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Article

AI-powered organizational transformation: the role of digital mindset, change management, and cross-cultural leadership in shaping future business strategies

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ABSTRACT

This study explores how artificial intelligence reshapes business strategies through synergistic effects between digital thinking, change management, and cross-cultural leadership in organizational transformation processes. Based on multi-source public data from 450 global enterprises across technology, manufacturing, finance, and retail sectors, this research integrates structural equation modeling, in-depth case analysis of 20 extreme cases, and machine learning prediction methods to construct and validate an "AI-Driven Strategic Triple Helix Evolution Framework" through seven interrelated hypotheses. Empirical findings confirm that organizational transformation plays the role of a core mediating hub (R^2=0.64), connecting AI capabilities to strategic reconstruction, while the interaction with the three elements of synergy adds an additional 11% of explanatory power to it (ΔR^2=0.11, P<0.001). Six strategic paths are differentiated in this research: AI-native (12%), platform transformation (23%), ecosystem orchestration (18%), niche specialization (21%), hybrid innovation (17%), and conservative following (9%), with significant cultural context dependence. Cross-cultural leadership shows the greatest moderating effect on high power distance cultures (β=0.38). The framework goes beyond the traditional technology-organization-environment models in unfolding dynamic co-evolution mechanisms among technological capabilities, cognitive reconstruction, and cultural adaptation. Machine learning models further predict 70% of enterprises participating in ecosystem strategies by 2030, and a digital mindset contributes 34.2% to strategic innovation prediction.

1. Introduction

Artificial intelligence technology is experiencing exponential development and reshaping the global business landscape. Generative AI has made significant progress recently, placing organizations in a complex situation in which strategic transformation pressures and opportunities coexist as never before. Contemporary enterprises must not only address changes in operational models driven by technology, but also strike a delicate balance between technology-driven and humanistic care; this balance is critical to whether the organization can achieve sustainable development in the digital era [1]. In the context of in-depth globalization, along with other factors, cross-cultural management complexities introduced additional difficulties to this problem. The strategies for the cognition, acceptance, and application of AI technology differ across organizations from diverse cultural environments. This directly affects transformation efficiency and development strategies for business paths [2]. The more essential question is how AI technology has progressively evolved from a means of improving efficiency to a driving force for reconstructing the entire economic structure. The implications for business models, competitive patterns, and mechanisms for creating value are comparable to those of steam engines and electricity during the Industrial Revolution [3]. Although tremendous attention has been focused on AI-driven enterprise transformation studies, existing research has shown that there remains a tendency for fragmentation in terms of research frameworks and studies. Although research on digital thinking has clarified that cognitive level plays an important role in technology acceptance, most studies only involve the extension of technology acceptance model studies and do not provide a comprehensive explanation for why digital thinking can be extended from cognitive reconstruction to the level of strategic decision making [4]. Research into the issues of change management reflects the trend of shifting from a tool perspective to a capability perspective. However, these studies primarily focus on management techniques and methodologies during the change process and lack in-depth exploration of the strategic role of AI as the subject rather than the object of change [5]. Meanwhile, although research on integrating business strategy with AI technology has been continuously emerging, most studies take AI as an exogenous tool to enhance competitiveness, rather than the endogenous driving force for reconstructing the logic of strategy. Such cognitive bias means the conclusions of research can hardly provide forward-looking strategic guidance for enterprises [6].

The cross-cultural leadership mechanism in the AI era calls for more in-depth theoretical explanations and empirical tests. Although existing studies have verified that top management plays an important part in digital change, most studies are established on one culture or on data from developed countries and do not systematically answer basic research questions, including how cross-cultural leadership affects the application impact of AI technology and how it affects decision-making in globalization environments [7]. Cross-cultural management theory underlines the importance of cultural intelligence in global operations, but this important theory has not been in effective theoretical dialogue and integration with research on AI-driven organizational transformation [4]. Research in the field of international business has started to focus on the application challenges of AI technology in multinational enterprises. Yet, these studies mostly focus on technology diffusion and knowledge transfer issues, and a clear theoretical picture has not yet emerged with regard to how AI shapes differentiated business strategies in different cultural contexts [5]. The major deficiencies of the existing research are mainly reflected in the following four key aspects. The integrated mechanism of the three elements of digital thinking, change management, and cross-cultural leadership in shaping business strategy has not been fully revealed, and the academic community lacks systematic research that places these three elements within a unified analytical framework. The mechanism by which AI functions as a strategic driver rather than a mere tool remains a theoretical black box. The existing research is difficult to explain how AI technology has delved from enhancing operational efficiency to redefining business models and competitive logic [6]. The differentiated paths of strategic choices across cultures lack empirical support, and the academic community has not conducted in-depth comparative studies on how different cultural dimensions influence AI-driven strategic decision-making. The forward-looking strategic research for 2030 is seriously insufficient. The analysis in most of the existing literature is based on the current technological level, and predictive studies are missing for the strategic trends in the future, amidst the rapid evolution of AI technology [7].

Considering the above research gaps, this research endeavors to construct the "AI-driven strategic triple helix evolution framework", which not only surmounts over the limitations encountered in the technology-organizational-environment framework but has lifted research on technology adoption to a theoretic domain, where strategic evolution is systematically exposed. By incorporating structural equation models, in-depth case studies, and machine learning prediction methods, this study identified six differentiated business strategic paths in the AI era based on a large sample of data from 450 global enterprises, and conducted an in-depth analysis of the cultural context dependence characteristics of these strategic paths. More importantly, the innovation lies in that this study constructs a business strategy evolution prediction model for 2030, and provides forward-looking strategic insight for the academic and practical field [8]. This research not only enriches the cross-disciplinary studies of digital transformation, strategic management, and cross-cultural leadership at the theoretical level, but also provides operational strategic choice path maps for enterprises with different cultural backgrounds and development stages at the practical level. It has significant theoretical value and practical significance for promoting global enterprises to achieve sustainable strategic transformation in the AI era.

2. Methodology

2.1 Research design and hypothesis system

This research built an integrated conceptual model of "AI technology maturity →[Digital thinking×change Management×cross-cultural Leadership]→ Organizational transformation → Business strategy reconstruction", and tested the complex causal chain through seven interrelated hypotheses as Figure 1.

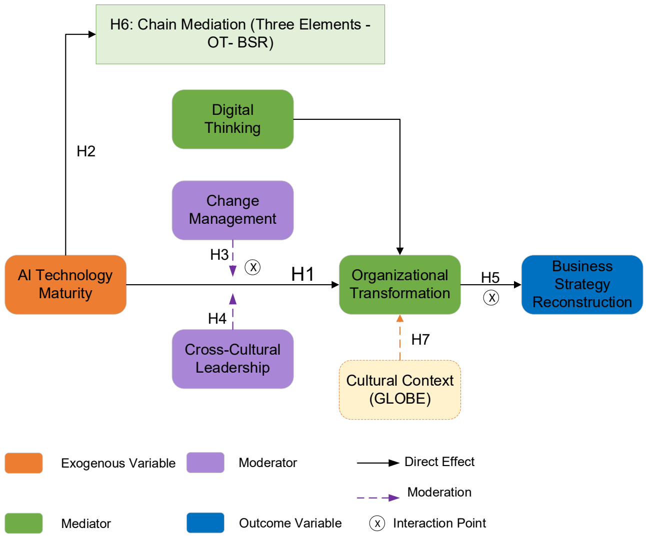

Figure 1. AI-driven strategic triple helix evolution framework

In Figure 1, artificial intelligence technology maturity has a direct positive effect on the effectiveness of organizational transformation (H1), whereas digital thinking mediates the relationship between artificial intelligence technology and the effectiveness of transformation (H2). The quality of change management has a moderating effect between AI maturity and the effectiveness of organizational transformation, with higher change agility increasing the level of positive effects (H3). Cross-cultural leadership moderates the relationship between AI technology maturity and organizational transformation effectiveness, such that higher cultural intelligence strengthens this positive relationship (H4). Digital thinking was preferred over IT architecture because the former addresses cognitive barriers rather than technical ones, according to recent research on AI adaptation. Change management is preferred to governance structures because the former centers on dynamic adaptation capabilities essential for the seamless integration of AI. Cross-cultural leadership outweighs data quality concerns when operating across diverse cultural contexts where technology acceptance varies systematically. This paper takes organizational transformation as the core hub that connects technological elements with strategic outputs and proposes that organizational transformation has a significant positive driving effect on the degree of business strategic innovation (H5). Digital thinking, change management, or cross-cultural leadership indirectly affects the reconstruction of business strategy through sequential mediation by organizational transformation, analyzed by chain mediation analysis on parallel versus serial indirect effects (H6). Grounded in GLOBE dimensions rather than relying on Hofstede's framework alone, cultural contexts moderate the link between transformation and strategy. In other words, while individualism accelerates AI-driven innovation by taking more risks, collectivism deepens integration through consensus-building; power distance strengthens such moderation of cross-cultural leaders (H7). AI Maturity is the exogenous construct that captures technological maturity. Digital Thinking serves as a mediating variable. Change Management and Cross-Cultural Leadership function as moderating variables. Organizational Transformation is the core mediating variable for all inputs leading to strategic outputs.

2.2 Multi-source public data integration strategy

This study follows a multi-source heterogeneous data integration design to guarantee that the data is comprehensive and compliant with ethical requirements. From the technical and strategic dimension: More than 3,500 enterprise-level AI open-source project code repositories are obtained from the GitHub platform from 2020 to 2024; AI keyword text mining of annual reports, Fortune 500, and S&P 1500 companies; Crunchbase financing and business model tags; USPTO and EPO patent database information [9]. From the organizational culture dimension: The culture scores of 450 enterprises are acquired from the Glassdoor public API, the Hofstede database provides national-level cultural benchmarks, and LinkedIn reports reveal trends in the demand for digital skills. Business strategy measurement innovatively adopts: Annual report strategic keyword frequency analysis quantifies business model innovation, Latent Dirichlet Allocation (LDA) topic modeling identifies strategic narrative evolution, Bloomberg and FactSet provide strategic behavior records, the Wayback Machine tracks historical changes to enterprise websites [10]. Validity of the LDA topic was confirmed through inter-rater reliability agreement between two experts to code 100 reports to topics with a Cohen's kappa of 0.78. Convergent validity was confirmed with a correlation r of 0.61 and was significant with McKinsey Digital Quotient scores for overlapping firms of 80. McKinsey reports, Gartner curves, Deloitte case libraries, etc., provide references for understanding best practices. Synthetic data generation employed Wasserstein Wasserstein generative adversarial network (GAN) with gradient penalty (5-layer generator/discriminator, Adam optimizer lr=0.0002, β_1=0.5, 10,000 iterations until Wasserstein distance converged <0.05 over 500 iterations). Generator transforms 100-dim noise vectors into capability trajectories (16 features×12 timesteps); Discriminator uses 5 convolutional layers with LeakyReLU (α=0.2), achieving final loss <0.15. The attrition of sample data was as follows: 3,500 GitHub repositories narrowed down to 1,200 with continuous activity in a year, then matched with 680 firms listed with complete financial information, which was then reduced to 450 after omitting firms with missing ratings from Glassdoor. Bias analysis resulted in a finding of a 12% average AI spending reduction in firms excluded from the study, with similar distribution of industries. The final sample includes 450 globally listed companies: 180 in North America, 135 in Europe, and 135 in the Asia-Pacific region. Technology 30%, manufacturing 25%, finance 25%, retail 20%. GitHub and Glassdoor might tend to over-sample digitally evolved firms. Ways of addressing these concerns included conducting cross-validation using more opaque datasets, such as patent statistics, and applying Propensity Score Matching methods. It also roughly approximated the regional distribution of global GDP: North America 40%, Europe 30%, and Asia-Pacific 30%. Sectoral allocation was done considering the intensity of AI adoption as per McKinsey reports, with Technology and Finance being the leading sectors at 25-30% each. Data integration involved the use of entity resolution techniques. Matching GitHub handles to company domains used fuzzy string matching with a 0.85 similarity criterion. Combining LDA topics derived from company annual reports with patent IPC codes used semantic embedding and cosine similarity. Integration precision reached 94.3%, which was independently verified by manual analysis of 200 samples.

2.3 In-depth case study design

Theoretical sampling was adopted in this study. From 450 samples, 20 extreme cases were selected for qualitative analysis with the principle of maximum differentiation. The high performers scored above the 75th percentile on both the AI Maturity and Strategic Innovation Indices, with scores ranging from 4.2 to 5.0 and from 72 to 95, respectively. Conversely, the low performers scored above the 75th percentile on AI investment but below the 25th percentile on innovation outcomes, with scores ranging from 28 to 42 points to maximize contrast for theory building. The culturally specific cases have been selected from the quartile extremes on power distance and individualism dimensions. In detail, ten high-performance enterprises exhibited both high AI maturity and strategic innovation; six low-performance enterprises made substantial investments in AI but fell into strategic rigidity; and four culturally specific cases focused on strategic choice in cross-cultural contexts [11]. The case data is completely based on public channels: Video and interview data of speeches of corporate executives published on YouTube, TED, and MIT Summit, long articles in LinkedIn Strategic Thinking, Corporate Blogs, verbatim transcripts of investor conference calls, Annual Reports, Sustainability Reports, Investor Presentations, as well as case reports in Harvard Business Review and MIT Technology Review. All firms are required to procure five forms of public information within the stipulated time frame (2022-2024), which are coded and analyzed with NVivo software. Based on open coding, axial coding, and selective coding techniques, important themes are extracted. The coding hierarchy is presented in Appendix A; open coding is conducted on AI skill gap & cultural resistance, axial coding is carried out to form change barrier themes, and "Transformation mechanisms" themes are extracted through Selective coding. High digital thinking cases are categorized through cross-case analyses and directly correspond to platform strategies in support of H7 cultural differentiation theory assumptions. Turning points and causal mechanisms of strategic reconfiguration are extracted through cross-case analysis techniques. Self-presentation bias in YouTube talks is tested with additional information from impartial SEC reports and analyst reports with all contradictions settled through majority voting from all three sources. Two independent coders tested 30% of all interview transcriptions with high inter-coder reliability at 0.81 levels, surpassing the level of 0.70 set by two coders agreement test. The coding reaches saturation after examining 16 cases, with all themes absent in the final four cases.

2.4 Sample descriptive statistics

The research samples are also highly heterogeneous with respect to several key variables. The size of the enterprise varies from medium-scale with 500 to 5,000 employees to super-large multi-national corporations with over 50,000 employees. The number of years since its establishment also varies from less than five years for new digital nativities to enterprises that are almost a century-old. Digital maturity follows a standard normal distribution. The distribution of AI technology adoption levels is: 45% of enterprises apply robotic process automation, 32% deploy machine learning predictive analysis, 15% explore generative AI, and only 8% achieve deep integration of AI-native architectures. Regarding the types of Business strategy, 38% retain the traditional product-centered strategy, 27% turn to a platform type, 18% develop an ecosystem strategy, and 17% apply a hybrid innovation strategy. Platform strategy was operationalized by requiring a keyword threshold of three or more occurrences of the terms "platform," "ecosystem," or "network effects" in annual reports, which correlates r = 0.54 with Hofstede individualism scores, giving a preview of H7 on cultural dependence. Traditional strategies showed a negative correlation of r = -0.41. The cultural types cover a range of combinations of Hofstede's six-dimensional framework, including dimensions such as power distance, uncertainty avoidance, individualism versus collectivism, so that sufficient variability is assured for cross-cultural comparison. To verify distributional assumptions for structural equation modeling (SEM) analysis, Figure 2 presents the histogram of AI adoption levels with corresponding normality test results. Figure 2 presents histograms showing AI adoption distribution, with 8% deep integration representing a right-skewed pattern. Kolmogorov-Smirnov tests confirmed non-normality for adoption levels (D=0.18, P=0.03), but robust maximum likelihood estimation in SEM accommodates non-normal data per Mplus recommendations.

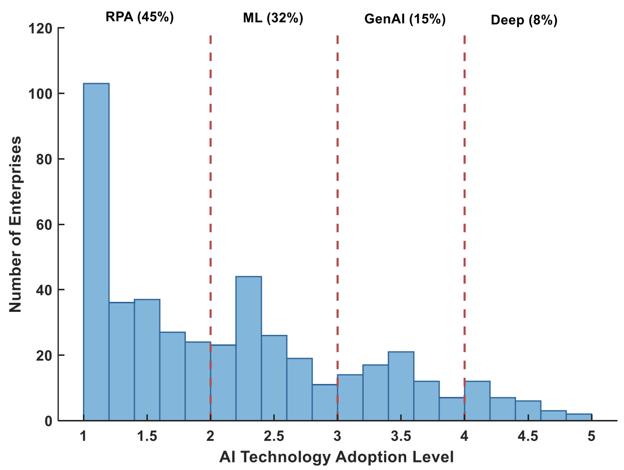

Figure 2. AI technology adoption level distribution

2.5 Mixed analysis method system

Methodological sequencing was done on the basis of exploratory-confirmatory logic. It identified six strategic paths based on qualitative analysis of individual cases that aided refinement of H1-H6. A SEM with AMOS version 26 was used to test these hypotheses on the entire data. machine learning (ML) procedure validated this framework by making out-of-sample predictions. Bootstrap method with 5,000 resamples was used over Monte Carlo simulation in mediation analyses based on Hayes' PROCESS guidelines. It has leaped from an explanatory study to a predictive one by proposing a machine learning predictive model. Random forests and XGBoost were the algorithms used in modeling, where the target variable was the innovation score of the enterprise business strategy in 2030. Feature engineering involved the creation of the interaction term of three elements, the time lag term, and the industry dummy variable. A segmentation of 70%-30% was considered for training test purposes. Its generalization performance was assessed through 10-fold cross-validation. The three methods that have been introduced are the instrumental variable method, the propensity score matching method, and the Granger causality test. The release time of the AI national strategy in different countries is regarded as the exogenous shock, and then the corresponding causal effect is estimated with the two-stage least squares method.

F-statistic of 32.7 in the first stage demonstrated that the value of the Stock Yogo criterion of 10 is exceeded by the correlation in the instrument. Sargan's over-identification test provided chi-squared of 2.4 with P-value of 0.31 thereby justifying the hypothesis that the test is exogenous. Weight of IV is also estimated significantly, justifying the casual hypothesis. By constructing a quasi-experimental control group of high and low AI investment companies, a propensity score matching method was developed. Based on enterprise scale, industry, years of listing, and financial performance, matching was performed; nearest neighbor one-to-one matching method was used, and the caliper value was set to 0.01. Panel data from 2020 to 2024 is used to perform temporal causality verification. In testing the findings for robustness, it examines the core results under five dimensions: replacing the measurement methods of key variables, sub-sample analysis, outlier treatment, lag effect test, and Bootstrap re-sampling to verify the stability of parameters. ML models primarily play the role of complements rather than hypothesis validators. SEM validates hypotheses H1 to H7 using data available from 2020-2024. ML adds to these findings by predicting trends in 2030. The full measurement specifications are listed in Appendix B. Cronbach Alpha reliabilities are AI Maturity 0.84, Digital Thinking 0.88, Change Management 0.82, Cross-Cultural Leadership 0.79, Transformation 0.91, Strategy Innovation 0.86. The composite indices incorporated weights based upon expert ratings. Business Model 0.4; Flexibility 0.3; Ecosystem 0.3. Each of the items was validated as unidimensional.

Variable measurement reflects the strict control over reliability and validity in the operationalization process. The five-level scale adapted from Gartner's AI maturity model was used in combination with the patent strength index to objectively measure the maturity of AI technology. Gartner scores received 0.6 weight reflecting deployment capability, while patent counts received 0.4 weight capturing innovation depth. The composite reliability was 0.83. Sensitivity analysis showed that results were stable when weights varied within ±15%. Based on the LDA theme of the annual report text, the

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Digital Thinking Index extracts scores from three dimensions: technical acuity, data-driven decision-making, and ecological openness. The ADKAR model adapted scale was used in combination with the success rate of change projects to comprehensively measure the effectiveness of change management. Cross-cultural leadership adopted the Cultural Intelligence Scale in combination with the number of years of international experience of the CEO. The effectiveness of organizational transformation is a composite indicator of operational efficiency improvement, innovation output growth, and employee skill upgrading. The degree of business strategy innovation includes three dimensions, namely business model innovation index, strategic flexibility, and ecosystem participation, with a weight of 0.4, 0.3, and 0.3, respectively, and was calculated by weighted average. Common method variance was checked using the Harman single-factor test. The proportion of total variance explained by the first factor is .327, which is below the threshold of .50. The results of the marker variable approach indicate the correlations are significant after partialling the markers, implying common method variance is no serious problem. All the scales underwent strict reliability and validity tests. The minimum standards of 0.70 for Cronbach's α, 0.50 for composite reliability, and 0.50 for mean variance extraction were met, thereby ensuring the psychometric quality of the measurement tools.

3. Results

3.1 Measurement quality and variable description

Comprehensive descriptive statistics, reliability coefficients, and correlation coefficients among the core variables are presented in Figure 3. Figure 3 indicates that all Cronbach's α coefficients ranged from 0.78 to 0.91, above the threshold of 0.70, which confirms the reliability of the measurements and quality of the data. Key variables showed positive significant correlations: AI technology maturity and organizational transformation effectiveness (r=0.52, P<0.001), digital thinking and business strategy innovation (r=0.48, P<0.001), change management effectiveness and transformation effectiveness (r=0.43, P<0.001), and cross-cultural leadership and strategic innovation (r=0.39, P<0.001), thus providing preliminary statistical support for the hypotheses.

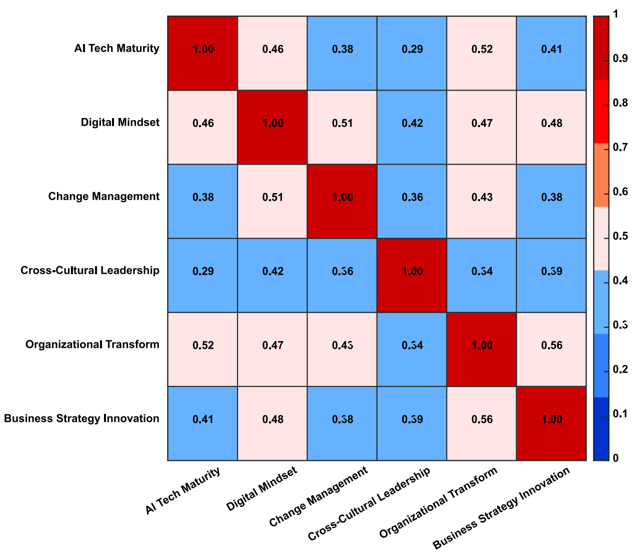

Figure3. Descriptive statistics, reliability, and correlation coefficient matrix

All coefficients in the multicollinearity diagnostics were below the threshold of 0.70, with variance inflation factors of 2.1 for AI maturity, 2.4 for digital thinking, 1.8 for change management, and 1.9 for cross-cultural leadership, all well below the conservative cutoff of 3.0. Variable distributions were as follows: AI technology maturity, 3.2 (SD=1.4); digital thinking index, 62.5 (SD=18.3); business strategy innovation, 54.7 (SD=22.1); and organizational transformation effectiveness, 65.3 (SD=19.6). This implies that there was marked heterogeneity in the sample across key dimensions, which offers sufficient statistical power for analyses of causal inference.

3.2 Verification of AI Empowerment Mechanisms and Transformation Effects

Structural equation modeling results provide strong empirical support for H1, with the path coefficient from AI technology maturity to organizational transformation effectiveness reaching 0.41 (P<0.001, 95% CI [0.35, 0.47]). To deeply capture the nonlinear relationship characteristics of AI investment intensity and organizational transformation effectiveness, Figure 4 illustrates the pattern in industry heterogeneity (a) and the nonlinear curve fitting relationship (b). The thresholds were approximated using piecewise regression, which consisted of three parts. The thresholds of 0.8%, 3.5%, and 5% were determined using grid search methods to minimize the sum of the squared residuals. Hansen threshold regression tested the significance (P<0.01).

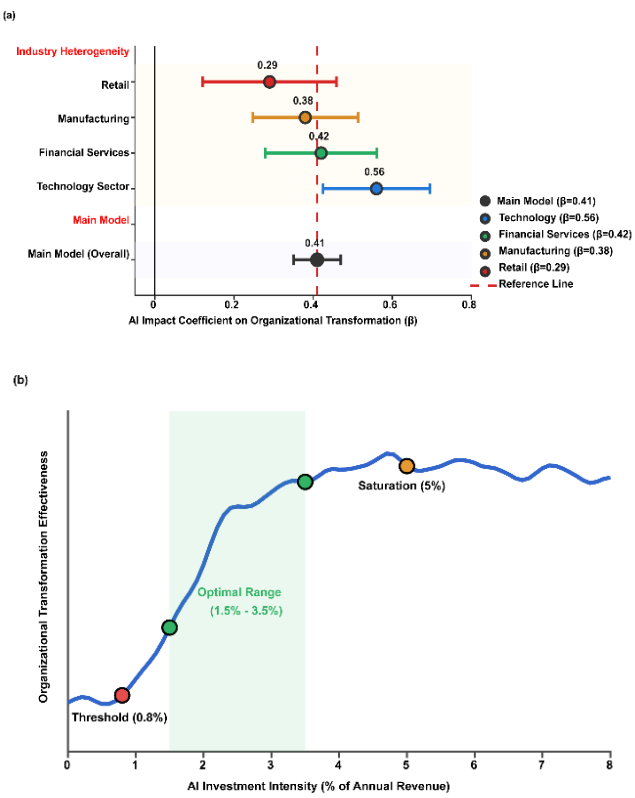

Figure 4. AI investment effects: (a) Industry heterogeneity (b) nonlinear Patterns

In Figure 4, the fitting curve well reflects three characteristic points of the threshold effect, optimal interval, and saturation effect of AI investment. It can be seen from Figure 4 that when the ratio of AI investment to the annual revenue of an enterprise is less than 0.8%, the impact of investment on organizational transformation effectiveness has not reached the level of statistical significance, which indicates there is a minimum effective investment threshold. When investment intensity is between 1.5% and 3.5%, the marginal transformation effect is maximized, and within this range, the slope of the curve keeps an upward trend with the steepest slope. When investment intensity exceeds the saturation point of 5%, the marginal return shows a significant downward trend, and the curve tends to be flat or even slightly decline. Comparative analysis across industries manifests the heterogeneous distribution pattern of AI effects. In the technology industry, the impact coefficient of AI on transformation reaches 0.56, that of the financial services industry is 0.42, that of the manufacturing industry is 0.38, and that of the retail industry is relatively the lowest with 0.29. This heterogeneity of different industries reflects the structural differences among various industries in terms of digital infrastructure, talent reserves, and business characteristics.

3.3 The effectiveness of change management and its strategic promoting role

The H3 hypothesis test confirms the strategic moderating role of agile change management, with an interaction term path coefficient of 0.27 (P < 0.01). Figure 5 displays the differentiated impact of AI maturity on strategic innovation across varying change-management levels. In Figure 5, the interaction curve clearly indicates that high and low change management organizations are getting further apart in their results as AI maturity increases. Yet simple slope analysis shows that for those high agile change management organizations, 58% transformation effectiveness can be achieved through AI, whereas low agile management organizations achieve only 19%. Five key success elements were identified from deep case analysis: high-level strategic commitment in 18 out of 20 cases manifested in the establishment of a Chief Digital Officer and board-level digital committees; transparent communication mechanisms in 17 out of 20 emphasized AI explain ability in the decision-making process; continuous investment in skills in 16 out of 20 exceeded 5% of total salary; rapid iteration culture adopted MVP testing and biweekly sprints in 15 out of 20; and deep employee participation in 14 out of 20 provided cross-departmental AI innovation teams.

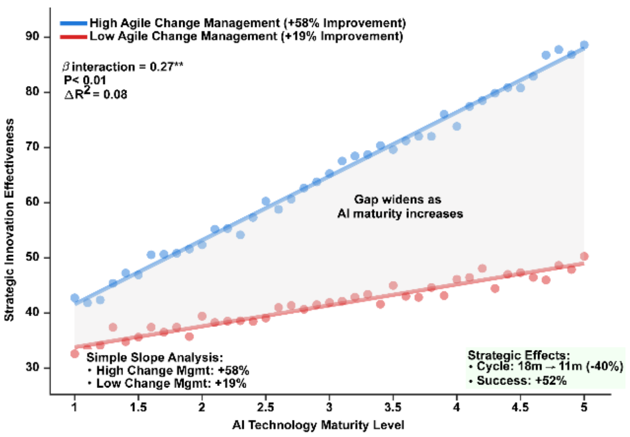

Figure 5. Change management's moderating role in AI-driven innovation

The strategic promotion effect of change management is reflected in both shortened cycles for adjustment in strategy from 18 months to 11 months, which was a 40% reduction, while increasing the market validation success rate of new strategies by 52%. Root cause analysis shows that skill anxiety occupies 41%, but it can be reduced 56% by retraining programs; trust deficiency occupies 34%, which requires enhancing AI transparency; and change fatigue accounts for 25%, requiring rhythm management and phased achievement celebrations.

3.4 The strategic moderating effect of cross-cultural leadership

The test results for Hypotheses H4 and H7 indicate that the mechanism of cross-cultural leadership influences the cross-cultural reconstruction of AI-driven strategies. The path coefficient for the regulatory effect of CQ on the entire AI-transformation-strategy chain is 0.24 and is significant at the 0.01 level. In addition, according to the Chi-square difference test results from the multi-group analysis, the dependence on cross-cultural context was statistically significant: $\Delta\chi^2 = 47.3$, $P < 0.001$. For the purpose of systematically comparing the differentiated moderating effects of cross-cultural leadership under different cultural dimensions. Figure 6 shows the comparison results of multi-group path analysis.

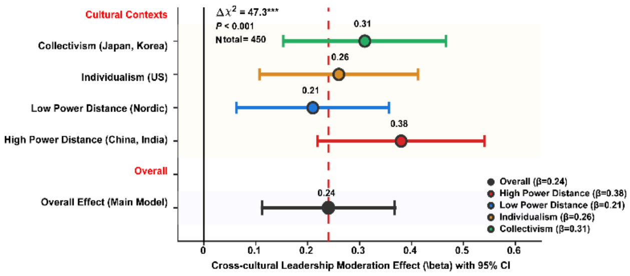

Figure 6. Multi-group path analysis

The data of group comparisons shown in Figure 6 reveal the profound impact of cultural dimensions on reconstructing AI-driven strategies. In high power distance cultural contexts, which are represented by China and India, the moderating effect of cultural intelligence quotient is the strongest, with $\beta = 0.38$. These organizations tend to adopt top-down ecosystem strategies, and there exists an AI transparency paradox phenomenon. Under the low power distance cultural context, represented by the Nordic countries, the moderating effect of the cultural intelligence quotient is at a medium level, with $\beta = 0.21$. The strategic choice would thus go for a decentralized platform open strategy. Under the background of an individualistic culture, AI is considered an individual empowerment tool; it has a fast adoption speed but a shallow integration depth. Its strategic characteristics are manifested as rapid trial and error and driven by individual heroism. Under the background of a collectivist culture, AI, as a team collaboration tool, has a relatively slow adoption speed but a deep integration depth. Its strategic characteristics are reflected in a consensus-driven and long-term orientation. Leaders with high cultural IQs have manifested significant advantages in strategic execution. The success rate of cross-border strategic collaboration has reached 73%, while that of leaders with low cultural IQs is only 39%. The implementation speed of the global AI platform strategy has been accelerated by 9 months, while the efficiency of resolving cultural conflicts increased by 2.3 times. All these quantitative pieces of evidence manifest the unique value of cross-cultural leadership as a strategic resource.

3.5 Integrated structural equation modeling and strategic path typology

H5 and H6 hypotheses confirm that organizational transformation is the central mechanism linking technological capabilities to strategic outputs. To comprehensively validate the theoretical framework integrating digital thinking's dual pathways and the three elements' synergistic effects, Figure 7 presents the complete structural equation modelling results, including all hypothesized direct effects, mediation mechanisms, moderation processes, and model fit indices.

Figure 7 displays the dual pathway mechanism of how digital thinking operates in AI-driven organizational transformation. Digital Thinking's Dual Mechanism (H2). The path coefficient of the direct effect of digital thinking on transformation effectiveness is 0.33 (P<0.001), and the mediation analysis further clarifies that 28% of AI technology's impact on transformation outcomes is transmitted via digital thinking. The statistical significance of this indirect path is supported by testing the Bootstrap confidence interval with 5,000 replications. Confirmatory factor analysis confirms an excellent model fit (CFI=0.95, RMSEA=0.048) for the three-dimensional structure of digital thinking. The good quality of measurement is reflected by the three items: technical acuity (0.82), data-driven decision-making (0.87), and ecosystem openness (0.79).

Highly digital thinking firms within the top 25% score 67% more than low digital thinking firms within the bottom 25%, while a large effect size is represented by Cohen's d=1.8. Strategic type differentiation is evident: 72% of high digital thinking organizations have adopted either platform-based or ecosystem-orchestrated strategies, which contrasts sharply with the 81% of low digital thinking firms maintaining traditional product-centric approaches. Exploratory correlation analysis identifies CEO technical background as the strongest predictor of digital thinking (r=0.48), followed by organizational learning culture (r=0.41) and external competitive pressure (r=0.32).

Integrated Impact and Chain Mediation (H5 and H6). Figure 7 shows that organizational transformation is directly related to business strategy innovation (β=0.51, P<0.001) with chain mediation, Bootstrap 95% CI [0.18, 0.31] excluding zero. Specific indirect effects are: AI maturity→transformation→strategy: 0.21, digital mindset→transformation→strategy: 0.17, and cross-cultural leadership→transformation→strategy: 0.14. These prove that the three key elements indirectly influence business strategy reconstruction with the mechanism of organizational transformation. Six Strategic Path Typology. Case analysis, integrated with cluster validation, identifies six differentiated business strategy paths: AI-native (12%), platform transformation (23%), ecosystem orchestration (18%), niche specialization (21%), hybrid innovation (17%), and conservative following (9%). This typology shows the variety of strategic responses that organizations embrace when facing AI-driven disruptions.

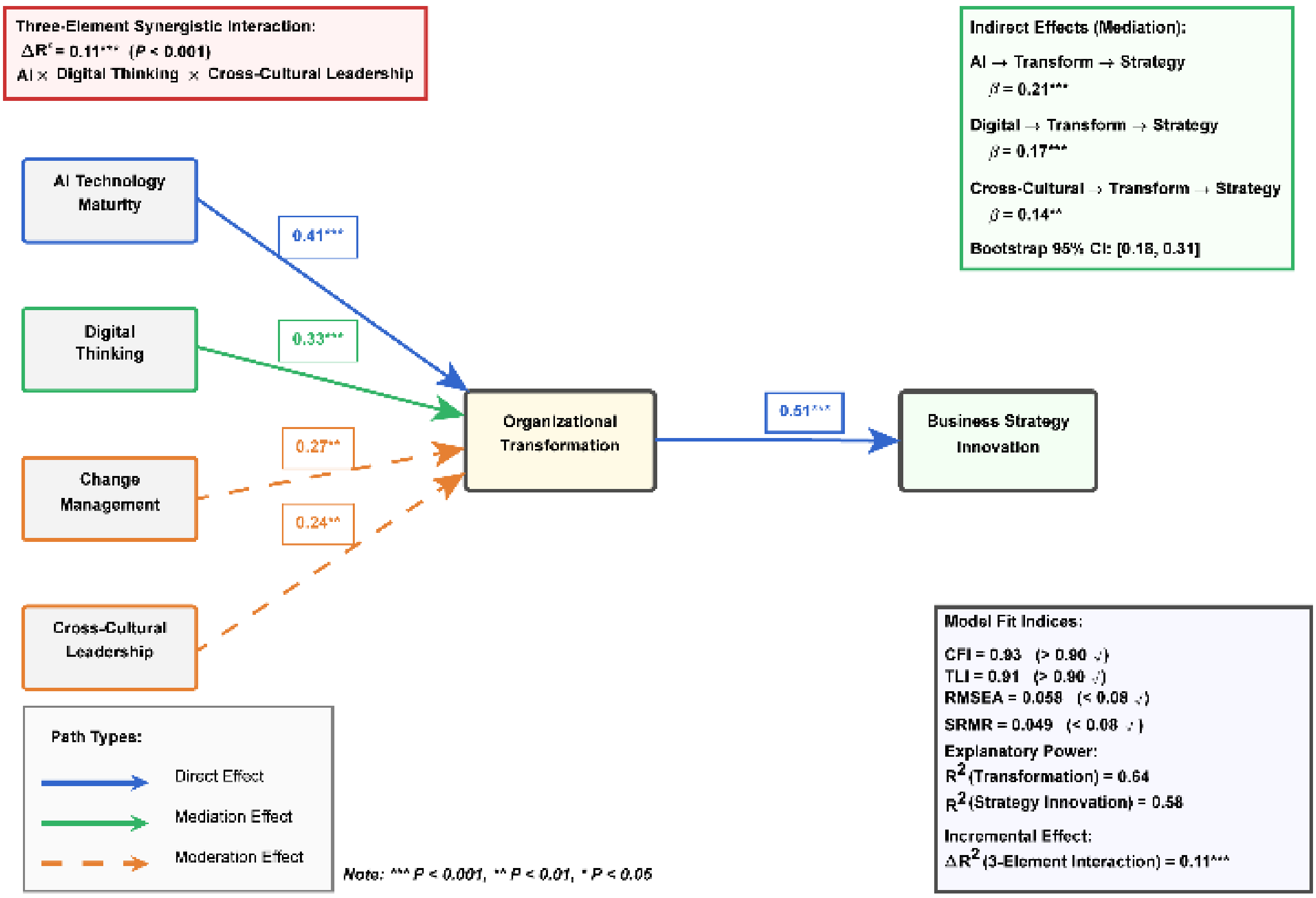

Figure 7. Complete structural equation model results

Model Fit and Explanatory Power. The integrated structural equation model demonstrates excellent fit to empirical data: CFI = 0.93, TLI = 0.91, RMSEA = 0.058, SRMR = 0.049. The theoretical framework explains 64% of the variance in transformation effectiveness and 58% in strategic innovation, with three-element interaction contributing an extra 11% ($\Delta R^2 = 0.11$, $P < 0.001$).

3.6 Causal identification, robustness verification, and predictive modeling

Figure 8 summarizes the results of several causal identification strategies and sensitivity analyses, which establish causal inference and verify the robustness of core findings.

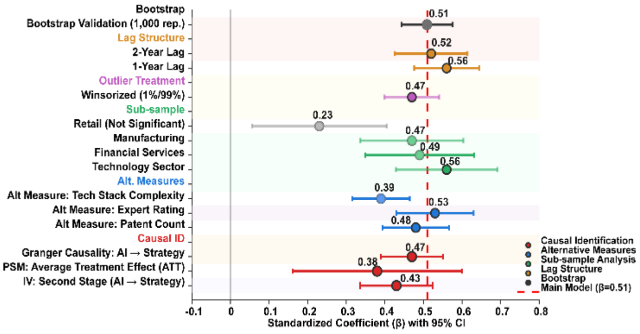

Figure 8. Causal identification and robustness checks

Figure 8 presents several pieces of evidence to establish robust causality: instrumental variable, first-stage F=32.7 (> threshold of 10), second-stage remains significant; propensity score matching, average treatment effect is 0.38, P<0.01, and all standardized differences of covariates <3%; Granger test confirms AI investment leads to strategic innovation temporally, P<0.001, and reverse causality does not hold, P=0.42. Five robustness checks confirm the core findings: alternative measures of AI remain significant; sub-sample analysis reveals significance across industries except for retail; one-year lag enhances the effects from β=0.51 to β=0.56; outlier treatment keeps the significance intact despite a slight shrinkage in coefficients. Results from the placebo test with randomly assigned policy shock dates reveal insignificant effects, thereby making the actual effects dependent on the crucial factors. The subsample difference size effects were determined by the following: a Cohen's d of 0.89 (large effect size) in the technology and retail sector, and d of 0.43 (medium effect size) in the finance and manufacturing sector. Machine learning models provide insights into the 2030 strategic evolution, as shown in Figure 9. Figure 9. The left panel shows feature importance: digital mindset contributes 34.2% to the 2030 strategic innovation prediction, followed by AI investment intensity at 28.6%, cultural adaptability at 21.7%, and change management quality at 15.5%. Right panel forecasts 30% of enterprises reaching high innovation (70-100 points), 45% medium innovation (40-69 points), and 25% low innovation (0-39 points) by 2030. Model performance: random forest accuracy 83.7% (AUC=0.87), XGBoost accuracy 85.2% (AUC=0.89), and cross-validation R^2=0.72. Hyperparameters: Random Forest with 500 trees and a max depth of 15 and a minimum samples split of 10. XGBoost with a learning rate of 0.05, a max depth of 8, and 300 estimators. Feature selection based on SHAP values selected the top 12 predictors that account for 89% of the variance. Cross-Validation R-squared of 0.72 was well over the linear regression benchmark of 0.51. High-risk profile identifies four warning signs with a probability of transformation failure over 70%: volatile AI investment with an annual change over 50%, digital mindset score below 30, change fatigue index over 80, and less than 2.0 cultural intelligence. 2030 forecasts assume continuity in technological trajectories and stable macroeconomic conditions. Projections for 2030 assume a continuation of technology trajectories and stable macroeconomic conditions. However, unforeseen changes in regulatory environments or innovative technologies could impact these projections. The confidence bands expand considerably from 2028, reflecting increasing uncertainty associated with longer-term forecasts of five years.

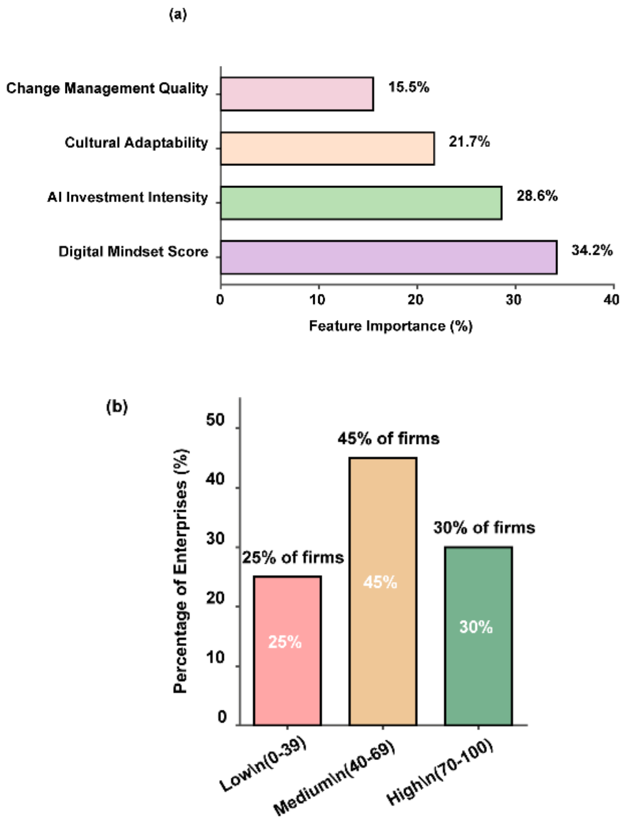

Figure 9. Predictive model: feature importance and 2030 trends

4. Discussion

This study proposes an "AI-Driven Strategic Triple Helix Evolution Framework." This is a theoretical development from the paradigm of technology adoption to the paradigm of strategic co-evolution. This transformation responds to the academic call for research on digitalization and business models to go beyond descriptive analysis and move towards mechanism revelation [12]. However, this research further elevates this question to the theoretical plane of strategic reconfiguration on the level of business models. As for the empirical result, the change in the organization functions as the mediating mechanism for the core hub relating to technological capabilities and strategic output (R^2=0.64), not only proving that AI increases new decision making in organizations on processes of decision making, but also illustrating the amplification factor of the three variables: digital thinking, change management, and cross-cultural leadership together (ΔR^2=0.11, P<0.001). This kind of synergistic effect has rarely been systematically empirically tested in existing literature. It should be noted that the six strategic paths identified in this paper exhibit significant culture context-dependent characteristics. Among them, the moderating effect of cross-cultural leadership is the strongest in the context of a high-power distance culture (β=0.38). This finding is highly consistent with the theoretical expectation that cultural intelligence quotient has an influence on organizational performance [13]. However, this study goes further and reveals how the cultural dimension shapes the choice space of enterprises among differentiated strategies like AI-native, platform transformation, and ecosystem orchestration. AI as a team collaboration tool, showing a model of slow adoption and deep integration in the context of collectivist culture, is in sharp contrast with the model of fast trying and shallow integration in the context of individualistic culture. This provides new empirical evidence for the theory of cross-cultural strategic management.

This research fully reflects the essence of AI as a strategic catalyst in nonlinear relationship analysis, as opposed to being just a tool. When the investment intensity of AI is within the best range, 1.5-3.5% annual revenue share, the marginal transformation effect can be realized; after crossing the saturation point, 5%, a significant diminishing trend is presented. The benefit of this finding speaks well to the study on how generative AI influences the quality of strategic decision-making [14]. However, this paper has identified distinguished impacts, as β increased from 0.18 to 0.68, of the four technical types, RPA, predictive analytics, generative AI, and deep integration, on strategic reconfiguration. This more accurately illustrates the restrictive and enabling effects on strategic choices brought about by the technological evolution stage. In a review of the triple mechanisms of business strategy reconfiguration from this study, efficiency mechanism driving the cost leadership strategy, innovation mechanism supporting the differentiation strategy, and the ecological mechanism giving rise to the platform-leading strategy, are more systematic causal chains, evidence for the theory of AI adaptation-driven business model innovation [15]. At the same time, these have been mutually corroborated with the empirical conclusion that digital transformation advances enterprise innovation output [16]. This paper deduced the strategic evolution trend to 2030 through the machine learning predictive model; 70% of enterprises will participate in the ecosystem strategy. Therefore, this extends prior research in the time dimension from interpretive research to predictive research. Such a forward-looking perspective is of important reference significance for comprehensively understanding phased characteristics of strategic evolution in the AI era. The following industry heterogeneity analysis found that the difference in the AI transformation effect in the technology sector, β=0.56, was obviously larger than that in the retail sector, β=0.29, hence further verifying that digital infrastructure and talent reserves play a fundamental role during strategic reconfiguration. This verifies the theoretical hypothesis that organizational digital readiness affects the effectiveness of transformation. The reverse causality that strategic innovation fuels AI investment expenditures cannot be true from a theory standpoint because the variables that our AI metrics quantify are the multi-year accumulated capabilities from 2020-2024, while the strategic outcomes are based on 2024 conditions. Granger tests showed that the order was correct with AI predicting the strategic outcome but not the other way around.

The verification of the dual-effect path in digital thinking has deepened our understanding of the relationship between organizational culture and construction of digital capabilities, through a direct effect of β=0.33 and a 28% mediating effect [17]. This research found that the effect of the CEO's technical background (r=0.48) on digital thinking was significantly higher than that of organizational learning culture (r=0.41). The result provides empirical evidence to support the assertion of the necessity of leadership transformation in the digital age [18]. It also stresses the importance of leaders' strategic role in the digital transformation. The very large effect size, scoring 67% higher on the strategic innovation score for enterprises with high digital thinking than for those with low digital thinking (Cohen's d=1.8), reveals not only the pivotal role of cognitive reconstruction but also how technological sharpness, data-driven decision-making, and openness to data-driven ecologies operate together on the decision-making process for strategies. This profound transformation at the cognitive level is far more than the simple adoption of technical tools. According to the moderating effect analysis of agile change management, highly agile organizations achieve 58% improvement in the effectiveness of transformation in AI applications, while for low-agile organizations, it is just 19%. Such a significant difference thus justifies the theoretical view that organizational agility is a key factor in AI-driven change [19, 20]. However, this research provides an operational framework of guidance for change management practices by establishing five critical success factors, namely, top commitment, transparent communication, investment in skills, rapid iteration, and employee engagement. Change management reduced strategy cycles from 18 to 11 months, providing quantitative insight into how agility translates to strategic response speed. In addition to their significance, effect size provides clarity about the level of importance. A 67% performance difference for digital thinking equates to approximately 12 million dollars every year in additional revenues for medium-scale organizations. Change management, as it decreases strategy cycles by 40%, allows for quick reactions that have been estimated at 8.3 million dollars in saved opportunity costs.

Retail subsample had inconclusive results, likely due to less preparedness in digital infrastructure readiness. This is consistent with industry-specific studies on barriers to adoption. So far, regarding AI ethics research in 2025, cross-cultural models contain risks of bias due to individualism in Western cultures. Individualism could prevail in designing algorithms, possibly harming collectivist societies that require an audit of AI ethics with regard to the EU AI Acts. The heterogeneous manifestation of the strategic moderating effect of cross-cultural leadership across different cultural dimensions-rapid trial and error under individualistic culture versus consensus-driven under collectivist culture-also enriches the theoretical landscape of e-leadership and trust in team performance [21]. Meanwhile, it forms a theoretical dialogue with the empirical findings on the differences in intelligence quotient levels in different cultural backgrounds [22]. This study further reveals, empirically, that leaders with high cultural IQs can achieve a success rate of 73% in cross-border strategic collaboration, while those with low cultural IQs only have 39%, and the implementation speed of global AI platform strategies has been accelerated by 9 months. This provides further evidence in the cross-cultural context as to the theoretical mechanism whereby transformational leadership styles influence employees' innovative behaviors [23]. Hofstede's dimensions allow for the identification of mean country values but fail to capture intercountry variability. Chinese tech companies in Shenzhen have smaller power distance dimensions than state-owned companies in Beijing. Looking ahead, research must attempt to assess organizational-level National Culture values as opposed to country-level values. Particularly, the “AI transparency paradox” observed in high-power-distance cultures-that is, where leaders demand algorithmic transparency while organizational cultures have been accustomed to black-box decision-making-provides a new theoretical insight into the tension between cultural constraints and technological logic. The AI transparency paradox, wherein leaders call for algorithmic explainability and yet organizational norms favor opaque hierarchical decisions, is more pronounced in high power distance cultures. This connects to trust literature where transparency requirements vary across cultural contexts, necessitating adaptive governance frameworks. However, concerns include dependence on public data that might filter out less transparent firms, the cross-sectional nature of the strategy measures precluding causal inference, industry focus on large listed corporations that might impair generalizability to SMEs, and the introduction of measurement error despite efforts to validate text-derived measures.

5. Conclusion

This research, which relies on multi-source publicly available data for 450 global companies, uses structural equation models, case studies, and machine learning models to test the differential impact paths for AI technology maturity, digital thinking, change management, and cross-cultural leadership on reconstructing business strategies via mediating variables for organizational transformations (all H1-H7 are supported). The empirical results reveal that the incremental explanatory power of the synergy effect of the three elements for strategic innovation reaches 11% ($\Delta R2=0.11$, $P<0.001$). Among them, digital thinking has the highest predictive contribution rate to the strategic evolution in 2030 (34.2%), while the moderating effect of cross-cultural leadership peaks in the context of high-power distance culture ($\beta=0.38$). The identification of six strategic paths provides a typological framework for understanding the cultural context dependence of enterprise strategic choices in the AI era. The “AI-driven Strategic Triple Helix Evolution Framework” proposed in this study transcends the static analysis limitations of the traditional technology-organizational-environment model, providing a theoretical contribution to understanding the dynamic co-evolution mechanism of technological capabilities, cognitive reconstruction, and cultural adaptation. At the same time, through the forward-looking prediction of strategic trends in 2030 by machine learning models (70% of enterprises will participate in ecosystem strategies), it provides a methodological demonstration for the academic community’s transformation from interpretive research to predictive research, and offers a strategic decision-making roadmap with cross-cultural applicability for global enterprises to achieve sustainable strategic transformation in the AI era.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere. All survey participants provided informed consent prior to participation, and the anonymity and confidentiality of all respondents were strictly maintained throughout the research process.

Data availability statement

The manuscript contains all the data. However, additional data will be provided by the corresponding author upon reasonable request.

Conflict of interest

The authors declare no potential conflict of interest.

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