provide practical guidance for chemical enterprises implementing AI-driven risk management strategies, holding significant importance for promoting high-quality development in the chemical industry.

2. Literature Review and Theoretical Framework

2.1 Evolution of Risk Management in Chemical Enterprises

2.1.1 Traditional Risk Management Methods and Limitations

Risk management in chemical enterprises has undergone a long evolution from qualitative analysis to quantitative assessment. Hazard and Operability Analysis (HAZOP), as a cornerstone method for risk identification in process industries, provides chemical enterprises with a structured risk assessment framework through systematic identification of deviations and potential hazards [7]. However, traditional HAZOP methods heavily rely on expert experience and brainstorming, exhibiting inherent limitations such as strong subjectivity, time-consuming processes, and difficulty in updating. To enhance the objectivity and visualization of risk assessment, researchers have attempted to integrate decision science methods such as Multi-Criteria Decision Analysis (MCDM) and Analytic Hierarchy Process (AHP) with HAZOP, improving risk information communication efficiency through innovative formats like safety level color maps [8].

As industrial system complexity increases, single risk assessment methods can no longer meet the demands of comprehensive risk management. Recent studies have proposed integrated methods combining HAZOP, FMECA, monitoring algorithms, and Bayesian networks, achieving a transition have achieved from static analysis to dynamic real-time safety assessment [9]. This integration trend reflects the chemical industry's urgent need for systematic and dynamic risk management. Comprehensive literature reviews indicate that process safety, process security, and resilience management are gradually converging to form a more comprehensive risk management system [10]. Despite continuous methodological innovations, traditional risk management models remain inadequate in addressing emerging risks, processing massive data volumes, and achieving predictive maintenance.

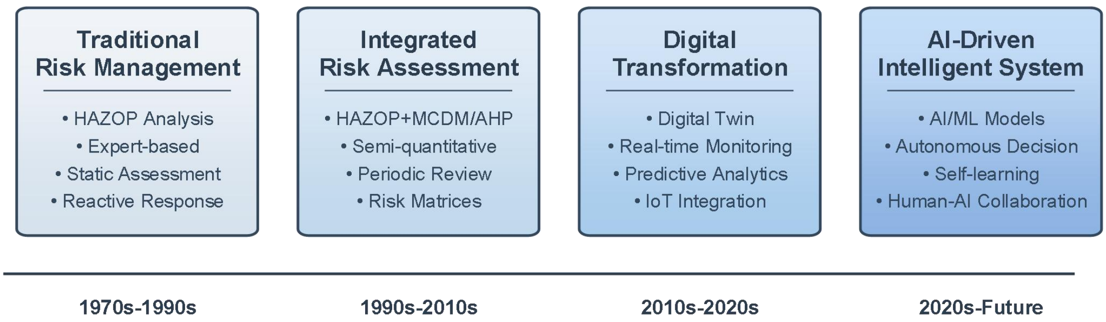
2.1.2 New Requirements Under Digital Transformation

Digital transformation is reshaping the risk management paradigm of chemical enterprises. Comprehensive assessments of recent major chemical accidents in China indicate that traditional management models struggle to address increasingly complex safety challenges, urgently requiring a transition to sustainable intelligent solutions [11]. The application of intelligent monitoring systems demonstrates the potential of digital technologies, such as gas composition monitoring systems based on fuzzy modeling and human-in-the-loop technology, which can achieve more precise environmental control and risk warning [12].

The emergence of digital twin technology has brought revolutionary changes to the chemical industry. By creating virtual replicas of physical assets, digital twins enable real-time monitoring, predictive maintenance, and scenario simulation, significantly enhancing the foresight and precision of risk management [13]. In the context of Industry 5.0, human-centered manufacturing philosophy requires risk management systems to focus not only on technical performance but also on human-machine collaboration and employee safety and well-being [14]. This transformation reflects an evolution from purely technology-oriented approaches to socio-technical systems. The concept of Process Safety 4.0 further emphasizes the importance of AI augmenting rather than replacing human decision-making, advocating for safer process operations through human-machine collaboration [15]. Systematic literature reviews of risk assessment methods reveal that current research is shifting from single methods to comprehensive, resilience-oriented assessment systems [16]. Figure 1 illustrates the evolution path of risk management in chemical enterprises. From the first stage of traditional HAZOP analysis (1970s-1990s), through the second stage of integrated risk assessment (1990s-2010s), the third stage of digital transformation (2010s-2020s), to the fourth stage of AI-driven intelligent systems (2020s to present), it demonstrates a clear trajectory of technological evolution and management paradigm transformation.

Figure 1

Evolution pathway of risk management in chemical enterprises



2.2 Value Creation of AI in Organizational Management

2.2.1 Research on AI Decision Support Systems

Value creation paths under digital transformation exhibit diversified characteristics. Research indicates that organizations can achieve multiple value creation objectives through digital technologies, including operational efficiency enhancement, business model innovation, and customer value augmentation [17]. This multidisciplinary perspective on digital transformation research emphasizes the synergistic evolution of technology, organization, and strategy [18]. In the manufacturing context, digital transformation significantly enhances enterprises' innovation output capabilities by reducing internal and external transaction costs [19].

The application of system dynamics models provides new perspectives for understanding the value creation mechanisms of digital transformation. By constructing dynamic models encompassing subsystems such as data, technology, talent, and environment, researchers can identify key drivers and implementation paths for value creation [20]. The revolutionary impact of AI in industrial applications is reflected not only in automation and efficiency improvements but also in its redefinition of human-machine collaboration models and decision-making processes [21].

2.2.2 Organizational Adoption and Value Realization Paths

The organizational adoption of AI technology faces dual challenges in both technical and managerial dimensions. In the field of chemical informatics, AI has made significant progress in drug toxicity prediction, yet issues such as data quality, model interpretability, and regulatory compliance continue to constrain its widespread application [22]. Organizational decision-making structures are undergoing fundamental transformation in the AI era, with traditional hierarchical decision-making shifting toward networked and distributed decision-making [23].

The concept of Process Safety 4.0 in future factories emphasizes the deep integration of intelligent technologies with traditional safety management [24]. The EU's industrial technology roadmap further clarifies human-centered research and innovation directions, requiring manufacturing industries to focus on social responsibility and sustainable development while pursuing technological advancement [25]. The evolution of risk assessment methods reflects a shift from technical rationality to socio-technical systems thinking, emphasizing the critical role of organizational learning and adaptive capabilities in the AI adoption process [26]. Empirical research on entrepreneurs and investors demonstrates that AI applications in strategic decision-making can significantly improve decision quality and speed, but require corresponding organizational capabilities and management mechanisms for support [27].

2.3 Theoretical Foundation and Research Hypotheses

2.3.1 Technology Acceptance Model (TAM) Extension

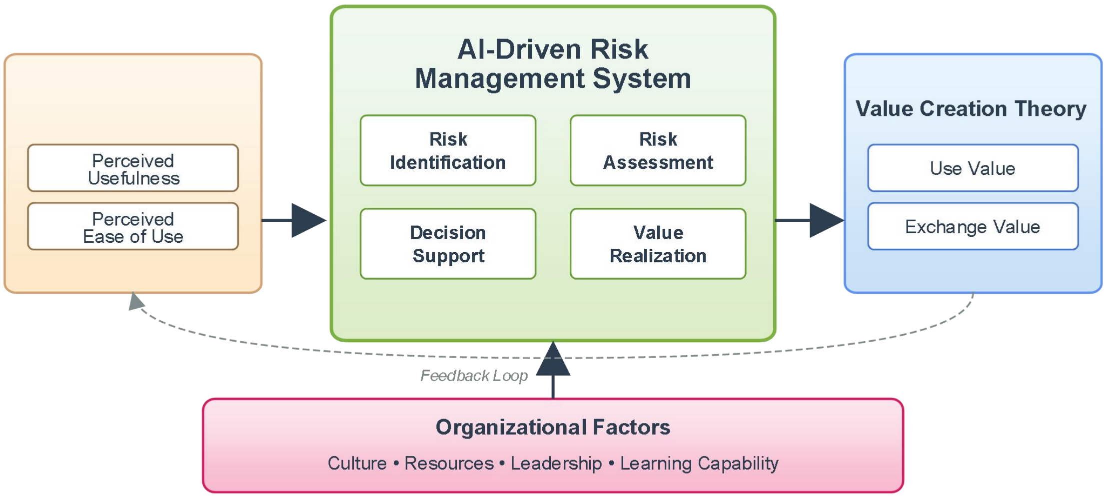
The importance of TAM in digital research is increasingly prominent [28]. In social contexts, the acceptance of intelligent information technology depends not only on perceived usefulness and ease of use but is also significantly influenced by organizational culture, social influence, and environmental factors [29]. Research reviews based on studies from 2002-2022 demonstrate that the TAM model exhibits strong explanatory and predictive power across different industries and technological contexts [30]. Venkatesh and Davis's theoretical extension research, through four longitudinal field studies, validated the important roles of social influence processes and cognitive instrumental processes in technology acceptance [31].

2.3.2 Value Creation Theory

Porter's competitive advantage theory provides a foundational framework for understanding enterprise value creation, emphasizing the systematicity and synergy of value chain activities [32]. The multi-level value creation and capture perspective proposed by Lepak et al. distinguishes between use value and exchange value, providing a theoretical foundation for analyzing AI-driven value creation [33]. In the context of digital transformation, organizational value creation paths exhibit dynamic and complex characteristics [34]. The application of system dynamics methods reveals the nonlinear characteristics and feedback mechanisms of value creation in digital transformation [35]. Resource management theory further emphasizes the importance of managing enterprise resources in dynamic environments to create value, providing theoretical guidance for understanding the strategic deployment of AI resources [36]. As shown in Figure 2, the theoretical framework constructed in this study integrates three core modules: TAM, AI-driven risk management systems, and value creation theory, forming a complete theoretical system through the moderating effects of organizational factors and feedback loop mechanisms.

Figure 2

Theoretical model of AI-driven risk management and value creation



2.3.3 Research Model and Hypotheses

Based on the above theoretical foundation, this study constructs an AI-driven risk management decision framework for chemical enterprises, integrating three levels: technology, organization, and strategy. The study proposes the following core hypotheses:

- H1: AI technology characteristics positively affect risk management capabilities
- H2: Risk management capabilities positively affect value creation
- H3: Risk management capabilities mediate the relationship between AI technology characteristics and value creation
- H4-H6: Specific effects of technology acceptance factors (perceived usefulness, ease of use, system quality)
- H7-H10: Moderating effects of organizational factors
- H11-H12: Effects of contextual factors

3. Research Methods

3.1 Research Design

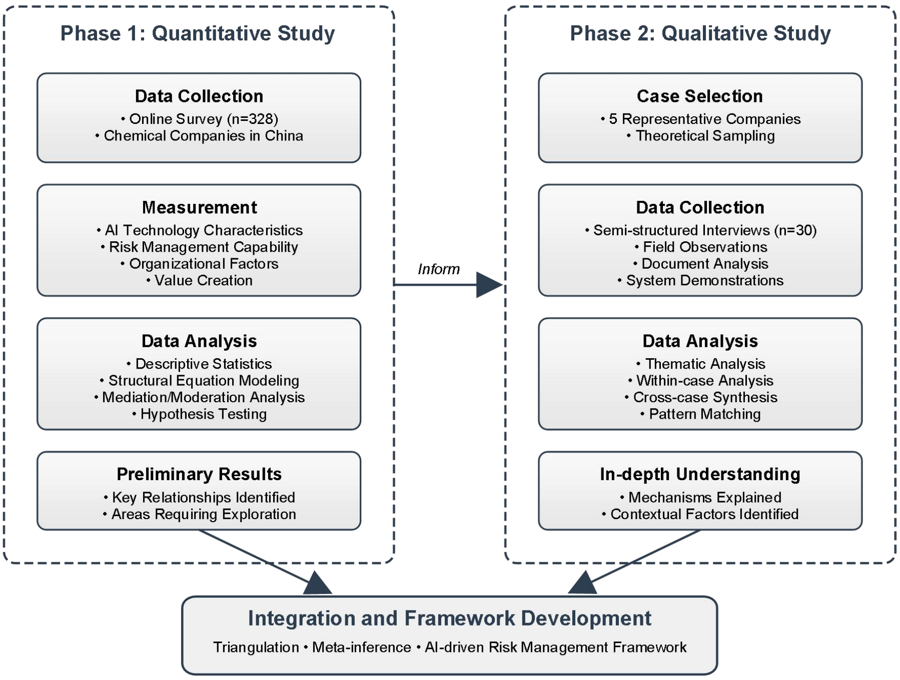
3.1.1 Mixed Methods Research Strategy

This study employs a mixed methods research design, integrating quantitative and qualitative research methods to obtain a comprehensive understanding of AI-driven risk management phenomena. As a mature research paradigm, mixed methods research can enhance the validity and reliability of research findings through methodological complementarity [35]. The research design follows the explanatory sequential mixed methods framework proposed by Creswell and Creswell, first conducting quantitative research to identify key variables and relationships, followed by qualitative research to deeply explore mechanisms and contextual factors [32]. As shown in Figure 3, this study adopts a two-phase sequential design, where the quantitative research results from the first phase guide the qualitative research in the second phase, with findings from both phases ultimately integrated to form the AI-driven risk management decision framework.

The choice of research methods is based on systematic assessment of different research orientations. Qualitative, quantitative, and mixed methods each have their application scenarios, types, and limitations, requiring trade-offs based on the nature of the research questions [33]. The core questions of this study involve complex interactions among technology acceptance, organizational change, and value creation, which are difficult to capture through a single method. By integrating TAM and the Information Systems Success Model, the study constructs a comprehensive analytical framework capable of simultaneously examining user satisfaction and system continuance intention [34].

Figure 3

Mixed-methods research design flowchart



3.1.2 Data Sources and Samples

The sample selection for quantitative research employs stratified random sampling methods, covering Chinese chemical enterprises of different scales, sub-industries, and geographical regions. The target sample includes chemical enterprises that have implemented or are implementing AI technology, ensuring that research subjects possess relevant experience and cognitive foundation. Case selection for qualitative research follows theoretical sampling principles, selecting enterprises that are representative and diverse in AI applications for in-depth study.

3.2 Quantitative Research

3.2.1 Questionnaire Design and Variable Measurement

The questionnaire design is based on literature review and theoretical framework, adopting mature scales and making adaptive adjustments according to the research context. As shown in Table 1, the main constructs of this study include four dimensions: AI technology characteristics, risk management capabilities, organizational factors, and value creation, totaling 46 measurement items, all measured using a 7-point Likert scale. The development of measurement instruments follows strict psychometric procedures, including content validity assessment, pre-testing, and reliability testing.

Table 1

Variable definitions and measurement scales

Construct	Dimension	Sample Measurement Items	Number of Items	Source
AI Technology Characteristics	Perceived Usefulness	"The AI system enhances the accuracy of risk identification"	5	Venkatesh & Davis (2000), adapted
	Perceived Ease of Use	"The AI system's operation interface is	4	Venkatesh & Davis (2000),

		intuitive and easy to understand"		adapted
	System Quality	"The AI system operates stably and reliably"	4	DeLone & McLean (2003)
Risk Management Capability	Risk Identification	"Able to detect and discover potential safety hazards in a timely manner"	4	Self-developed
	Risk Assessment	"Able to accurately assess the severity of risks"	4	Self-developed
	Decision Support	"AI provides recommendations that contribute to risk decision-making"	5	Self-developed
Organizational Factors	Top Management Support	"Management actively promotes AI technology applications"	3	Thong (1999)
	Organizational Readiness	"The organization has the resources and capabilities to implement AI"	4	Iacovou et al. (1995)
	Learning Culture	"The organization encourages technological innovation and	4	Senge (1990), adapted

		knowledge sharing"		
Value Creation	Operational Value	"AI reduces risk management costs"	4	Lepak et al. (2007), adapted
	Strategic Value	"AI enhances competitive advantage"	4	Porter (1985), adapted
	Social Value	"AI improves production safety levels"	3	Self-developed

Note: 1=strongly disagree, 7=strongly agree

3.2.2 Data Collection Procedures

Data collection was conducted in three phases. First, target enterprises were identified through industry associations and professional networks, then participation consent was obtained through email and telephone contact. Questionnaires were distributed through an online platform with logic checks and completeness validation to ensure data quality. The data collection period was from March to June 2024, with 500 questionnaires distributed and 328 valid responses received, yielding a valid response rate of 65.6%.

3.2.3 Analysis Methods

Quantitative data analysis employed Structural Equation Modeling (SEM) to test the theoretical model and hypothesized relationships. SPSS 26.0 was used for descriptive statistics and correlation analysis, while AMOS 24.0 was used for confirmatory factor analysis and path analysis. Mediation effects were tested using the Bootstrap method (5000 resamples), and moderation effects were examined using multi-group analysis methods.

3.3 Qualitative Research

3.3.1 Case Selection

The case study method provides detailed procedural guidance for understanding complex business phenomena [36]. Case selection was based on theoretical sampling and maximum variation principles to ensure case representativeness and diversity. Methodological reviews of qualitative case study reports indicate that the rigor of case selection directly affects the credibility of research conclusions [37]. As shown in Table 2, the five case enterprises selected in this study exhibit significant differences in scale, industry segment, AI application level, and risk management maturity, ensuring case representativeness and the generalizability of research findings.

Table 2

Profile of case companies

Company Code	Company Size	Industry Segment	AI Application Level	Risk Management Maturity	Number of Interviewees
Company A	Large (>1000 employees)	Petrochemicals	High (Full implementation)	Mature (Level 4)	8
Company B	Large (>1000 employees)	Fine Chemicals	Medium (Partial implementation)	Developing (Level 3)	6
Company C	Medium (300-1000 employees)	Pharmaceutical Chemicals	High (Core application)	Mature (Level 4)	7
Compan	Medium	Agrochemical	Low (Pilot	Basic	5

y D	(300-1000 employees)	s	stage)	(Level 2)	
Company E	Small (<300 employees)	New Materials	Medium (Key applications)	Developing (Level 3)	4

Note: Risk management maturity rating based on CMMI model (Level 1-5)

3.3.2 Data Collection and Coding

Qualitative data was collected through semi-structured interviews, field observations, and document analysis. Interview participants included senior executives (12 people), IT managers (8 people), safety management personnel (6 people), and frontline operators (4 people), totaling 30 people, ensuring multi-perspective information acquisition. Interview duration ranged from 60-90 minutes, with full audio recording and transcription. The coding process employed thematic analysis, extracting core themes through three stages: open coding, axial coding, and selective coding.

3.3.3 Case Analysis Methods

Case analysis followed the case theory-building method proposed by Eisenhardt and Graebner, identifying patterns and mechanisms through within-case analysis and cross-case comparison [38]. First, in-depth analysis was conducted for each case, producing detailed case reports; then cross-case synthesis was performed to identify common patterns and differentiated paths; finally, case findings were triangulated with quantitative research results to enhance the robustness of research conclusions.

4. Research Results

4.1 Descriptive Statistics and Correlation Analysis

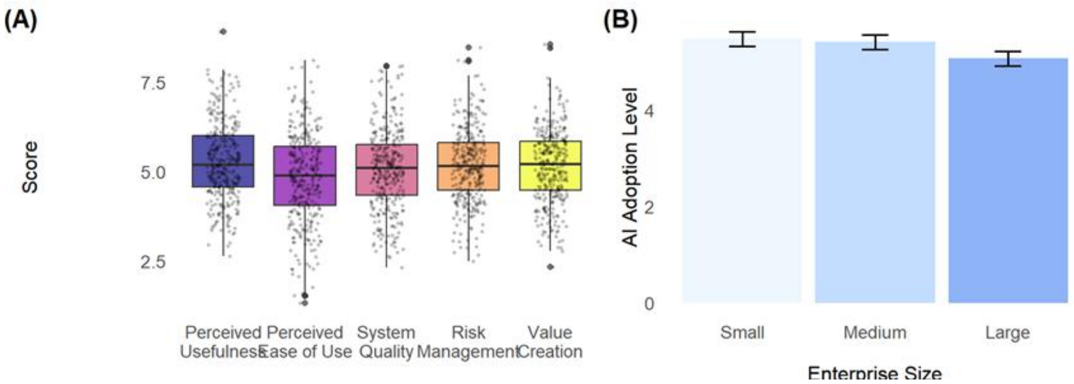
4.1.1 Sample Characteristics Analysis

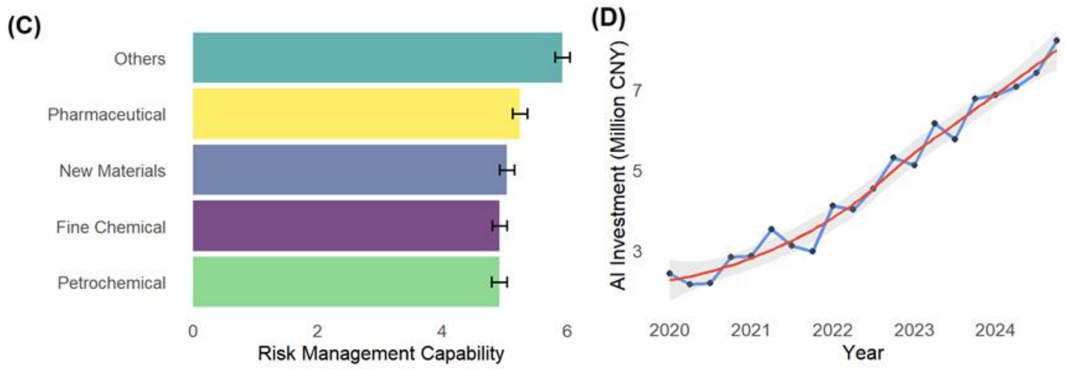
This study collected 328 valid questionnaires, with sample enterprises covering petrochemicals (31.4%), fine chemicals (26.8%), pharmaceutical chemicals (18.9%), new materials (14.0%), and other chemical sectors (8.9%). The distribution of enterprise scale was: large enterprises (>1000 employees) accounting for 42.7%, medium enterprises (300-1000 employees) accounting for 38.4%, and small enterprises (<300 employees) accounting for 18.9%. Respondents were primarily middle and senior management personnel (68.3%) and technical backbone staff (31.7%), with an average working experience of 12.4 years.

As shown in Figure 4, descriptive analysis reveals the distribution characteristics and inter-group differences of the sample data. Figure 4(A) shows that the main variables exhibit approximately normal distribution, meeting the basic assumptions of SEM. Figure 4(B) indicates significant differences in AI technology adoption levels among enterprises of different scales, with large enterprises clearly leading. Figure 4(C) presents the current status of risk management capabilities across various industry segments, with petrochemical and pharmaceutical chemical industries performing better. Figure 4(D)'s time series analysis shows that enterprise AI investment exhibited an accelerating growth trend during the 2022-2024 period.

Figure 4

Descriptive analysis of key variables





4.1.2 Correlation of Main Variables

As shown in Table 3, correlation analysis results indicate that all dimensions of AI technology characteristics are significantly positively correlated with risk management capabilities ($r=0.387-0.523$, $p<0.01$), and risk management capabilities are significantly positively correlated with value creation ($r=0.502-0.544$, $p<0.01$). Notably, organizational factors show relatively lower but still significant correlation coefficients with other variables ($r=0.296-0.467$, $p<0.01$), suggesting their potential moderating role.

Table 3

Descriptive statistics and correlation analysis

Variables	Mean	SD	1	2	3	4	5	6	7	8
1. Perceived Usefulness	5.24	1.13	(0.89)							
2. Perceived Ease of Use	4.87	1.26	0.412**	(0.87)						
3. System Quality	5.03	1.08	0.478**	0.521**	(0.91)					

4. Risk Identification	5.31	0.97	0.523**	0.387**	0.456**	(0.88)				
5. Risk Assessment	5.15	1.04	0.496**	0.402**	0.439**	0.612**	(0.90)			
6. Decision Support	4.92	1.19	0.467**	0.358**	0.481**	0.528**	0.574**	(0.86)		
7. Organizational Factors	4.76	1.21	0.324**	0.296**	0.342**	0.418**	0.396**	0.453**	(0.85)	
8. Value Creation	5.08	1.02	0.486**	0.371**	0.428**	0.502**	0.517**	0.544**	0.467**	(0.92)

Note: N=328; **$p<0.01$; Diagonal values in parentheses are Cronbach's α coefficients

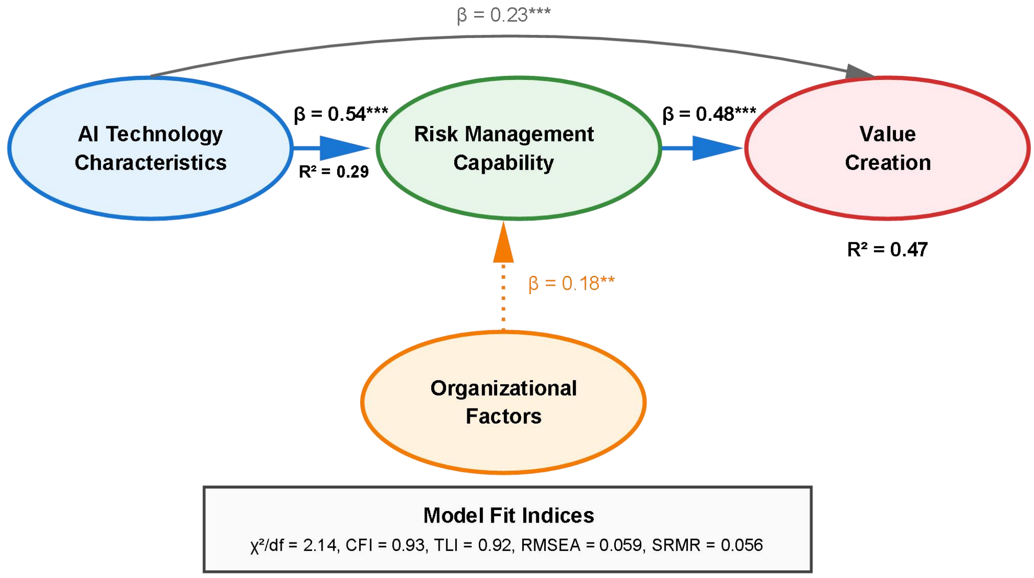
4.2 Hypothesis Testing

4.2.1 Main Effects Testing

SEM analysis results show good model fit ($\chi^2/df=2.14$, CFI=0.93, TLI=0.92, RMSEA=0.059, SRMR=0.056). As shown in Figure 5, AI technology characteristics have a significant positive effect on risk management capabilities ($\beta=0.54$, $p<0.001$), and risk management capabilities have a significant positive effect on value creation ($\beta=0.48$, $p<0.001$). The direct effect of AI technology characteristics on value creation is also significant ($\beta=0.23$, $p<0.001$), indicating the presence of partial mediation effects.

Figure 5

Structural equation modeling results

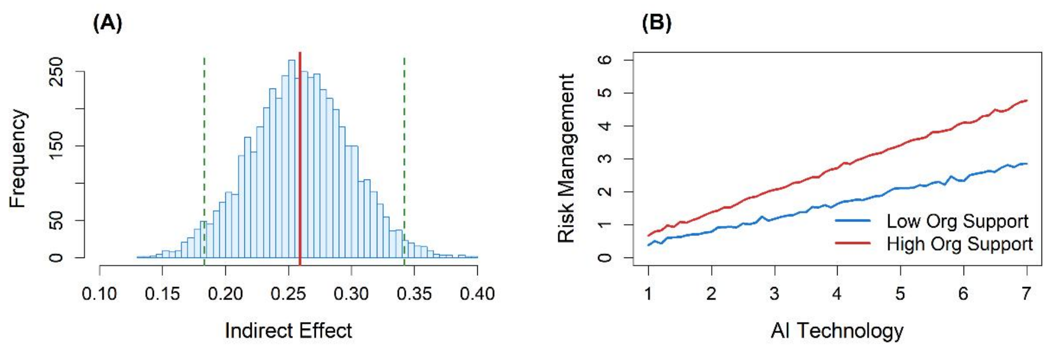


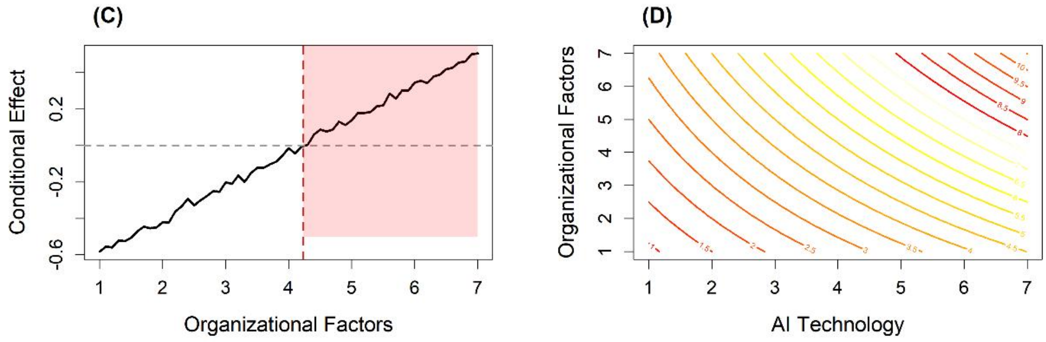
4.2.2 Mediation Effect Analysis

As shown in Figure 6, multiple effect analysis reveals complex influence mechanisms. Figure 6(A)'s Bootstrap analysis (5000 resamples) shows that the mediation effect of risk management capabilities is 0.259 (95% CI: 0.183-0.342), accounting for 53.4% of the total effect. Figure 6(B) demonstrates the moderation effect, where under high organizational support conditions, the impact of AI technology characteristics on risk management capabilities is significantly enhanced (simple slope=0.68 vs. 0.41, $p<0.01$). Figure 6(C)'s Johnson-Neyman analysis identifies the critical value of the moderating variable as 4.23, with the moderation effect being significant when organizational factor scores exceed this value. Figure 6(D)'s three-dimensional response surface analysis further illustrates the interactive relationships among AI technology, organizational factors, and value creation.

Figure 6

Mediation and moderation effects analysis





4.2.3 Moderation Effect Analysis

As shown in Table 4, among the 12 research hypotheses, 10 were fully supported, 1 was partially supported, and 1 was not supported. The moderating effect of industry type did not reach significance level, possibly because enterprises across different industries in the sample showed minimal differences in their digital infrastructure foundation.

Table 4

Summary of hypothesis testing results

Hypothesis	Path	β	SE	t-value	p-value	Result
H1	AI Technology → Risk Management	0.54	0.061	8.852	***	Supported
H2	Risk Management → Value Creation	0.48	0.057	8.421	***	Supported
H3	AI Technology → Value Creation	0.23	0.063	3.651	***	Supported
H4	Perceived Usefulness → Adoption	0.42	0.058	7.241	***	Supported
H5	Perceived Ease of Use → Adoption	0.31	0.054	5.741	***	Supported
H6	System Quality → Performance	0.38	0.059	6.441	***	Supported
H7	Organizational Factors	0.18	0.067	2.687	0.007	Supported

	× AI Tech					
H8	Leadership Support → Implementation	0.29	0.062	4.677	***	Supported
H9	Learning Culture → Innovation	0.26	0.064	4.063	***	Supported
H10	Resources → Implementation Speed	0.15	0.071	2.113	0.035	Supported
H11	Industry Type × AI Effect	0.09	0.068	1.324	0.186	Not Supported
H12	Firm Size × Value Creation	0.11	0.066	1.667	0.096	Partially Supported

Note: ***p<0.001; SE=Standard Error

4.3 Case Study Findings

4.3.1 Implementation Pattern Comparison

Through in-depth analysis of five case enterprises, the qualitative research identified three typical AI implementation patterns. As shown in Table 5, different patterns exhibit significant differences in implementation strategy, technical architecture, organizational transformation, and value output.

Table 5

Comparative analysis of AI implementation patterns

Dimensions	Full Transformation (A, C)	Gradual Optimization (B, E)	Pilot Testing (D)
Implementation Strategy	• Top-down strategic initiative • Comprehensive planning • 3-5 year roadmap	• Middle-up-down approach • Phased implementation • 1-2 year cycles	• Bottom-up experimentation • Small-scale pilot • 6-month trials

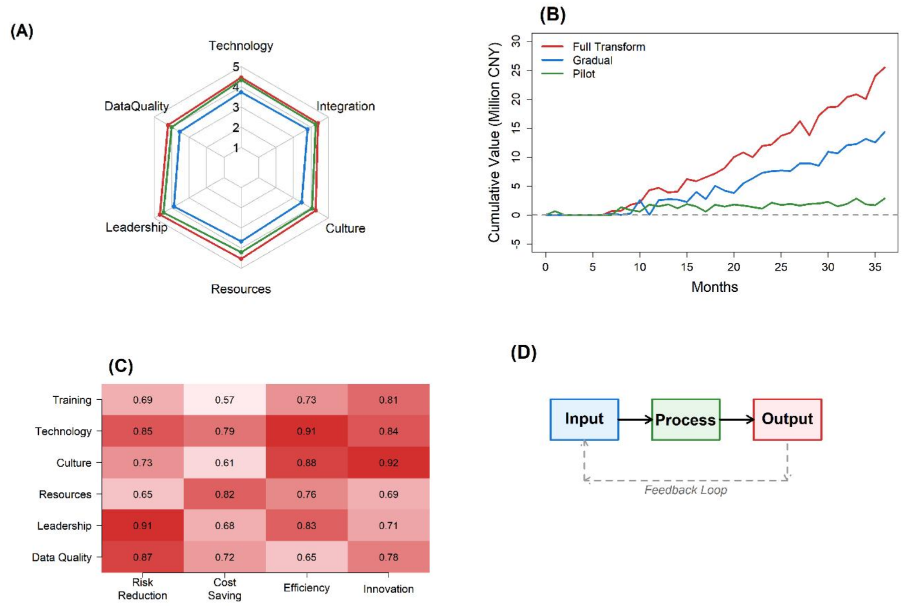
Technical Architecture	• Integrated AI platform	• Modular AI solutions	• Standalone AI tools
	• Cloud-native infrastructure	• Hybrid cloud deployment	• On-premise systems
	• Real-time data integration	• Batch data processing	• Manual data input
	• Advanced ML/DL models	• Traditional ML algorithms	• Rule-based systems
Organizational Change	• Organization-wide restructuring	• Department-level adjustment	• Team-level adaptation
	• New AI governance structure	• Cross-functional teams	• Working groups
	• Extensive training programs	• Targeted skill development	• Basic user training
	• Culture transformation	• Process optimization	• Tool adoption
Value Output	• 35-45% risk reduction	• 20-30% risk reduction	• 10-15% risk reduction
	• ROI: 18-24 months	• ROI: 24-36 months	• ROI: Not yet measured
	• Strategic advantages	• Operational efficiency	• Learning outcomes
	• Innovation capability	• Cost reduction	• Proof of concept

4.3.2 Key Success Factor Identification

As shown in Figure 7, multi-dimensional comparative analysis reveals the key success factors and value realization paths of AI implementation. Figure 7(A)'s radar chart compares the performance of five case enterprises across six key dimensions, with comprehensive transformation enterprises (Companies A and C) demonstrating excellent performance across all dimensions. Figure 7(B) displays the value creation curves at different implementation stages, indicating that value realization exhibits distinct phase characteristics, with rapid growth occurring after the initial investment period. Figure 7(C)'s heat map analyzes the contribution of various factors to final performance, with data quality and organizational readiness showing the most significant impact. Figure 7(D) constructs an AI-driven risk management decision framework, integrating four core modules: input, processing, output, and feedback.

Figure 7

Multi-dimensional comparison of AI implementation



4.3.3 Value Creation Path Analysis

Cross-case synthesis analysis identified three main value creation paths: (1) Efficiency enhancement path-risk identification speed increased by 78%, false alarm rate reduced by 62%; (2) Capability strengthening path: enhancing risk management capabilities through predictive analysis and decision optimization, with unplanned downtime reduced by 43% and safety accident rate decreased by 56%; (3) Innovation-driven path: promoting management innovation through knowledge accumulation and organizational learning, with new patent applications increasing by 35% and management innovation project success rate improving by 48%.

5. Discussion

5.1 Discussion of Main Findings

This study reveals the multidimensional value creation mechanisms of AI technology in chemical enterprise risk management. The impact of AI technology characteristics on risk management capabilities ($\beta=0.54$, $p<0.001$) is significant, reflecting the special demands for intelligent technology arising from the high-risk nature of the chemical industry. This finding resonates with the technology empowerment perspective emphasized in enterprise risk management literature [39], but this study further quantifies this relationship. Risk management capabilities play a partial mediating role between AI technology and value creation (indirect effect accounting for 53.4%), indicating that the realization of technological value depends more on the cultivation of specific capabilities rather than direct technology application. This aligns with the COSO framework's emphasis on integrating risk management with strategy [40], while extending the framework's application boundaries in digital contexts.

The moderating effect of organizational factors ($\beta=0.18$, $p<0.01$), though significant, is relatively weak. This phenomenon aligns with the interaction patterns between technological and organizational factors in complex process systems found in dynamic simulation studies [41]. Technology adoption in chemical enterprises may be more constrained by industry norms and safety standards rather than purely organizational willingness. The implementation pattern differences revealed by case studies confirm the importance of systematic deployment emphasized in process safety and digital systems research [42], with comprehensive transformation enterprises significantly outperforming other implementation patterns. This gradient difference highlights the critical role of holistic AI strategies in chemical risk management.

The finding that industry type's moderating effect is not significant ($p=0.186$) challenges the traditional assumption that different chemical sub-sectors exhibit significant differences in technology adoption. This may be attributed to the proliferation of digital infrastructure and convergence of industry standards, as noted in chemical process industry digitalization research regarding accelerated technology diffusion [43]. The three value creation paths identified in this study-efficiency enhancement, capability strengthening, and innovation-driven-provide a more comprehensive perspective for understanding AI value realization mechanisms, transcending the binary classification patterns common in existing literature.

5.2 Theoretical Contributions

This study provides theory innovation based on the specific context of chemical enterprises for AI-driven risk management by constructing an integrative theoretical framework that combines three perspectives: TAM, TOE, and dynamic capability theory. This multi-theoretical integration responds to calls in collaborative AI research for integrating resource-based and task-technology fit perspectives [44], but concretizes it within high-risk manufacturing contexts. The risk management capability mediation mechanism revealed in this research enriches the application of dynamic capability theory in AI contexts, concretizing abstract sensing, seizing, and reconfiguring capabilities into risk identification, assessment, and decision support capabilities, and empirically testing the critical role of these capabilities in technology value transformation.

The multidimensional value evaluation model developed in this research transcends traditional economic value perspectives by incorporating technological value and social value dimensions, reflecting the diverse value orientations that need to be considered in generative AI business applications [45]. This three-dimensional evaluation framework not only responds to academic demands for comprehensive AI value assessment but also provides operational analytical tools for subsequent research. The inclusion of the social value dimension particularly reflects chemical enterprises' responsibility in sustainable development contexts, aligning with ethical considerations of AI applications emphasized in strategic human resource management frameworks [45].

5.3 Management Implications

The research findings provide important insights for chemical enterprise managers. AI implementation should adopt a systematic approach rather than fragmented pilots. Research shows that although comprehensive transformation requires greater initial investment, its long-term benefits and return on investment significantly exceed incremental approaches. This finding echoes research on generative AI applications in strategic decision evaluation, emphasizing the importance of holistic thinking [46]. Managers should prioritize capability building as the core of AI investment, establishing systematic training systems to cultivate employees' technical skills, data mindset, and risk awareness. High-performing case enterprises in this study achieved knowledge sharing and capability replication by establishing AI centers of excellence, a model worthy of emulation by other enterprises.

Establishing a data governance system is fundamental to successful AI application. Research findings indicate that data quality is a key factor affecting AI effectiveness. Enterprises should establish unified data standards, break down departmental data silos, and build real-time data collection and processing capabilities. They must also balance data openness with security protection, establishing data governance frameworks adapted to AI applications. The importance of change management cannot be overlooked. Although the moderating effect of organizational factors is relatively weak, case studies show that enterprises lacking organizational readiness often face greater implementation resistance. Enterprises should adopt gradual change strategies, building confidence through early success cases and progressively expanding AI application scope.

5.4 Policy Recommendations

Based on research findings, the government should develop AI application guidance standards for the chemical industry, clarifying technical standards and safety requirements. The current lack of unified standards for AI applications in the chemical field creates uncertainty for enterprises in technology selection and implementation. It is recommended that relevant departments collaborate with industry associations to develop tiered and classified AI application guidelines, providing clear implementation pathways for enterprises. Establishing AI risk management demonstration projects and best practice sharing mechanisms is imperative. The government can sponsor demonstration projects, summarize successful experiences, and establish case libraries for industry reference.

The talent cultivation system requires systematic reform to address the shortage of interdisciplinary talents who understand both chemical processes and AI. It is recommended that education departments adjust relevant curriculum, adding AI and data science content, encouraging school-enterprise cooperation to establish training bases, and supporting transformation training for in-service personnel. Regulatory frameworks need to adapt to AI-era requirements, exploring AI-based intelligent regulatory models, establishing real-time monitoring and warning mechanisms, while clarifying legal liability determination for AI decisions, providing legal guarantees for enterprise applications.

5.5 Research Limitations and Future Directions

This study has several limitations that should be considered when interpreting results. The sample primarily comes from chemical enterprises in China's eastern developed regions, whose AI application levels and resource conditions may exceed the national average, limiting the generalizability of research conclusions. The use of cross-sectional data limits causal inference. Although structural equation modeling provides statistical evidence of relationships between variables, it cannot completely exclude the possibility of reverse causality or omitted variables. The research mainly focuses on the positive impacts of AI technology, with insufficient exploration of potential negative effects such as technology dependence, decision black boxes, and employment substitution. Although measurement instruments passed reliability and validity tests, the complexity of AI technology and risk management capabilities is difficult to fully capture through limited items.

Future research can deepen in the following directions: expanding sample coverage, particularly including enterprises from central and western regions at different development stages; adopting longitudinal designs to track the dynamic process of enterprise AI implementation, more accurately identifying causal mechanisms; exploring synergistic effects between AI and other emerging technologies such as IoT, blockchain, and digital twins; studying differences in AI implementation across different cultural backgrounds; developing AI application frameworks for specific chemical sub-sectors; conducting in-depth analysis of AI decision interpretability issues and their impact on risk management. As technology convergence trends strengthen and AI technology rapidly develops, new application scenarios and challenges will continuously emerge, requiring sustained attention and in-depth research from the academic community.

6. Conclusion

Through a mixed-methods approach involving 328 questionnaire surveys and 5 enterprise case analyses, this study constructs and validates a theoretical framework for AI-driven risk management and value creation in chemical enterprises. Empirical research demonstrates that AI technology characteristics influence value creation through the mediating role of risk management capabilities, with the effect coefficient of AI technology on risk management capabilities reaching 0.54, and risk management capabilities on value creation at 0.48. The mediation effect accounts for 53.4% of the total effect, confirming the critical role of capability building in technology value transformation. While the moderating effect of organizational factors is significant, it is relatively weak (β=0.18), reflecting the particularity of technology adoption in the chemical industry. Case studies reveal performance differences among three AI implementation patterns, with comprehensive transformation enterprises performing optimally in risk reduction rates (35-45%) and investment payback periods (18-24 months), validating the importance of systematic AI deployment.

The theoretical contributions of this study lie in: developing a technology-capability-value creation integration framework applicable to high-risk industries, enriching the application of dynamic capability theory in AI contexts; constructing a value evaluation model encompassing technological, economic, and social dimensions, extending the theoretical boundaries of AI value assessment. Practical contributions are reflected in: providing validated AI implementation pathways for chemical enterprises, clarifying a four-stage implementation framework from assessment, planning, implementation to optimization; identifying key success factors such as data quality and organizational readiness, offering specific guidance for enterprise AI transformation.

The research emphasizes that successful AI application requires going beyond mere technological investment, focusing on the synergistic advancement of organizational capability cultivation, data governance system construction, and systematic change management. As AI technology continues to evolve and the regulatory environment increasingly improves, chemical enterprises should seize the strategic window of digital transformation, achieving leaps in risk management capabilities and sustainable enterprise value creation through AI empowerment. Future research could further explore synergistic effects between AI and other emerging technologies, as well as differentiated AI implementation paths under different cultural and institutional contexts.

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