Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 9, No. 6, December, 2025

Linking Psychological Safety Climate to Dual Innovation Through AI-Enabled Dynamic Capabilities

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Abstract

Objective: This study develops and empirically validates an integrated model that explains how the psychological safety climate influences dual innovation through AI-enabled dynamic capabilities in Chinese design organizations. ***Methods***: A cross-sectional survey was conducted among 281 designers from industry design firms and departments. Data analysis employed partial least squares-structural equation modeling, including mediation bootstrapping analysis, importance-performance map analysis, necessary condition analysis, and quadratic effect analysis. ***Findings***: All hypotheses received strong empirical support. The psychological safety climate has a significant influence on AI-enabled dynamic capabilities, with a path coefficient of 0.452 at $p < 0.001$, and on dual innovation, with a coefficient of 0.383 at $p < 0.001$. AI-enabled dynamic capabilities have a positive impact on dual innovation, with a coefficient of 0.384 at $p < 0.001$, and significant mediation effects, indicating an indirect effect of 0.174 at $p < 0.001$. The model explains 42.7% of the variance in dual innovation. Importance-performance analysis reveals a psychological safety climate as highly important but moderately performing, indicating strategic opportunities for improvement for organizations. Necessary condition analysis confirms both constructs as essential requirements for innovation outcomes. The findings demonstrate that psychological safety climate, as a higher-order cultural resource, enables lower-order AI-enabled dynamic capabilities, supporting socio-technical systems structure for dual innovation. Organizations should prioritize investments in psychological safety while maintaining their AI capabilities. ***Novelty***: This research introduces AI-enabled dynamic capabilities as a second-order formative construct and establishes the meta-capability role of psychological safety climate in AI-enabled dynamic capabilities and dual innovation, thereby extending the resource-based view and dynamic capabilities theories through micro-foundational perspectives.

Keywords:

AI-Enabled Dynamic Capability;

Psychological Safety Climate;

Dual Innovation;

Industrial Design;

Resource-Based View.

Article History:

Received:	25	August	2025
Revised:	18	October	2025
Accepted:	06	November	2025
Published:	01	December	2025

1- Introduction

China's economic transformation from manufacturing-driven to design innovation-led development represents one of the most significant strategic shifts in the global business landscape. This transition, emphasized in national initiatives such as "Made in China 2025" and the "14th Five-Year Plan," positions design innovation as fundamental to achieving autonomous technological breakthroughs and industrial upgrading [1]. Organizations operating within this transformative context face the dual challenge of maintaining operational efficiency while simultaneously pursuing radical innovations; a capability known as dual innovation [2]. To achieve radical innovation, which is often quite complex, organizations have begun to invest in artificial intelligence (AI)'s technological infrastructure, treating it as a strategic resource advantage [3]. While AI has the capacity to help organizations mitigate risks [4] and respond to market uncertainties with fitted products and services, its utilization at the strategic and organizational level remains at a nascent stage, drawing researchers to study the challenges currently faced by AI [5] and the adoption factors [6].

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DOI: http://dx.doi.org/10.28991/ESJ-2025-09-06-022

Despite growing recognition of AI's innovation potential, existing literature reveals three critical gaps that limit the understanding of how organizations can effectively harness AI for dual innovation. Initially, although research has begun to examine the dynamic capability perspectives of AI adoption [7] and its strategic benefits, including knowledge [8] and entrepreneurial innovation [9], it has afforded scant attention to the specific ways in which AI transforms core organizational processes and mechanisms for capability development—termed dynamic capability. Many studies regard AI as an external instrument instead of an integral element of dynamic capacities, neglecting to recognize the intricate ways in which AI integration alters organizational sensing, seizing, and reconfiguring processes [10]. Secondly, innovation research has primarily analyzed incremental and radical innovation as distinct phenomena [11], lacking a comprehensive knowledge of the synergistic mechanisms that allow firms to pursue both forms of innovation simultaneously.

The third gap primarily concerns the absence of higher-order cultural and environmental elements that foster the lower-order dynamic capability and dual innovation outcomes. Although technological and strategic variables have garnered significant attention, the organizational climate conditions that facilitate successful AI adoption and innovative ambidexterity are still insufficiently examined. Research has not sufficiently investigated the factors that influence the psychological safety climate, which is characterized by collective judgments of organizational policies, procedures, and practices that promote psychological health and safety [12]. The aforementioned three gaps can be addressed with the subsequent two research questions: How does a psychological safety climate, as a higher-order cultural resource, enable the development of AI-enabled dynamic capabilities to foster dual innovation, and what is the relative importance of this socio-psychological resource compared to the technological capability it enables? Accordingly, addressing these two questions leads to the following research purpose: to develop and empirically validate an integrated model that elucidates the influence of psychological safety climate on dual innovation via AI-enabled dynamic capabilities.

This study considers the Chinese industry design context. The Chinese context provides an ideal setting. China's rapid digital transformation [13], government support for AI development [14], and emphasis on design innovation [3, 15] create conditions that enable design organizations to integrate AI technologies while actively pursuing dual innovation strategies. China has prioritized AI adoption as a national development objective through initiatives such as the "New Generation Artificial Intelligence Development Plan" and the "Shanghai Declaration on Global AI Governance," aiming to achieve global leadership in intelligent manufacturing [16]. The experience of Chinese design organizations in reconciling efficiency and flexibility—anchored in institutional contexts that prioritize both stability and adaptability—offers significant insights into how a climate of psychological safety fosters the advancement of AI-enabled dynamic capabilities in intricate environments.

The remainder of this paper is organized as follows: Section 2 elucidates the theories and how they support the conceptual model, encompassing the creation of hypotheses. Section 3 describes the research methodology, including the research design, sampling approach, data collection procedures, and analytical methods employed in the study. Section 4 presents the results needed for discussions. Section 5 discusses the findings, their theoretical and practical implications, research limitations, and directions for future research. Finally, Section 6 concludes the study.

2- Literature Review

2-1- Underpinned Theories

Three theories; psychological safety climate theory, the dynamic capability-based view (DCV), and the resource-based view (RBV); constitute the theoretical foundations for elucidating the conceptual model presented in Figure 1.

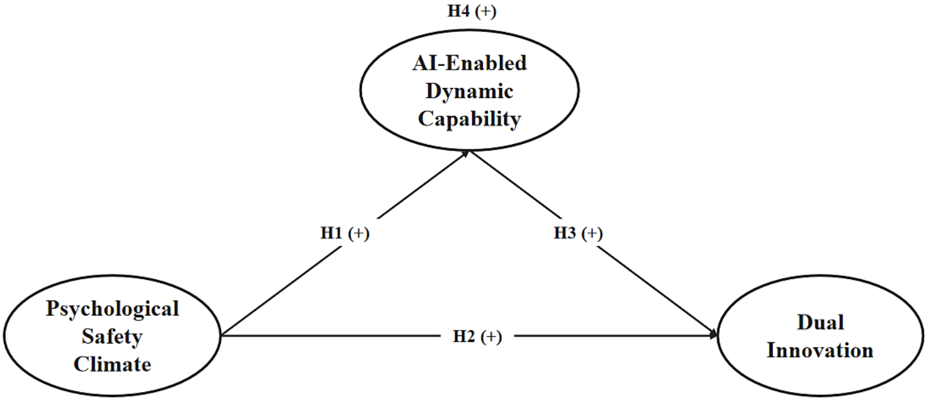


Figure 1. The Conceptual Model

A psychological safety climate denotes an organizational environment characterized by a shared perception of a non-punitive culture of experimentation [17, 18], implying interpersonal trust and respect among colleagues [19]. Members can express views, share ideas, and make mistakes without worrying about negative consequences [20]. In the context of AI adoption, the psychological safety climate helps alleviate technology-related anxiety, encourages experimentation with new AI tools, and promotes knowledge sharing [12]. The seminal systematic review by Newman et al. [21] explicitly discusses psychological safety climate as a “meta-capability” that shapes and enables more specific, “lower-order” operational capabilities, giving it a higher-order capacity for competitive advantage [12]. While organizational culture and psychological safety climate are related, “culture” is a deep-seated set of values, beliefs, and assumptions. In contrast, climate is reckoned as a tangible manifestation of the culture – that is, it is how employees perceive and experience the cultural values in their daily work environment [12] that gives the employees a perception of psychological safety to engage in challenging tasks [22], such as the AI-enabled dynamic capability and dual innovation (e.g., incremental and radical innovation) that this study anchors. In addition, psychological safety climate is distinct from trust. Trust typically operates at the dyadic or small group level between specific individuals, whereas a psychological safety climate operates at the organizational level, encompassing collective judgments of organizational policies, procedures, and practices that promote psychological health and safety [12].

The dynamic capability-based view (DCV) explains how organizations develop, deploy, and reconfigure resources to address changing environments through sensing, seizing, and transforming processes [23, 24]. DCV’s significance lies in explaining how organizations achieve sustainable competitive advantage through adaptive capabilities rather than static resource positions [25]. In AI-intensive environments, DCV becomes crucial for understanding how organizations integrate artificial intelligence into their strategic processes to enhance innovation capabilities [8].

The resource-based view (RBV) focuses on how organizations achieve a competitive advantage through the strategic deployment and integration of their organizational resources and capabilities, which involves AI [26] and psychological safety climate. RBV emphasizes that organizational success depends on effectively combining diverse resource portfolios (e.g., psychological safety climate and AI-enabled dynamic capabilities) to create value. In this study, RBV explains how two fundamentally different yet complementary resource types—psychological safety climate and AI-enabled dynamic capabilities—serve as strategic resources enabling innovation performance. Psychological safety climate represents an intangible and socially complex organizational resource embedded in culture and climate [12]. On the other hand, AI-enabled dynamic capabilities represent technology-enhanced resources that combine artificial intelligence with organizational processes [23]. The integration of these heterogeneous resources creates unique configurations that provide the foundation for achieving dual innovation capabilities through the integration of socio-psychological and technical resources [27].

This theoretical integration not only provides additional insights into RBV and DCV through combined socio-technological resources but also demonstrates a micro-foundation base for enacting organizational change, emphasizing strategic management that stresses the atmosphere and interactions between individuals within the organization [28]. In doing so, the micro-foundations perspective can offer another degree of freedom to explain why some organizations are more successful in developing AI-enabled dynamic capabilities. As noted by Zhang et al. [29] and Bağış et al. [30], numerous strategic management theories often overlook the micro-foundations related to psychology and sociology. However, although still under development, micro-foundational research has emerged as a distinct branch of strategic management, with the potential to contribute to the deepening and development of strategic constructs [31]. This research proposes the application of social contextual logic through a micro-foundational lens, given that organizational strategies are often formulated within social settings directly related to personal experiences [31].

2-2- Hypotheses Development

The psychosocial safety climate (PSC) refers to the collective belief among employees that senior management and the organization will support the pursuit of projects and strategic initiatives that may involve risks of suboptimal performance [32]. Based on a comprehensive bibliometric and systematic literature review, Dong et al. [12] suggest that psychological safety climate theory offers a broad range of explanations for the roles of psychological safety climate. First and foremost, the psychological health and safety that the working environment provides to individual employees, such as product designers, can lead to a more effective understanding of environmental opportunities and threats. This rationale elucidates the social learning mechanism that is incorporated into the psychological safety climate [33], thereby enabling an organization to utilize AI-enabled dynamic capabilities more effectively. This is demonstrated by the transformation of resources to attain strategic objectives and the sensing and seizing of opportunities. It is possible to infer that a psychological safety climate, which allows employees to perceive it as secure to perform behaviors [12], can be a substantial contributor to AI-enabled dynamic capability when Kahn’s psychological conditions are applied to the workplace. Furthermore, a psychological safety climate can serve as an indicator of the fit between employees and their organization at both the socio-psychological and commitment levels [34].

In addition to the aforementioned comprehension, the organization can benefit from the socio-technical resources of psychological safety climate and AI-enabled dynamic capability in dual innovation. The provision of socio-psychological resources can be a robust motivator for employees to engage [35] actively in AI-enabled sensing and seizing of opportunities, as well as the transformation of resources for a dual innovation advantage.

Drawing on RBV, psychological safety climate and AI-enabled dynamic capability comprise unique, heterogeneous resources (e.g., socio-psychological and technical resources) that are not perfectly mobile across organizations [36, 37], as evident in the generative AI training that contributes to differentiation [38]. Additionally, CBV explains why organizations with the same AI infrastructure can differ significantly in terms of innovation outcomes, depending on whether they can strategically orchestrate those resources using dynamic capabilities. Thus, AI-enabled dynamic capability is not merely the possession of AI technology. However, instead, it manifests the organization's ability to integrate AI in the strategic management process to gain systematic competitive advantages. Through advanced data analytics, machine learning algorithms, and predictive modeling, organizations can simultaneously identify optimization opportunities in existing products and services, as well as potentially disruptive trends for the future [39]. Furthermore, [40] observes that AI can support the development of dynamic capability, enhancing decision accuracy with data-informed knowledge, enabling the estimation of exploitation returns more effectively, and facilitating organizations to secure a more balanced allocation of resources between exploitation and exploration innovation efforts [41]. The implication for design organizations is that they will be able to decide more effectively when to fine-tune familiar design templates and when to shift direction toward entirely different design solutions.

Accordingly, the following three hypotheses form the core conceptual logic of the study:

***H1.** Psychological safety climate has a positive impact on AI-enabled dynamic capabilities.*

***H2.** Psychological safety climate has a positive impact on dual innovation.*

***H3.** AI-enabled dynamic capabilities have a positive impact on dual innovation.*

It has been shown that a psychological safety climate can alleviate the psychological distress of employees in high-demand environments [42]. However, it will remain at a prospective level unless it is employed to develop learning and systems capabilities, which in turn influence performance levels [43]. Consequently, the following hypothesis, H4, which is based on a resource-based view (RBV) and DCV, posits that the potential of a higher-order psychological safety climate is realized through AI-enabled dynamic capabilities, leading to the following hypothesis, H4.

***H4.** AI-enabled dynamic capabilities mediate the relationship between psychological safety climate and dual innovation.*

3- Research Method

The research methodology follows a systematic six-stage process, as shown in Figure 2, beginning with data preparation (questionnaire design, IOC validation, pilot testing, data collection via Credamo, and descriptive analysis), followed by common method bias assessment using marker variables, measurement model evaluation through Smart PLS for both reflective and formative constructs, and structural model evaluation with path coefficient estimation. The final stages involve hypothesis testing through bootstrap analysis, including the examination of the mediation effect, culminating in advanced analytics using Importance-Performance Map Analysis (IPMA), Necessary Condition Analysis (NCA), and the quadratic effect analysis to provide strategic insights for practitioners.

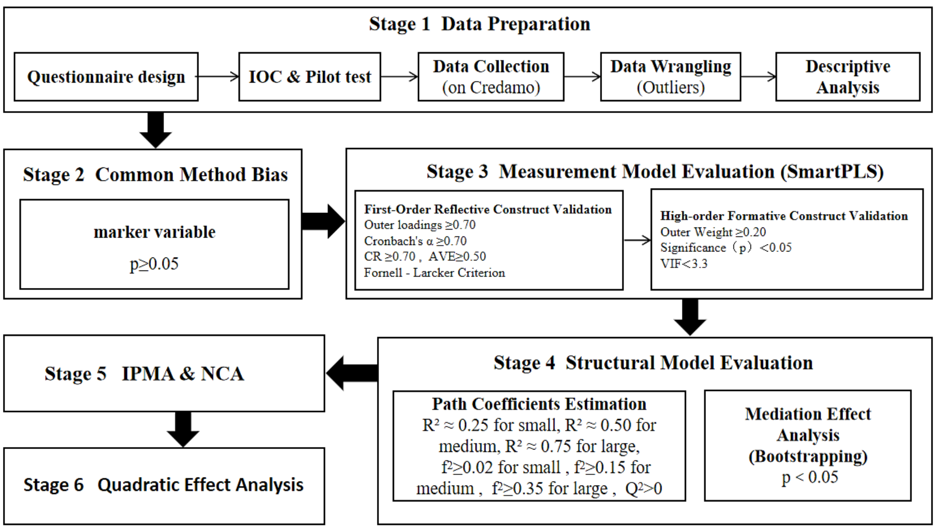


Figure 2. The Methodological Flowchart

3-1- Population and Sample

This study focuses on designer populations in China's industrial design industry, including practitioners in design departments of manufacturing enterprises and professionals in independent design companies. These groups are at the forefront of integrating AI and design innovation, aligning with China's strategic focus on transitioning from a manufacturing-driven to a design-driven economic transformation. Since research subjects require experience with AI applications, a purposive sampling strategy was adopted to ensure that participants possess relevant knowledge and background to respond to the survey's subject of interest.

The sample was recruited using Credamo, a powerful and popular platform in China, but like any platform that relies on a panel of voluntary participants, it has potential vulnerabilities. To overcome the inherent vulnerability to self-selection bias, this study utilizes the platform's filtering options, ensuring that only designers from industry design firms were selected. Additionally, the survey allows only one participant from one firm, so there is no requirement for multi-level analysis. Moreover, the Cremado platform has been widely used in top-tier journal publications [44].

Data collection was conducted from May to June 2025.

Besides using the criteria provided by Hair et al. [45] on 5-10 cases per measurement indicator and Kline's [46] recommendation that 200+ cases generally provide stable structural equation modeling (SEM) results, the Monte Carlo simulation [47], given in Figure 3, shows that sample size of 280 is sufficient, with convergence rate at 94.4% (exceeding 92% threshold), adequate fit rate at 94.4% (exceeding 85% threshold), and the statistical power determined at 79.9%, which is sufficient (exceeding 75% threshold) for a robust Smart PLS-SEM analysis.

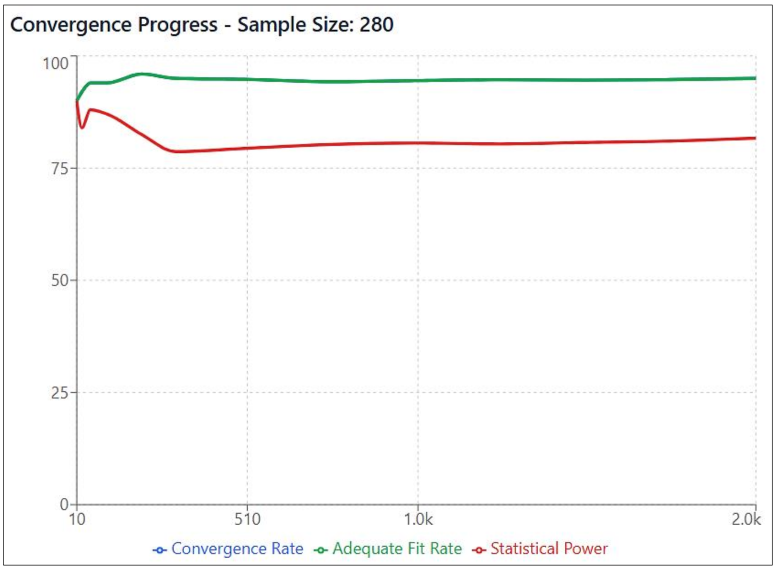


Figure 3. Monte Carlo Simulation for Sample Size Computation

3-2- Measurement Methods

The psychological safety climate is assessed using a 6-item first-order reflective scale proposed by Andersson et al. [48], which measures perceived safety, openness, and respectful climate within organizations. The sampled measurements for psychological safety climate include: employees respect and value each other's contributions; employees feel safe taking on high-risk projects; and employees are usually supported and understood when mistakes are made. AI-enabled dynamic capabilities constitute a second-order formative structure comprising three reflective dimensions: sensing, seizing, and transforming, with measurement items adapted from Yoshikuni et al. [49], which emphasizes the role of AI systems in trend scanning, opportunity capturing, and process reconfiguration. Dual innovation also constitutes a second-order formative structure, encompassing reflective dimensions of both radical and incremental innovation, with scales adapted from Su et al. [50], which reflect an enterprise's behaviors related to incremental and radical innovation. The sampled measurement for radical innovation is that our unit accepts demands that go beyond existing products and services. Incremental innovation is characterized by the frequent refinement of existing products and services. All items use a 7-point Likert Scale (1 = strongly disagree to 7 = strongly agree).

To ensure content validity, this study adapted the measurement scales to the contextual characteristics of the Chinese industrial design industry. It employed a back-translation procedure to refine the semantic accuracy of the original English scales, thereby producing an initial structured draft of the Chinese questionnaire. Subsequently, the Item-Objective Congruence (IOC) method was used to evaluate the content validity of the questionnaire. Four management scholars and three design scholars (all holding doctoral degrees and serving as university professors) conducted two rounds of assessment on each measurement item. Based on the IOC scores, items with unclear wording, ambiguous semantics, or insufficient relevance to the research objectives were revised and refined. Following the IOC-based revision, the researchers conducted a small-scale pilot survey (n = 100) to assess the clarity and appropriateness of the wording of each measurement item, as well as to perform a preliminary test of reliability and validity. The pilot test results indicated that both the first-order reflective constructs and the second-order formative constructs met the required statistical standards, thus laying a solid foundation for subsequent formal data collection and empirical analysis.

3-3- Common Method Bias

To ensure the survey design mitigates common method bias, this study employs both procedural and statistical remedies following established methodological practices [51]. Procedural measures include survey instructions that promote transparency, ensure complete anonymity, and utilize randomized item ordering to minimize evaluation apprehension and response bias. Additionally, a marker variable approach using the "blue color preference" construct [52] was employed to statistically assess systematic method variance. The study's use of second-order formative constructs for both AI-enabled dynamic capabilities and dual innovation offers additional protection, as formative constructs are less susceptible to common method variance. The comprehensive approach, which combines procedural remedies with statistical validation, provides confidence that observed relationships reflect substantive theoretical phenomena rather than methodological artifacts.

4- Statistical Analysis and Results

This section presents a comprehensive analysis of the 281 valid datasets using Smart PLS structural equation modeling. The study follows a systematic approach, beginning with descriptive statistics of the sample, followed by measurement model validation, structural model assessment, and specialized analytical techniques to ensure robust findings.

4-1- Sample Characteristics and Descriptive Analysis

Table 1 provides crucial insights into the composition of the research sample, revealing important patterns that contextualize the study’s findings. The overwhelming representation of in-house design departments (93.60%) compared to independent design companies (6.4%) reflects the current structure of China’s industrial design landscape. This distribution suggests that most design innovation activities occur within established manufacturing enterprises rather than standalone design firms, indicating a vertical integration approach where companies maintain internal design capabilities to ensure closer alignment with production processes and market strategies.

Table 1. Descriptive Statistics of the Sample

	Choice	Percent	Choice	Percent
Organization type	Independent design company	6.4%	In-house design department	93.6%
Region	Eastern region	48.10%	Central region	22.4%
	Western region	15.3%	Northeastern region	14.2%
Industry	High-tech	61.9%	Non-high-tech	38.1%
Firm Age	≤ 5 years	4.3%	Over five years	95.7%

The regional distribution offers significant insights into China's economic geography and design innovation hubs. The Eastern region's substantial representation (48.10%) aligns with China's established manufacturing and design centers, particularly the Yangtze River Delta economic zone, which encompasses Shanghai, Jiangsu, and Zhejiang provinces. This region's dominance can be attributed to several factors: historical advantages in advanced manufacturing capabilities, extensive international design collaboration networks, higher R&D investment density, and strategic proximity to major ports that facilitate global supply chains and knowledge exchange. The presence of leading universities and research institutions in this region also contributes to a more sophisticated talent pool for design.

The Central region's notable participation (22.4%) signals an important economic shift currently underway in China. This presence reflects the ongoing migration of manufacturing activities inland, driven by multiple factors, including lower operational costs, government incentives promoting development in the central region, emerging local design capabilities, and the formation of innovation clusters in cities such as Wuhan, Changsha, and Zhengzhou. This geographic diversification suggests that AI-enabled design innovation is not confined to traditional coastal manufacturing hubs but is spreading across China's interior regions.

The industry classification reveals a 61.9% to 38.1% split between high-tech and non-high-tech industries, respectively. This distribution is particularly significant for understanding the context of AI adoption in design processes. High-tech industries typically demonstrate higher innovation intensity and R&D spending ratios, characterized by more sophisticated design processes, the adoption of advanced digital tools, and a greater willingness to experiment with AI technologies. These industries often face shorter product lifecycles and more intense competitive pressures, necessitating rapid design iteration and innovation to stay ahead of the competition. Conversely, non-high-tech industries generally emphasize incremental innovation and process optimization approaches, operating with longer product lifecycles that allow for more deliberate design refinement and gradual technology adoption.

The firm age distribution, showing that 95.7% of participating organizations are over five years old, indicates that the sample consists primarily of established enterprises with sufficient organizational maturity and accumulated resources to invest in AI technologies and dual innovation strategies. This characteristic strengthens the study's validity, as these firms possess the organizational foundations necessary to develop both psychological safety climates and AI-enabled dynamic capabilities.

4-2- Common Method Bias Assessment

Table 2 presents the results of the marker variable testing, addressing potential concerns about common method bias. The marker variable approach uses an unrelated construct ("blue color preference") to assess whether systematic method variance affects the study's findings. The result demonstrates no significant relationships between the marker variable and any of the study's core constructs. The path coefficients are minimal (ranging from 0.010 to 0.045) with corresponding t-values well below significance thresholds and p-values substantially above 0.05. These findings provide strong evidence against concerns of common method bias.

Table 2. Marker Variable Testing.

Path	β	T-value	P-values
BP → AI-DC	0.010	0.142	0.887
BP → DUI	0.018	0.335	0.738
BP → PSC	0.045	0.602	0.548

The non-significant marker variable results, combined with the procedural remedies employed during data collection (anonymity assurance, item order randomization, and clear instructions), provide comprehensive evidence that common method bias does not threaten the study's validity. This confirmation strengthens confidence in the observed relationships between psychological safety climate, AI-enabled dynamic capabilities, and dual innovation.

4-3- Measurement Model Validation

4-3-1- First-Order Reflective Construct Assessment

The measurement model evaluation begins with assessing the quality of first-order reflective constructs, as presented in Table 3. The discriminant validity assessment using Fornell & Larcker's [53] criterion demonstrates that each construct's diagonal value (representing the square root of AVE) exceeds all cross-correlations with other constructs. This pattern confirms that each construct captures phenomena that are conceptually distinct from those of the others in the model, providing confidence that the measures adequately differentiate between psychological safety climate, AI-enabled dynamic capability dimensions, and dual innovation components. Furthermore, the convergent validity results reveal robust measurement properties across all constructs. All Average Variance Extracted (AVE) values substantially exceed the 0.50 threshold [45], with values ranging from 0.63 to 0.78. These results indicate that each construct explains more variance in its indicators than the measurement error, demonstrating strong convergent validity. Particularly noteworthy are the high AVE values for radical innovation (0.78) and incremental innovation (0.73), suggesting that these constructs are well-defined and reliably measured.

Table 3. First-Order Reflective Construct Validation.

	Constructs	1	2	3	4	5	6
1	Psychological Safety Climate	0.79					
2	Incremental Innovation	0.430	0.86				
3	Radical Innovation	0.494	0.393	0.88			
4	Seizing	0.386	0.439	0.376	0.85		
5	Sensing	0.377	0.331	0.430	0.577	0.80	
6	Transforming	0.330	0.296	0.368	0.450	0.397	0.85
	Mean	4.47	4.47	4.71	4.49	4.69	4.68
	Standard Deviation	1.30	1.11	1.23	1.05	1.08	1.23
	AVE	0.63	0.73	0.78	0.73	0.65	0.73
	Cronbach's Alpha	0.88	0.82	0.86	0.88	0.82	0.87
	Composite Reliability	0.88	0.82	0.86	0.88	0.82	0.88

Note: 1=Psychological safety climate, 2=Incremental Innovation, 3=Radical Innovation, 4=Seizing, 5=Sensing, 6=Transforming.

Besides ensuring measurement validity, the reliability assessment consistently shows strong internal consistency. Cronbach's Alpha values range from 0.82 to 0.88, all of which exceed the 0.80 threshold [54]. Similarly, composite reliability values demonstrate the same pattern, indicating that the measurement scales consistently capture their intended constructs. The outer loadings, exceeding 0.80, further confirm that individual measurement items strongly relate to their respective constructs.

Additionally, the mean values across constructs (ranging from 4.47 to 4.71 on a 7-point scale) suggest that respondents generally report moderate to moderately high levels of psychological safety climate and innovation capabilities. The relatively similar means indicate balanced perceptions across different aspects of the psychological safety climate and AI-enabled capabilities. Standard deviations ranging from 1.05 to 1.30 demonstrate adequate variability in responses, suggesting that the sample captures diverse organizational contexts rather than homogeneous conditions.

4-3-2- Second-Order Formative Construct Assessment

Table 4 presents the validation results for the two second-order formative constructs: AI-enabled dynamic capability and dual innovation. The formative nature of these constructs requires different evaluation criteria compared to reflective measures, focusing on the weights and significance of the first-order dimensions that compose each construct. For AI-enabled dynamic capabilities, the analysis reveals that all three dimensions contribute significantly to the formation of the construct ($p < 0.001$). The seizing dimension exhibits the highest weight (0.454), suggesting that the organization's ability to capture and exploit AI-identified opportunities represents the most critical component of AI-enabled dynamic capabilities in the design context. This finding aligns with the practical reality that identifying opportunities through AI sensing is valuable only when organizations can effectively act upon these insights.

Table 4. High-order Formative Construct Validation.

Construct	Measures	Weight	Significance	VIF
AI-enabled dynamic capability	Sensing (SEN)	0.430	$p < 0.001$	1.554
	Seizing (SEI)	0.454	$p < 0.001$	1.642
	Transforming (TRA)	0.349	$p < 0.001$	1.300
Dual Innovation	Incremental Innovation (INC)	0.521	$p < 0.001$	1.183
	Radical Innovation (RAD)	0.673	$p < 0.001$	1.183

Furthermore, the sensing dimension weight (0.430) indicates substantial importance in scanning the environment and identifying patterns through AI systems. This dimension reflects the organization's capacity to leverage artificial intelligence for environmental monitoring, trend detection, and opportunity recognition. The transforming dimension weight (0.349), while lower than the other two, remains statistically significant and practically meaningful, representing the organization's ability to reconfigure resources and processes based on AI insights.

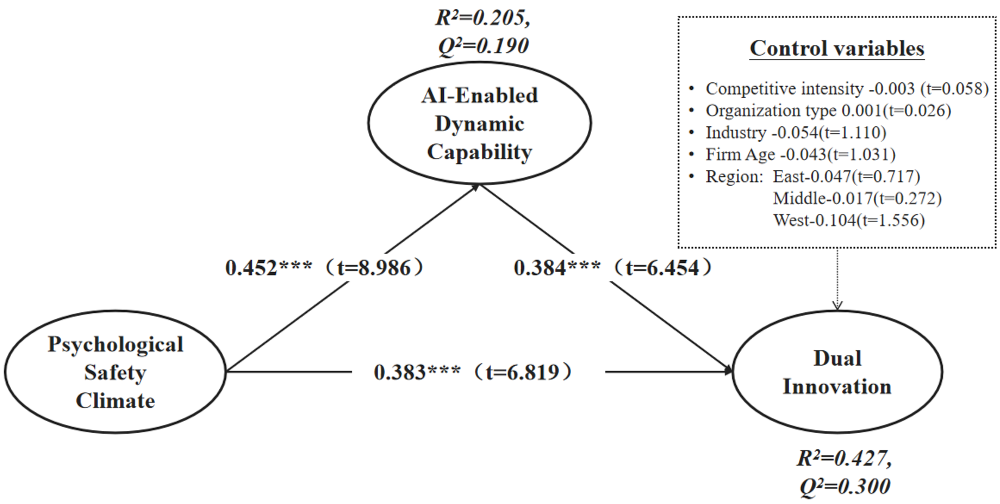
On the other hand, the dual innovation construct demonstrates a fascinating pattern. Radical innovation carries a higher weight (0.673) compared to incremental innovation (0.521), both of which are significant at $p < 0.001$. Finding challenges conventional assumptions about the balance of innovation in established organizations. The higher weight for radical innovation suggests that in the context of AI-enabled design organizations, breakthrough innovations contribute more substantially to overall dual innovation capabilities than incremental improvements. This pattern may reflect the transformative nature of AI technologies, which enable more dramatic innovation leaps rather than just marginal improvements.

The Variance Inflation Factor (VIF) values provide crucial evidence against concerns of multicollinearity. All VIF values remain well below the conservative threshold of 3.3, with the highest being 1.642. These low values confirm that the formative indicators are not overly correlated, supporting the distinctiveness of each dimension within the respective constructs.

4-4- Structural Model Assessment

4-4-1- Path Analysis Results

Figure 4 presents comprehensive structural model results, revealing the relationships between psychological safety climate, AI-enabled dynamic capabilities, and dual innovation. The path coefficients provide strong empirical support for the theoretical framework, with all hypothesized relationships demonstrating statistical significance at $p < 0.001$. The relationship between psychological safety climate and AI-enabled dynamic capabilities ($\beta = 0.452$, $t = 8.986$, $p < 0.001$) represents a substantial effect size, indicating that organizations with higher levels of psychological safety climate develop significantly stronger AI-enabled dynamic capabilities. This finding supports H1, confirming that psychological safety climate has a positive impact on AI-enabled dynamic capabilities. The strong statistical significance ($t = 8.986$) provides robust evidence that this relationship is not due to chance, validating the theoretical proposition that psychological safety serves as a foundational condition for technological capability development.



Note: *** p < 0.001, ** p < 0.01, * p < 0.05

Figure 4. The Path Structure Result

The direct path from psychological safety climate to dual innovation ($\beta = 0.383$, $t = 6.819$, $p < 0.001$) demonstrates that psychological safety climate influences innovation outcomes both directly and through AI-enabled dynamic capabilities. This finding supports H2, confirming that psychological safety climate has a positive impact on dual innovation. This dual pathway suggests that psychological safety climate operates through multiple mechanisms, directly fostering innovative behaviors while simultaneously enabling the development of AI capabilities that further enhance innovation.

The path from AI-enabled dynamic capabilities to dual innovation ($\beta = 0.384$, $t = 6.454$, $p < 0.001$) confirms that organizations' ability to sense, seize, and transform through AI technologies significantly enhances their capacity for both incremental and radical innovation. This finding supports H3, validating that AI-enabled dynamic capabilities have a positive impact on dual innovation. The similar magnitude of this coefficient to the direct PSC-dual innovation path indicates that both pathways contribute equally to innovation outcomes.

The control variables (competitive intensity, organizational type, industry, firm age, and region) show no significant effects on dual innovation, suggesting that the model's explanatory power derives from the theoretical constructs rather than contextual factors. This finding strengthens confidence in the validity of the theoretical framework across different organizational contexts within the Chinese design industry.

The model's explanatory power demonstrates substantial theoretical and practical significance. The R^2 value of 0.205 for AI-enabled dynamic capabilities indicates that psychological safety climate explains 20.5% of the variance in organizations' AI-enabled dynamic capabilities. While this may appear modest, it represents a substantial effect in organizational research, where multiple factors typically influence complex capabilities. The remaining unexplained variance likely reflects other factors, such as technological infrastructure, leadership capabilities, and organizational resources, that are not captured in this model. The R^2 value of 0.427 for dual innovation indicates that the combined influence of psychological safety climate and AI-enabled dynamic capabilities accounts for 42.7% of the variance in dual innovation outcomes. This represents a strong explanatory power in organizational innovation research, where numerous complex and interconnected factors typically influence innovation outcomes. The substantial explained variance suggests that the theoretical framework captures key drivers of innovation performance in design organizations.

Additionally, the f^2 values provide additional insights into effect sizes. The f^2 value of 0.257 for AI-enabled dynamic capabilities exceeds Cohen's (1988) threshold of 0.15 for medium effects, indicating that psychological safety climate makes a substantial contribution to explaining AI-enabled dynamic capabilities. Similarly, the f^2 value of 0.205 for dual innovation confirms that the predictors collectively contribute meaningfully to innovation outcomes. Furthermore, the predictive relevance assessment using Stone-Geisser's Q^2 criterion yields values of 0.190 for AI-enabled dynamic capabilities and 0.300 for dual innovation. Both values substantially exceed zero, confirming that the model possesses predictive relevance beyond sample-specific patterns. The Q^2 values suggest that the model can effectively predict out-of-sample observations, supporting its practical utility for organizations seeking to enhance their innovation capabilities.

4-4-2- Overall Model Fit Assessment

Table 5 presents the overall model fit evaluation using multiple criteria, providing comprehensive evidence for the model's adequacy. The Standardized Root Mean Square Residual (SRMR) value of 0.045 falls at the boundary of the 95% confidence interval, indicating acceptable model fit. SRMR values below 0.08 are generally indicative of a good fit, and the observed value suggests that the model adequately reproduces the observed covariance patterns.

Table 5. Overall Model Fit Evaluation

Discrepancy	Overall, the saturated model fit evaluation		
	Value	HI95	Conclusion
SRMR	0.045	0.045	Supported
d_ULS	0.133	0.133	Supported
d_G	0.051	0.056	Supported

The d_ULS (unweighted least squares discrepancy) and d_G (geodesic discrepancy) values both fall within their respective 95% confidence intervals, providing additional confirmation of model fit adequacy. These bootstrapped fit indices offer robust assessments that account for sampling variability, strengthening confidence in the model's appropriateness.

4-5- Mediation Analysis

Table 6 presents the mediation analysis results, which utilize bias-corrected bootstrapping with 5,000 subsamples, providing robust evidence for the indirect effect of psychological safety climate on dual innovation through AI-enabled dynamic capabilities. The indirect effect coefficient of 0.174 demonstrates statistical significance ($t = 5.254$, $p < 0.001$) with bias-corrected confidence intervals [0.117, 0.245] that exclude zero. This finding supports H4, confirming that AI-enabled dynamic capabilities mediate the relationship between psychological safety climate and dual innovation. This mediation effect reveals that psychological safety climate enhances dual innovation not only directly but also indirectly by fostering the development of AI-enabled dynamic capabilities. The indirect effect represents approximately 31% of the total effect (0.174/0.557), indicating that nearly one-third of the psychological safety climate's influence on dual innovation operates through AI-enabled dynamic capabilities.

Table 6. Summary Table of Hypotheses

	Structural Path	Original sample (O)	T statistics (|O/σ|)	Intervals Bias Corrected			Conclusion
				Bias	2.50%	97.50%	
H1	PSC → AI-DC	0.452	8.986***	0.006	0.339	0.540	Supported
H2	PSC → DUI	0.557	12.678***	0.003	0.459	0.631	Supported
H3	AI-DC → DUI	0.384	6.454***	-0.001	0.269	0.501	Supported
H4	PSC→AI-DC→DUI	0.174	5.254***	0.002	0.117	0.245	Supported

Note: Hypotheses H1, H2, H3, and H4. *** $p<0.001$, ** $p<0.01$, * $p<0.05$

The mediation finding provides crucial theoretical insights into the mechanisms through which psychological safety climate influences innovation outcomes. Rather than operating solely through direct motivational effects, psychological safety climate creates conditions that enable organizations to develop sophisticated AI-enabled dynamic capabilities, which in turn drive innovation performance. This finding supports the resource-based view proposition that higher-order resources (psychological safety climate) enable the development of lower-order operational capabilities (AI-enabled dynamic capabilities).

4-6- Advanced Analytical Techniques

4-6-1- Importance-Performance Map Analysis

Figure 5 presents the importance-performance map analysis (IPMA) for dual innovation, offering strategic insights into resource allocation priorities. The analysis plots each predictor's importance (x-axis) against its performance (y-axis), creating four quadrants that guide managerial decision-making. Psychological safety climate emerges as a high-importance, moderate-performance factor, positioning it in the "concentrate here" quadrant. With an important value of approximately 0.66 and a performance score of around 53 points, this finding suggests that while the psychological safety climate significantly influences dual innovation, organizations have substantial room for improvement in this area. This gap represents a critical strategic opportunity, as investments in psychological safety climate could yield significant returns in innovation performance.

On the other hand, AI-enabled dynamic capabilities reside in the high-performance, moderate-importance quadrant, with performance levels exceeding 65 points and importance values of around 0.39. This positioning suggests that organizations have successfully developed their AI-enabled capabilities beyond the threshold required for their current level of importance. However, this should not be interpreted as over-investment, as these capabilities serve as necessary foundations for innovation.

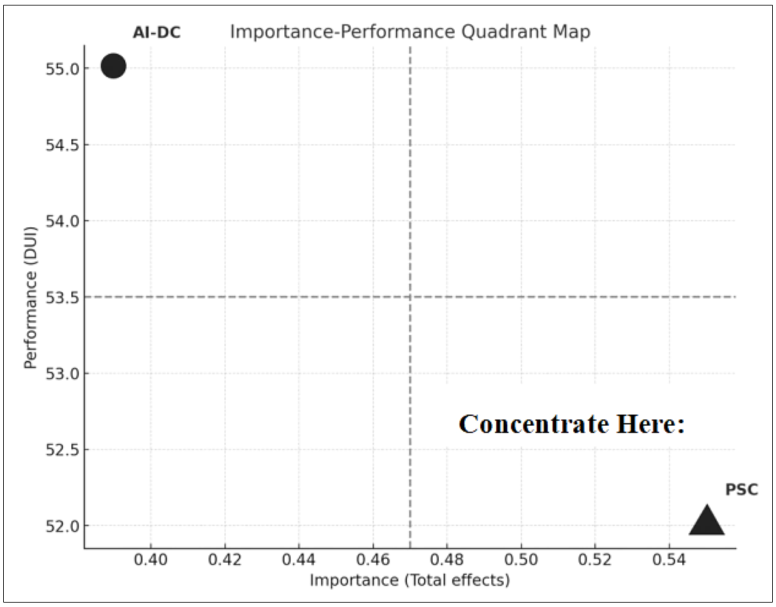


Figure 5. **Importance-Performance Quadrant Map on Dual Innovation**

Additionally, the IPMA results provide actionable insights for practitioners: organizations should prioritize investments in developing a psychological safety climate while maintaining their AI-enabled dynamic capabilities. This finding aligns with the resource-based view's emphasis on developing rare, valuable, and inimitable resources, as psychological safety climate represents a socially complex resource that is difficult for competitors to replicate.

Overall, the finding, as exhibited in Figure 5, provides a clear strategic directive for resource-constrained managers: investments in enhancing psychological safety climate are likely to yield the highest marginal returns on innovation performance, as it is the most important driver currently performing below its potential."

4-6-2-Necessary Condition Analysis

Figures 6 and 7 present the Necessary Condition Analysis (NCA) results for AI-enabled dynamic capabilities and psychological safety climate, respectively. The NCA technique identifies conditions that are necessary (but not sufficient) for achieving specific outcome levels, providing insights beyond traditional regression-based approaches. Figure 6 illustrates that AI-enabled dynamic capabilities are a necessary condition for dual innovation. The ceiling line (CE-FDH) displays a clear ascending pattern from left to right, indicating that higher levels of dual innovation require minimum thresholds of AI-enabled dynamic capabilities. The absence of data points above the ceiling line confirms that organizations cannot achieve high levels of dual innovation without corresponding levels of AI-enabled capabilities. The practical implication is significant: organizations cannot compensate for low AI-enabled dynamic capabilities through other means when seeking high innovation performance. This finding suggests that AI capabilities represent a bottleneck constraint rather than a linear contributor to innovation outcomes.

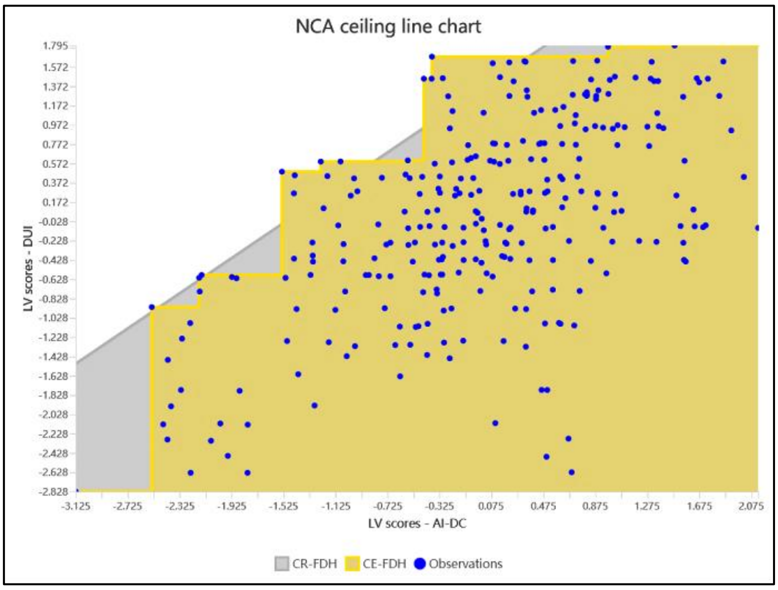


Figure 6. **Necessary Condition Analysis (NCA) of AI-enabled Dynamic Capability on Dual Innovation**

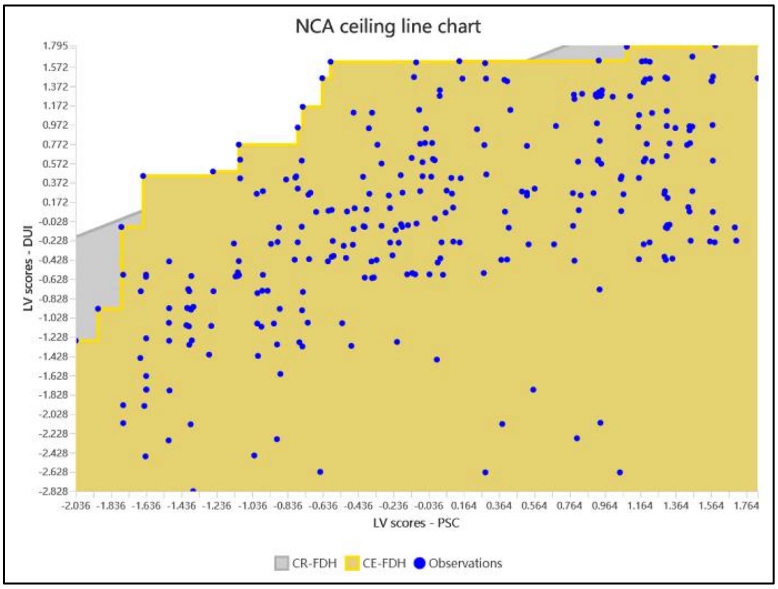


Figure 7. Necessary Condition Analysis (NCA) of Psychological Safety Climate on Dual Innovation

Additionally, Figure 7 demonstrates that psychological safety climate also functions as a necessary condition for dual innovation. The ceiling line pattern suggests that organizations must maintain a minimum level of psychological safety climate to achieve corresponding levels of innovation performance. This necessity relationship reinforces the theoretical proposition that psychological safety serves as a foundational condition for innovation activities.

The NCA results collectively suggest that both psychological safety climate and AI-enabled dynamic capabilities represent essential requirements rather than optional contributors to dual innovation. Organizations must invest in both areas simultaneously, as deficiencies in either condition will constrain innovation outcomes regardless of strengths in other areas.

4-6-3- Quadratic Effect Analysis

The quadratic effects analysis, as shown in Figure 8, reveals significant non-linear patterns in the following relationships: **PSC → DUI**: Quadratic coefficient = -0.133 ($p < 0.01$, significant), and **AI-DC → DUI**: Quadratic coefficient = -0.073 ($p < 0.042$, significant). It indicates that while both psychological safety climate and AI-enabled dynamic capabilities initially enhance dual innovation, there are optimal thresholds beyond which additional increases may yield diminishing or even negative returns.

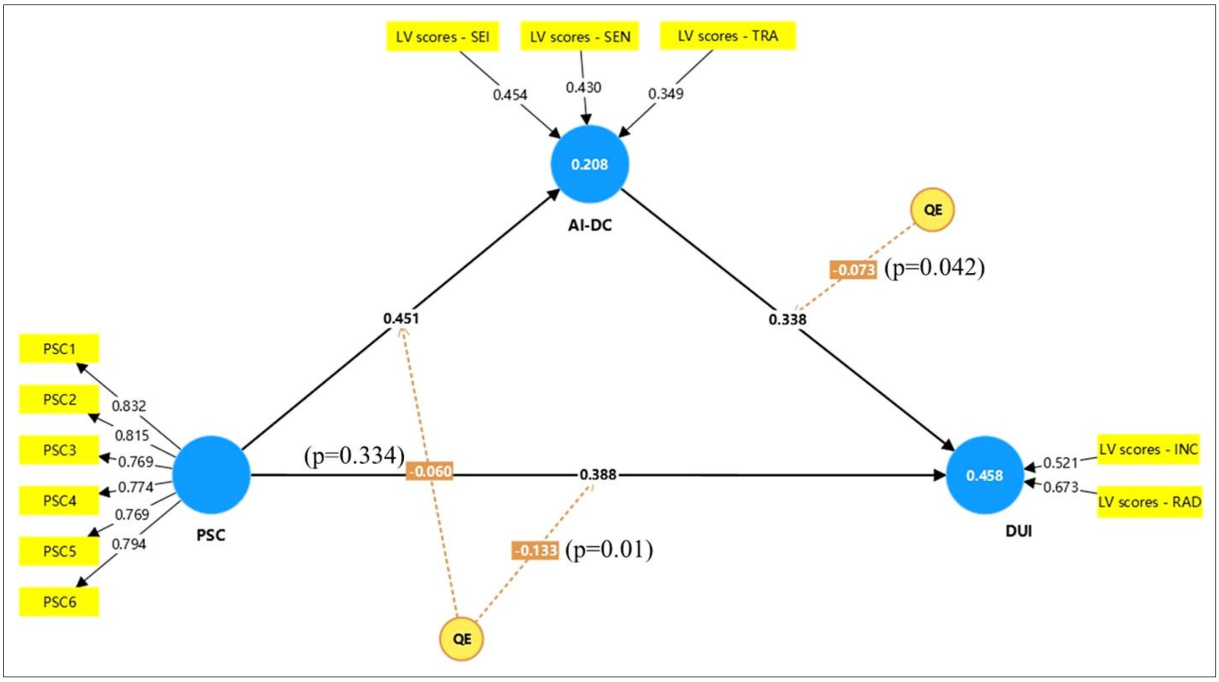


Figure 8. Quadratic Effect

The results demonstrate a significant negative quadratic effect of psychological safety climate on dual innovation ($\beta = -0.133$, $p = 0.01$), indicating an inverted U-shaped relationship. The negative quadratic coefficient suggests that beyond a certain threshold, additional increases in psychological safety climate may yield diminishing returns in innovation performance.

Additionally, the curvilinear relationship **AI-DC → DUI** demonstrates diminishing returns from AI-enabled capabilities beyond an optimal level. The inverted U-shaped pattern suggests that excessive development of AI capabilities may not lead to proportional improvements in innovation.

5- Discussion

Being an intangible asset, psychological safety climate offers a type of resource that is not only valuable but difficult to imitate [55], giving it a higher-order resource that this study has shown to significantly and positively shape lower-order operations-type capability, namely, the AI-enabled dynamic capability (H1. **β**= 0.452, $p < 0.001$), which diverges from the technology adoption literature that typically views AI implementation as primarily driven by technical factors rather than psychological conditions [56]. Furthermore, the support of H1 extends the research findings that a psychological safety climate can positively influence team dynamics and customer involvement [43], opportunity identification and learning [57], and aligns with [58] in the sense that a feeling of insecurity can be a barrier to technological adoption.

The study also contributes by recognizing that both the psychological safety climate and AI-enabled dynamic capability can be viewed as socio-technical resources required for dual innovation, offering valuable insights into the resource-based view (RBV). Thus, it highlights the significant role of social context in AI applications [8, 38] for achieving a dual innovation advantage. The formative construct validity also shows that the three formative contents – AI-enabled sensing, seizing, and transforming – are equally critical in contributing towards dual innovation.

In addition, the psychological safety climate is also shown to have a significant and positive impact on dual innovation (**β** = 0.383, $p < 0.001$), supporting hypothesis H2. It aligns with the findings of Andersson et al. (2020), which is crucial for understanding firm-level outcomes and phenomena [12]. Furthermore, it transcends the innovation climate [59], acknowledging that psychological safety climate constitutes a resource that can adeptly mitigate demanding job requirements, such as innovation, which embodies the conservation of resources (COR) theory advocated by Demerouti [60].

The hypothesis that AI-enabled dynamic capability positively influences dual innovation (H3) is consistent with Chen et al. [61] and Ji [62], who assert that dynamic capability enhances an organization's ability to adapt to market changes and promote innovation. While psychological safety climate is critical to alleviate the psychological distress that employees face in high-demand environments [42], this study further shows that AI-enabled dynamic capability serves as a critical mediator between psychological safety climate and dual innovation. Part of the rationale is that the ability to leverage innovation through psychological safety climate may remain at a prospective level unless the organization engages in dynamic capability. This extends Santana et al.'s [43] finding that a psychological safety climate requires learning and systems capabilities to influence organizational performance.

Furthermore, the IPMA finding demonstrates the substantial strategic importance of the psychological safety climate (0.66) compared to AI-enabled dynamic capabilities (0.39), which highlights the socio-technical roles in AI applications, extending AI as the primary driver of innovation performance [49, 63, 64]. From an RBV perspective, this study uniquely demonstrates how heterogeneous resources—psychological safety climate, an intangible and socially complex organizational resource, and AI-enabled dynamic capabilities, as technology-enhanced resources—create synergistic value configurations that are difficult to imitate [65]. This extends traditional RBV logic by demonstrating how the integration of socio-technical resources, rather than individual resource excellence, creates a sustainable competitive advantage. The necessary condition analysis further reveals that both psychological safety climate and AI-enabled dynamic capabilities serve as essential, yet not sufficient, conditions for dual innovation, indicating that organizations must invest in both psychological infrastructure and technological capabilities simultaneously. This finding provides empirical support for socio-technical systems theory [66] while offering practical guidance for balanced capability development.

Additional insight is provided in the context of dual innovation, which reveals that radical innovation (weight = 0.673) is more influential than incremental innovation (weight = 0.521) in defining dual innovation capability within design-intensive organizations, which offers an additional insight to research that does not stress the formative nature of the construct [67]. Nevertheless, the formative and PLS-SEM results suggest that dual innovation represents a synergistic capability, where radical and incremental improvements complement each other rather than compete, providing evidence for complementarity rather than trade-offs in innovation strategies. This insight is more revealing than research separating radical from incremental innovation [68].

5-1- Theoretical Implications

This study makes numerous theoretical contributions. First, the study extends psychological safety climate theory from its traditional focus on individual and team-level outcomes to organizational-level innovation capabilities. Building on Dong et al.'s [12] comprehensive review, our findings demonstrate that the psychological safety climate operates as a meta-capability, enabling the development of AI-enabled dynamic capabilities and thereby conferring a higher-order capability [12].

This extends beyond Dollard & Bakker's [69] original conceptualization by showing how psychological safety climate functions as a strategic resource that combines with technological resources to create unique innovation configurations. Furthermore, psychological safety climate serves not only as an intangible resource (RBV perspective) but also as a signal of organizational support for innovation and risk-taking. This dual role—as both a resource and a signal—provides a more comprehensive theoretical understanding of how the psychological safety climate influences innovation outcome.

Second, this study introduces AI-enabled dynamic capabilities (AI-DC) as a second-order formative construct. Unlike traditional dynamic capabilities, which rely primarily on human cognition and organizational routines, AI-DC represents a hybrid form of capability that combines artificial intelligence with human judgment across the sensing, seizing, and transforming dimensions [23]. The formative nature of this construct (with sensing weight = 0.430, seizing weight = 0.454, transforming weight = 0.349) suggests that all three dimensions are essential for AI-DC, but seizing capabilities may be particularly critical in design innovation contexts. This finding extends the dynamic capabilities literature by introducing technology augmentation as a fundamental characteristic of modern organizational capabilities.

Third, from the resource-based view (RBV) perspective, this study demonstrates the significant value of heterogeneous resources, consisting of psychological climate and AI-enabled dynamic capabilities, as socio-technical resources. In particular, it contributes to the knowledge of RBV and DCV (dynamic-based view) by recognizing psychological safety climate as a higher-order resource that supports the development of lower-order operations-type capabilities, namely, AI-enabled dynamic capability, leading to an RBV-enabled DCV concept in the extant literature.

5-2- Practical Implications

This study identifies four strategic domains with practical implications: strategic resource prioritization, optimal threshold management of the psychological safety climate, calibration of technology investment in AI-enabled dynamic capabilities, and integrated monitoring and assessment systems that reflect the dynamics of the conceptual model.

The IPMA analysis offers essential guidance for resource-constrained managers in strategic resource prioritization, indicating that the psychological safety climate holds considerably greater strategic significance (0.66) than AI-enabled dynamic capabilities (0.39), while exhibiting moderate performance (approximately 53 points), thereby highlighting a substantial opportunity gap. This study suggests that managers should prioritize establishing a psychological safety environment as a crucial facilitator of effective AI-enabled dynamic capability leveraging. Based on the mediation results (H4: $\beta = 0.174$, $p < 0.001$), businesses are recommended to implement a concurrent yet prioritized strategy for competence enhancement by first building a strong psychological safety climate to enable risk-taking and experimentation, followed by leveraging this climate to enhance AI-enabled sensing, seizing, and transforming capabilities.

The notable inverted U-shaped correlation between psychological safety climate and dual innovation ($\beta = -0.133$, $p = 0.01$) suggests that businesses should prioritize establishing balanced psychological safety settings rather than striving for optimal levels. Managers should implement psychological safety initiatives through leadership training programs centered on psychological safety principles, while concurrently upholding suitable performance accountability measures. Organizations must implement monitoring systems to identify optimal threshold levels, preventing under-investment that hinders creativity and over-investment that diminishes the productive tension essential for breakthrough innovations. This requires conducting a structured psychological safety assessment while upholding clear performance standards and constructive feedback mechanisms that distinguish between productive experimentation and unfocused exploration.

An inverted U-shaped association with dual innovation ($\beta = -0.073$, $p = 0.042$) suggests the need for strategic calibration of AI technology investments to leverage the organization's dynamic capability and prevent diminishing returns. Organizations must challenge the presumption that more AI-enabled dynamic capability inherently leads to superior innovation results. Design businesses ought to prioritize AI integration that augments, rather than supplants, human creativity. This entails creating collaborative AI systems with explicit norms that guarantee humans' creative participation. Organizations ought to establish AI-enabled environmental scanning systems and AI-facilitated consumer feedback analysis systems, while monitoring signs of technological saturation.

Regarding the integrated monitoring and assessment system, the complementary nature of these curvilinear relationships suggests that managers should establish advanced monitoring and calibration systems that track both psychological climate conditions and the effects of AI-enabled dynamic capabilities on innovation quality metrics. Organizations must conduct regular evaluations through staff surveys that examine the perceived psychological safety climate, AI-driven market sensing and seizing, AI-facilitated resource transformation, and innovation outcomes. Organizations must acknowledge that ideal levels may fluctuate based on whether the emphasis is on incremental enhancements or radical innovations, necessitating distinct strategies for diverse innovation scenarios.

6- Conclusion

This study addresses a critical gap in understanding how organizations can effectively leverage artificial intelligence for innovation by examining the role of psychological safety climate as a higher-order cultural resource that enables AI-enabled dynamic capabilities. Through empirical analysis of 281 Chinese design organizations, the research demonstrates that the psychological safety climate functions as a meta-capability that simultaneously influences dual innovation both directly and indirectly, through the development of AI-enabled dynamic capabilities. The findings reveal that organizations with stronger psychological safety climates develop more sophisticated AI-enabled sensing, seizing, and transforming capabilities, which in turn enhance their capacity for both incremental and radical innovation. The mediation analysis confirms that approximately 31% of psychological safety climate's influence on dual innovation operates through AI-enabled dynamic capabilities, highlighting the importance of socio-psychological foundations in technological capability development. Importantly, supplementary quadratic analysis reveals significant inverted U-shaped relationships for both psychological safety climate on dual innovation ($\beta = -0.133$, $p = 0.01$) and AI-enabled dynamic capabilities on dual innovation ($\beta = -0.073$, $p = 0.042$), indicating optimal thresholds beyond which additional investments may yield diminishing returns.

The theoretical contributions extend psychological safety climate theory beyond individual and team-level outcomes to organizational innovation capabilities, introduce AI-enabled dynamic capabilities as a second-order formative construct, and advance resource-based view understanding through the integration of heterogeneous socio-technical resources. The identification of curvilinear relationships provides empirical evidence for optimal resource configurations rather than simple maximization strategies, suggesting that even valuable organizational resources exhibit threshold effects. The study's practical implications emphasize that achieving a sustainable competitive advantage in AI-intensive environments requires calibrated approaches that balance psychological safety with performance accountability and optimize AI investments without overwhelming human creativity. Organizations must recognize that both psychological infrastructure and technological capabilities follow inverted U-shaped performance curves, necessitating strategic moderation rather than unlimited expansion. This study presents a socio-technical perspective on dynamic capabilities, demonstrating that optimal innovation outcomes emerge from carefully balanced combinations of human-centered conditions and technological capabilities, rather than maximizing either dimension independently.

6-1- Limitations and Future Research

This study offers both theoretical contributions and practical implications; however, some limitations hinder the deliberate application of its findings.

Although the Credamo platform is recognized for its reliability and trustworthiness in research by Tang et al. [44], additional research should gather data from diverse platforms, such as Wenjuanxing [70], to facilitate cross-platform comparison and model consistency.

Second, this study focuses on the Chinese design firms, which may, to some extent, limit the generalizability of its findings to other industry contexts. At the same time, prior research suggests that different industries also rely on dynamic capabilities in varying ways to improve organizational performance—for example, in banking [26] and supply chain management [71]. Thus, future research should extend the inquiry across more industries, diverse organizational settings, and cross-national contexts to further test the model's applicability and explore potential differences arising from cultural dimensions or industry-specific contingencies, thereby enriching the understanding of its boundary conditions. Furthermore, although the control variables show no significant effects on dual innovation, future research should test them in other industries, as their roles may be altered in different contexts.

The constraints of cross-sectional data collection methods limit the scope of this study. A subsequent study may employ a three-wave longitudinal design, assessing the independent variable and control variables at Time 1, the mediator at Time 2, and the outcome at Time 3. This approach will eliminate potential reverse causality concerns and furnish more robust proof for causality.

Building upon the resource-based view and capability-based view informed by socio-technical and social cognitive resource perspectives, which acknowledge the micro-foundations of dynamic capability, future inquiries may leverage social cognitive theory to elucidate social-cognitive capabilities in the context of dynamic capability [72], incorporating notions of socio-technical systems [73] and the Technology-Organization-Environment (TOE) framework [74].

Moreover, a psychological safety climate, as a cultural environment, facilitates the application of various theories to enhance psychological safety, ultimately benefiting businesses. Consequently, the subsequent theories may be expanded in the future: "social learning theory, psychological contract theory, conservation of resources theory, social exchange theory, uncertainty reduction theory, affective events theory, team learning theory, regulatory focus theory, person-supervisor fit theory, person-environment theory, relational attachment theory, social information processing theory, social cognitive theory, social identity and self-categorization theory" [12]. This would provide a significant contribution to the micro-foundational basis of AI-enabled dynamic capability.

Another critical limitation of our primary linear analysis is revealed by the significant negative quadratic effect of psychological safety climate on dual innovation ($\beta = -0.133$, $p < 0.01$), indicating an inverted U-shaped relationship where excessive psychological safety may diminish innovation performance. This suggests that beyond an optimal threshold, overly high psychological safety levels may reduce productive tension and performance accountability necessary for breakthrough innovations. Future research should investigate these threshold effects to identify optimal balance points between psychological safety and performance pressure across different organizational contexts. Furthermore, there is a significant negative quadratic effect of AI-enabled dynamic capabilities on dual innovation ($\beta = -0.073$, $p < 0.042$), demonstrating diminishing returns beyond optimal AI capability levels. This curvilinear relationship suggests that excessive investment in AI capabilities may lead to overdependence on technology at the expense of human creativity and intuition, which are essential for radical innovation. Future studies should examine how organizations can calibrate their AI investments to maximize innovation benefits while avoiding technological saturation that constrains creative exploration.

7- Declarations

7-1- Author Contributions

Conceptualization, K.T. and C.C.T.; methodology, K.T. and C.C.T.; software, K.T.; validation, K.T. and C.C.T.; formal analysis, K.T.; investigation, K.T.; resources, K.T.; data curation, C.C.T.; writing—original draft preparation, K.T.; writing—review and editing, C.C.T.; visualization, K.T.; supervision, C.C.T.; project administration, C.C.T. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

Funded Project: High-end Talent Introduction Project for Enhancing the Resilience of the Manufacturing Industry Chain in Panzhihua City Driven by the Digital Economy (Project No. 2025HJRC0051).

7-4- Institutional Review Board Statement

The study was approved by the Human Research Committee of the Researchers Association of Thailand, with the IRB certificate number ARE 15-04-68.

7-5- Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

8- References

[1] Li, S., Zhang, Y., Wang, Z., & Li, H. (2023). The influence of national policies on the evolution of industrial design education in China. Heliyon, 9(7), 17504. doi:10.1016/j.heliyon.2023.e17504.

[2] An, Z., Yin, Z., & Yin, Z. (2025). Dual innovation and enterprise productivity: A resource conservation perspective. International Review of Economics & Finance, 103. doi:10.1016/j.iref.2025.104537.

[3] Wang, S., & Zhang, H. (2025). Generative artificial intelligence and internationalization green innovation: Roles of supply chain innovations and AI regulation for SMEs. Technology in Society, 82, 102898. doi:10.1016/j.techsoc.2025.102898.

[4] Ghaemi Asl, M. (2026). An AI-optimized strategy for intelligent risk mapping of Islamic and conventional sustainable markets: Assessing the enduring dynamics of technological risk spillovers. Expert Systems with Applications, 296(Part A), 128945. doi:10.1016/j.eswa.2025.128945.

[5] Hosseini, H., Atazadeh, B., & Rajabifard, A. (2025). Towards intelligent land administration systems: Research challenges, applications and prospects in AI-driven approaches. Land Use Policy, 157, 107652. doi:10.1016/j.landusepol.2025.107652.

[6] Bianchini, S., Müller, M., & Pelletier, P. (2025). Drivers and barriers of AI adoption and use in scientific research. Technological Forecasting and Social Change, 220, 124303. doi:10.1016/j.techfore.2025.124303.

[7] Wong, D. T. W., & Ngai, E. W. T. (2025). Impact of artificial intelligence (AI) on operational performance: The role of dynamic capabilities. Information & Management, 62(6), 104162. doi:10.1016/j.im.2025.104162.

[8] Shi, Q., Zhiwei, L., Jie, W., Zeng, G., & Han, W. (2025). Generative AI on innovation performance of construction enterprises: A knowledge-based dynamic capabilities perspective. Journal of Engineering and Technology Management, 76, 101871. doi:10.1016/j.jengtecman.2025.101871.

[9] Abdelfattah, F., Dahleez, K., Halbusi, H. Al, & Salah, M. (2025). Strategic green alliances: Integrating green dynamic capabilities, AI, and electronic entrepreneurial innovation for sustainability. Sustainable Futures, 9, 100433. doi:10.1016/j.sftr.2025.100433.

[10] Khan, O. (2026). Dynamic Capabilities for Circular Economy Business Models. International Encyclopedia of Business Management, 4, 185–188. doi:10.1016/b978-0-443-13701-3.00542-9.

[11] Cai, Y., Lin, J., Zhang, R., Qiao, J., & Shang, Y. (2025). When does design thinking promote radical and incremental innovation? The moderating role of the innovation stage. Technovation, 146, 103298. doi:10.1016/j.technovation.2025.103298.

[12] Dong, R. K., Li, X., & Hernan, "Banjo" Roxas. (2024). Psychological safety and psychosocial safety climate in workplace: A bibliometric analysis and systematic review towards a research agenda. Journal of Safety Research, 91, 1–19. doi:10.1016/j.jsr.2024.08.001.

[13] He, R., Liao, X., & Xu, Y. (2025). How does digital transformation affect high-quality development of China's power industry? Renewable and Sustainable Energy Reviews, 217, 115789. doi:10.1016/j.rser.2025.115789.

[14] Fu, Z. L., Cao, C., & Gao, F. (2025). Current status, problems and promotion strategies of AI application in industrial energy management: A case study from China. Journal of Cleaner Production, 506, 145533. doi:10.1016/j.jclepro.2025.145533.

[15] Li, X. L., & Si, D. K. (2024). Does financial market liberalization promote corporate radical innovation? Evidence from China. International Review of Financial Analysis, 95(Part B), 103500. doi:10.1016/j.irfa.2024.103500.

[16] Xi, K., & Shao, X. (2025). Impact of AI applications on corporate green innovation. International Review of Economics and Finance, 99, 104007. doi:10.1016/j.iref.2025.104007.

[17] (Robert), H. G., Russen, M., & Guchait, P. (2025). Climate perceptions for underrepresented leaders: Influencing service employees' proactive behaviors through psychological safety and knowledge sharing. International Journal of Hospitality Management, 129, 104204. doi:10.1016/j.ijhm.2025.104204.

[18] Vallabh, P., Dhir, S., & Budhwar, P. (2024). Does psychological safety matter for innovative behaviour in hybrid workforce? The role of proactive personality, inclusive leadership and affective climate. International Journal of Organizational Analysis. doi:10.1108/ijoa-08-2023-3920.

[19] Arthachinda, P., & Charoensukmongkol, P. (2024). Effect of spiritual leadership on psychological safety climate and team innovation in consulting teams: the moderating role of occupational self-efficacy. International Journal of Productivity and Performance Management, 73(10), 3231–3251. doi:10.1108/IJPPM-04-2023-0192.

[20] Edmondson, A. C., & Kerrissey, M. J. (2025). What people get wrong about psychological safety? Harvard Business Review, 103(3), 52-59.

[21] Newman, A., Donohue, R., & Eva, N. (2017). Psychological safety: A systematic review of the literature. Human resource management review, 27(3), 521-535. doi:10.1016/j.hrmr.2017.01.001.

[22] Demirarslan, E. I., Yalap, O., & Dağ, M. (2025). Exploring innovation in healthcare: the mediating role of safety perception between organizational climate and innovative work behavior. Safety Science, 191, 106943. doi:10.1016/j.ssci.2025.106943.

[23] Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319–1350. doi:10.1002/smj.640.

[24] Wetsandornphong, S. T., Farr, R., Coleman, J., Salimi, Z., & Sweeney, E. (2025). Performance, integration and dynamic capabilities in supply chains: an interpretive investigation of their relationships. Supply Chain Management, 30(4), 452–475. doi:10.1108/SCM-10-2024-0704.

[25] Hunt, S. D., & Madhavaram, S. (2020). Adaptive marketing capabilities, dynamic capabilities, and renewal competences: The "outside vs. inside" and "static vs. dynamic" controversies in strategy. Industrial Marketing Management, 89, 129–139. doi:10.1016/j.indmarman.2019.07.004.

[26] Abdurrahman, A. (2025). Examining the impact of digital transformation on digital product innovation performance in banking industry through the integration of resource-based view and dynamic capabilities. Journal of Strategy & Innovation, 36(1), 200540. doi:10.1016/j.jsinno.2025.200540.

[27] Zhao, L., Xu, J., Zhang, B., & Lu, J. (2025). Leveraging AI to enhance firms' resource efficiency: ecological modernization theory and resource-based view perspectives. International Journal of Production Economics, 109723. doi:10.1016/j.ijpe.2025.109723.

[28] Samara, K., Mulholland, G., & Aluko, A. O. (2024). Impact of technology driven change on individuals' readiness in higher education: grounded in micro-foundations. International Journal of Organizational Analysis, 33(5), 1096–1113. doi:10.1108/ijoa-03-2024-4388.

[29] Zhang, X., Liu, Y., Tarba, S. Y., & Giudice, M. Del. (2020). The micro-foundations of strategic ambidexterity: Chinese cross-border M&As, Mid-View thinking and integration management. International Business Review, 29(6), 101710. doi:10.1016/j.ibusrev.2020.101710.

[30] Bağış, M., Kryeziu, L., Akbaba, Y., Ramadani, V., Karagüzel, E. S., & Krasniqi, B. A. (2022). The micro-foundations of a dynamic technological capability in the automotive industry. Technology in Society, 70, 102060. doi:10.1016/j.techsoc.2022.102060.

[31] Busco, C., Giovannoni, E., Riccaboni, A., & Frigo, M. L. (2024). The micro-foundations of corporate purpose: Performance management in dynamic environments. Management Accounting Research, 63, 100890. doi:10.1016/j.mar.2024.100890.

[32] Truchon, M., Gilbert-Ouimet, M., Zahiriharsini, A., Girouard, A., Thibeault, J., Parent, N., Lachapelle, É., & Biron, C. (2025). Assessing the Psychometric Properties of the French-Canadian Version of the Psychological Safety Climate Questionnaire (PSC-12). Safety and Health at Work, 16(1), 21–26. doi:10.1016/j.shaw.2024.11.001.

[33] Men, C., Fong, P. S. W., Huo, W., Zhong, J., Jia, R., & Luo, J. (2020). Ethical Leadership and Knowledge Hiding: A Moderated Mediation Model of Psychological Safety and Mastery Climate. Journal of Business Ethics, 166(3), 461–472. doi:10.1007/s10551-018-4027-7.

[34] Ehrhardt, K., & Ragins, B. R. (2019). Relational attachment at work: A complementary fit perspective on the role of relationships in organizational life. Academy of Management Journal, 62(1), 248–282. doi:10.5465/amj.2016.0245.

[35] Dhir, S., & Vallabh, P. (2025). Do social relationships at work enhance creativity and innovative behavior? Role of psychological safety. Acta Psychologica, 253, 104751. doi:10.1016/j.actpsy.2025.104751.

[36] Hunt, S. D., & Morgan, R. M. (2005). The Resource-Advantage Theory of Competition. Review of Marketing Research, 153–206. Emerald Group Publishing Limited, Leeds, United Kingdom. doi:10.1108/s1548-6435(2004)0000001008.

[37] Varadarajan, R. (2023). Resource advantage theory, resource based theory, and theory of multimarket competition: Does multimarket rivalry restrain firms from leveraging resource Advantages? Journal of Business Research, 160, 113713. doi:10.1016/j.jbusres.2023.113713.

[38] Li, J., Wang, Y., Zeng, W., & Liang, K. (2025). Impact of AI on firm ambidextrous innovation: Mediating role of digital knowledge coupling. International Journal of Information Management, 84, 102935. doi:10.1016/j.ijinfomgt.2025.102935.

[39] Ahmad, Z. (2025). Unlocking AI capabilities: exploring strategic fit, innovation ambidexterity and digital entrepreneurial intent in driving digital transformation. Journal of Management Development, 44(2), 194–218. doi:10.1108/JMD-05-2024-0171.

[40] Burton, A. M., & Dickinger, A. (2025). Innovation in Crisis. The role of leadership and dynamic capabilities for a more innovative hospitality industry. International Journal of Hospitality Management, 124, 103946. doi:10.1016/j.ijhm.2024.103946.

[41] Xing, M., Gong, C., Moon, G. H., & Ge, X. (2025). Digital economy, dual innovation capability and enterprise labor productivity. International Review of Financial Analysis, 101, 104005. doi:10.1016/j.irfa.2025.104005.

[42] Inoue, A., Eguchi, H., Kachi, Y., & Tsutsumi, A. (2025). Moderating Effect of Psychosocial Safety Climate on the Association of Job Demands and Job Resources with Psychological Distress among Japanese Employees: A Cross-sectional Study. Safety and Health at Work, 16(2), 213–219. doi:10.1016/j.shaw.2025.02.001.

[43] Santana, B., Monte, L., de Araújo Silva, B. S., Carneiro, G., Freire, S., Santos, J. A. M., & Mendonça, M. (2025). Psychological safety in software workplaces: A systematic literature review. Information and Software Technology, 187, 107838. doi:10.1016/j.infsof.2025.107838.

[44] Tang, J., Liu, J., & Kim, J. J. (2025). Shall I follow them? How destination image and ambivalent emotions influence tourists' responsible behavioral intentions. Journal of Hospitality and Tourism Management, 64. doi:10.1016/j.jhtm.2025.101327.

[45] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8^{th} Ed.). Cengage Learning Press, Boston, United States.

[46] Kline, R. B. (2023). Principles and practice of structural equation modeling. Guilford publications, New York, United States.

[47] Muthén, L. K., & Muthén, B. O. (2002). How to use a Monte Carlo study to decide on sample size and determine power. Structural Equation Modeling, 9(4), 599–620. doi:10.1207/S15328007SEM0904_8.

[48] Andersson, M., Moen, O., & Brett, P. O. (2020). The organizational climate for psychological safety: Associations with SMEs' innovation capabilities and innovation performance. Journal of Engineering and Technology Management, 55, 101554. doi:10.1016/j.jengtecman.2020.101554.

[49] Yoshikuni, A. C., Dwivedi, R., de Aguiar Vallim Filho, A. R., & Wamba, S. F. (2025). Big data analytics-enabled dynamic capabilities for corporate performance mediated through innovation ambidexterity: Findings from machine learning with cross-country analysis. Technological Forecasting and Social Change, 210, 123851. doi:10.1016/j.techfore.2024.123851.

[50] Su, X., Zeng, W., Zheng, M., Jiang, X., Lin, W., & Xu, A. (2021). Big data analytics capabilities and organizational performance: the mediating effect of dual innovations. European Journal of Innovation Management, 25(4), 1142–1160. doi:10.1108/ejim-10-2020-0431.

[51] Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. doi:10.1037/0021-9010.88.5.879.

[52] Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of E-Collaboration, 11(4), 1–10. doi:10.4018/ijec.2015100101.

[53] Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39–50. doi:10.1177/002224378101800104.

[54] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on PLS-SEM. SAGE Press, Thousand Oaks, United States.

[55] Navarro-García, A., Ledesma-Chaves, P., Gil-Cordero, E., & De-Juan-Vigaray, M. D. (2024). Intangible resources, static and dynamic capabilities and perceived competitive advantage in exporting firms. A PLS-SEM/fsQCA approach. Technological Forecasting and Social Change, 198, 123001. doi:10.1016/j.techfore.2023.123001.

[56] D'Amato, V., Tosca, E., Ricciardelli, A., & Tuporini, L. (2025). How to measure management innovation for a human-centric organization. Measuring Business Excellence, 29(3), 573–585. doi:10.1108/MBE-06-2024-0096.

[57] Cui, C. L., Tuttle, B., & Coleman, D. M. (2025). A narrative review of psychological safety in the surgical learning environment. Seminars in Vascular Surgery, 38(2), 176–183. doi:10.1053/j.semvascsurg.2025.04.008.

[58] Dwivedi, Y. K., Balakrishnan, J., Das, R., & Dutot, V. (2023). Resistance to innovation: A dynamic capability model based enquiry into retailers' resistance to blockchain adaptation. Journal of Business Research, 157, 113632. doi:10.1016/j.jbusres.2022.113632.

[59] Jiang, J., & Xia, Z. (2025). From guerrilla warfare legacy to green transparency: The lasting impact of collectivism on corporate environmental disclosure. Economics Letters, 255. doi:10.1016/j.econlet.2025.112521.

[60] Demerouti, E. (2025). Job demands-resources and conservation of resources theories: How do they help to explain employee well-being and future job design? Journal of Business Research, 192, 115296. doi:10.1016/j.jbusres.2025.115296.

[61] Chen, W., Lu, H., Mora, L., Chen, T., Beckers, D., & Hu, M. (2025). Linking manufacturing digitalization and technological Innovation: The mediating role of dynamic capabilities. Technology in Society, 83, 103041. doi:10.1016/j.techsoc.2025.103041.

[62] Ji, B. (2025). Supply chain finance and corporate persistent innovation—from the perspective of dynamic capabilities enhancement. International Review of Economics & Finance, 103, 104570. doi:10.1016/j.iref.2025.104570.

[63] Fengyi, D., Zichen, Z., Yajun, L., Xiaoping, M., & Yue, Z. (2025). When everyone is talking about AI: The development of fear of missing out on AI scale. Telematics and Informatics, 100, 102283. doi:10.1016/j.tele.2025.102283.

[64] Xie, Y., & Lin, B. (2025). Does AI-driven innovation improve green productivity? The role of heterogeneous information infrastructure. Journal of Environmental Management, 389, 126116. doi:10.1016/j.jenvman.2025.126116.

[65] Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. Journal of Management, 17(1), 99–120. doi:10.1177/014920639101700108.

[66] Münch, C., Marx, E., Benz, L., Hartmann, E., & Matzner, M. (2022). Capabilities of digital servitization: Evidence from the socio-technical systems theory. Technological Forecasting and Social Change, 176, 121361. doi:10.1016/j.techfore.2021.121361.

[67] Iftikhar, A., Ali, I., Zhan, Y., Stevenson, M., & Tarba, S. Y. (2025). Firms' strategic responses to rising uncertainty amid ongoing geopolitical tensions: The synergistic mediating role of network capability and innovation ambidexterity. Transportation Research Part E: Logistics and Transportation Review, 199, 104146. doi:10.1016/j.tre.2025.104146.

[68] Ragazou, K., Passas, I., Garefalakis, A., & Dimou, I. (2022). Investigating the Research Trends on Strategic Ambidexterity, Agility, and Open Innovation in SMEs: Perceptions from Bibliometric Analysis. Journal of Open Innovation: Technology, Market, and Complexity, 8(3), 118. doi:10.3390/joitmc8030118.

[69] Dollard, M. F., & Bakker, A. B. (2010). Psychosocial safety climate as a precursor to conducive work environments, psychological health problems, and employee engagement. Journal of Occupational and Organizational Psychology, 83(3), 579–599. doi:10.1348/096317909X470690.

[70] Peng, K. L., Chan, X., & Wu, C. H. (2023). Space tourism flow generated from social media data. Data in Brief, 48, 109061. doi:10.1016/j.dib.2023.109061.

[71] Huang, K., Wang, K., Lee, P. K. C., & Yeung, A. C. L. (2023). The impact of industry 4.0 on supply chain capability and supply chain resilience: A dynamic resource-based view. International Journal of Production Economics, 262, 108913. doi:10.1016/j.ijpe.2023.108913.

[72] Refoua, E., Elyoseph, Z., Wacker, R., Dziobek, I., Tsafrir, I., & Meinlschmidt, G. (2025). The next frontier in mindreading? Assessing generative artificial intelligence (GAI)'s social-cognitive capabilities using dynamic audiovisual stimuli. Computers in Human Behavior Reports, 19, 100702. doi:10.1016/j.chbr.2025.100702.

[73] Lv, B., He, Z., & Bao, X. (2025). Research on green design of major railway tunnel projects based on "environmental-social-technical" system. Journal of Cleaner Production, 517, 145579. doi:10.1016/j.jclepro.2025.145579.

[74] Ul Haq, F., Suki, N. M., Zaigham, H., Masood, A., & Rajput, A. (2025). Exploring AI Adoption and SME Performance in Resource-Constrained Environments: A TOE–RBV Perspective with Mediation and Moderation Effects. Journal of Digital Economy, 1-48. doi:10.1016/j.jdec.2025.07.002.