RESEARCH PAPER

Intelligent Strategic Management in the Context of Digital Transformation: The Path for Shandong SMEs to Gain Competitive Advantage in Large Projects through AI-Enhanced Culture and Advertising

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ABSTRACT
This study aims to examine the moderating effect of the adoption of artificial intelligence (AI) on the relationship between corporate culture, advertising strategy, competitive advantage, and the success of strategic management in small and medium-sized enterprises (SMEs) in large-scale project supply chains in the Shandong province of China. According to the research, the research model was developed by integrating the dynamic capabilities theory and the AI capability views, and the partial least squares path modeling analysis was conducted on the data collected from 255 participants in the manufacturing, services, and technology industries. Results indicate that the adoption of AI has a positive moderating effect on the relationship between corporate culture and competitive advantage, advertising strategy and competitive advantage, as well as competitive advantage and strategic management effectiveness. Moreover, the mediated relationship between organizational resources and strategic management effectiveness through competitive advantage is also affected by the moderating role of the adoption of AI, which simultaneously acts as a moderator for the two stages of the mediated relationship, thereby offering compounded performance returns in the form of dual-stage mediated moderation. These findings expand the dynamic capabilities theory by showing that AI adoption is actually operating as a system-level organizational capability whose strategic effect is cumulative across the whole resource-performance chain, thus having managerial and policy-oriented implications for SME managers and policymakers in competitive supply chain environments.

Keywords: artificial intelligence adoption, corporate culture, competitive advantage, strategic management effectiveness, moderated mediation
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1. INTRODUCTION

The relationship between organizational resources and strategic performance is a traditional subject of interest in management research, although the circumstances of this relationship are subject to controversy. SMEs experience a specific form of this problem. They exhibit significant organizational strengths in terms of well-defined corporate cultures (CC) and advertising strategies, but turning these strengths into substantial and meaningful competitive advantage (CA) and, subsequently, into viable strategic management is not a standard or predictable event [1]. Understanding the determinants of this process has become ever more important as the nature of the competitive environment has become ever more complex, both in terms of its digital nature and the performance differential between firms that can facilitate this process and those that cannot.

AI has emerged as a potentially transformative technology for the organization. The research on the adoption of AI has shifted from the early optimism about the potential for efficiency gains to a more nuanced approach in examining the impact of AI on the quality of decision-making in the organization and the responsiveness of the strategic processes [2]. With regard to marketing and advertising campaigns, for example, it has been demonstrated that AI-based platforms hold the capacity to alter the nature of the competition faced by resource-constrained firms through more accurate targeting and credible signaling beyond what a firm's financial resources afford [3]. The suggestion here is that it is not simply the case that AI enables faster processing but rather alters the nature of the circumstances within which resources have a competitive return.

What has not been explicitly explained in the literature is whether this conditioning process is also applicable to the entire performance process. The literature on AI and firm competitiveness has, in most cases, focused on the process of resources to advantage and the process of advantage to

**Author for Correspondence: rozaini@lincoln.edu.my* strategy separately, without the possibility of these two processes being intertwined as AI-related processes under the same framework [4]. This selective focus leads to an important question. Indeed, if the adoption of AI increases the competitiveness of corporate culture and advertising strategy (AD) at the front end of the model, does it similarly affect the propagation of this competitiveness to strategic management effectiveness (SM) at the back end of the model and is this effect of practical importance to SMEs' approaches to AI investment?

This is particularly evident in the area of supply chain management, where the impact of strategic execution is considerable and the level of required information for the manager is considerable. The strategic momentum of digital transformation in SMEs has been shown to depend critically on the extent to which AI tools are integrated into core decision-making processes rather than peripheral operational functions [5]. However, the mechanisms through which this integration influences strategic outcomes are currently unspecified in empirical research. Ellström et al. also highlighted the need to investigate the association between digital capability adoption and strategic performance across the entire organizational pathway [6].

This study explores the moderating role of AI adoption on the entire performance chain from corporate culture, advertising strategy, competitive advantages, and effectiveness of strategic management for SMEs in the large-scale project supply chain. With the evaluation of both front-end and back-end moderation in a unified framework of moderated mediation, this study seeks to provide a more complete understanding of the investments in AI and the generation of strategic value in a constrained organizational environment.

2. LITERATURE REVIEW AND HYPOTHESES

2.1 Corporate Culture, Advertising Strategy, and Competitive Advantage

The resource-based theory confirms that competitive advantage is achieved through resources that are valuable, scarce, and difficult to imitate, and corporate culture has always been recognized as a resource that fits into this definition [1]. Unlike physical or financial resources, corporate culture is something that is difficult for competitors who have not gone through a similar historical experience to imitate. For SMEs that are part of long project-based supply chains, cultural robustness in isolation is not sufficient. In a situation where procurement decisions are characterized by high levels of information uncertainty, the attributes that are embedded in the culture of an organization are not likely to manifest themselves in a way that can be observed by external actors. As a result, the relative competitiveness of culture depends on the circumstances that make it visible to the relevant decision-makers. According to empirical research findings, organizations operating within a culturally consistent environment are at a better position to compete compared to those operating within a fragmented environment. This is because of the alignment of employees and the adaptability of the organizations [7]. Truong et al. further extended these findings by examining how different national contexts shape the strategic performance of SMEs [8]. The findings indicated that organizational culture does impact the competitive advantage of organizations.

The advertising strategy is a means of attaining competitive advantage, but it does so through another route. While culture is a means of attaining competitive advantage from within, advertising is about how external stakeholders perceive an organization's credibility, technical capability, and reliability as a supply chain partner [9]. The externalization of competitive advantage for a resource-constrained SME is complicated by structural constraints on marketing budgets and expertise, even for those organizations with underlying quality strengths. Enhanced advertising capability has been linked to differentiated competitive positioning [10], while marketing capability has been shown to contribute meaningfully to competitive performance across diverse SME contexts [11]. Corporate culture and advertising strategy are the two main paths through which the SMEs in question could develop their competitive advantage, and the following sections will discuss the conditions that maximize the two paths.

2.2 Competitive Advantage and Strategic Management Effectiveness

Competitive advantage is an important construct of strategic management theories, both as an outcome of organizational performance and as a contextual condition of organizational environment. Porter argued that a defensible competitive position provides the informational and motivational foundation for strategic decision-making, enabling management to allocate resources and set goals based on a systematic assessment of the firm's capabilities [12]. Teece extended this logic within dynamic capabilities theory, positioning competitive advantage as a mechanism for sensing market opportunities, exploiting them through timely resource allocation, and reconfiguring firm capabilities in response to environmental change [13]. All these are considered as components of strategic management, and competitive advantage should be understood as a state that makes it possible to conduct strategic management.

What the literature has subsequently underemphasized is the inconsistent nature of this relationship in the demonstration of strategic effectiveness. Empirical research undertaken within the SME context has shown the positive impact of competitive advantage on strategic performance outcomes; however, the strength of this relationship is subject to considerable variation [14]. Competitive positioning has been shown to depend on strategic management effectiveness, which in turn relies on the development of dynamic capabilities to translate competitive intelligence into actionable outcomes[15]. This means that those organizations without this capacity to translate competitive advantages into adaptive strategic management may have competitive advantages, but they may not be able to translate these into the desired adaptive strategic management; therefore, there is a need to research the factors that affect this conditionality between CA and SM.

AI capability is a unique boundary condition. AI has been shown to improve both the speed and quality of decision-making, partially mediating the relationship between AI adoption and organizational performance [16]. This is an immediately applicable mechanism. Competitive advantage generates strategic value to the extent to which managers can interpret the competitive signals conveyed by the competitive advantage and transform them into meaningful strategic direction. Tools assisted by AI enhance the rigor of this interpretive process in a way that makes it not only more systematic in its analysis of competitive intelligence, but also more precise in its identification of strategic options, which is particularly important for SME managers in a resource-constrained environment with complex supply chain systems. The strength of a firm's capability in AI serves to enhance the extent to which its position as a competitor becomes informative of its strategic planning and execution, and this is what is being empirically tested through the moderation hypothesis as discussed further in the following section.

2.3 AI Adoption in SME Contexts

AI, as a competence of organizations, is now increasingly regarded as qualitatively different from other information technology-based infrastructures within an organization. Unlike other information technology-based systems, which are intended for specific process automation and for information storage and transmission, AI-based systems allow for the analysis of complex information, meaningful inferences, and strategic decision-making, which are beyond the scope of rule-based systems [17]. Building on this distinction, Sahoo et al. conceptualized AI capability in a B2B context as encompassing data processing, pattern recognition, and strategic intelligence generation to drive competitiveness and innovativeness [17]. In this study, the adoption of AI is conceptualized as the adoption of AI-based marketing tools, systems for competitive analysis with the help of AI, and decision support systems enabled by AI, as opposed to other digital technologies or conventional business software. This conceptualization captures the qualitatively different competitive implications of these two levels of technology.

In SMEs, this differentiation has significant implications. Resources have historically prevented SMEs from aligning the scope of their marketing efforts with the analysis and intelligence capabilities of larger rivals. IT adoption has historically not addressed these differences. However, with the advent of artificial intelligence tools, SMEs can analyze competitive intelligence and target procurement decision-makers with a level of accuracy previously impossible with the scale of SMEs [3]. In B2B procurement environments specifically, the choice of suppliers is greatly influenced by the quality and authenticity of information being conveyed by the signals of competition. The use of AI alters the nature of competition from the volume of resources to the analytical intelligence and accuracy of identifying and approaching the most relevant buyers [18]. AI capability has been shown to influence organizational performance not only through marketing effectiveness but also through the quality of managerial decisions, extending into the broader domain of strategic responsiveness [2]. These are the major factors which make the use of AI capability particularly significant for SMEs, especially when they are looking for ways to use their organizational resources for generating the required returns in a challenging supply chain environment.

2.4 AI Moderation of Resource-to-Advantage Pathways

The extent to which cultural resources create competitive advantage is not only related to the quality of the cultural resources but also to the conditions under which the cultural resources become legible to buyers who would procure them. Procurement decisions for large-scale projects take place under conditions of informational asymmetry. This means that buyers who need to evaluate suppliers must do so through observable signals rather than through direct experience. Cultural attributes, as internalized experiences and organizational constructs, do not necessarily provide verifiable and externally accessible evidence that procurement decision-makers can readily evaluate and act upon [19]. The integration of AI changes this reality by actively transforming the information environment through which cultural strengths are communicated. Supplier evaluation tools enabled by AI and digital procurement platforms help in creating performance records, which in turn help in transforming intangible attributes of organizations into quantifiable data points for use in vendor evaluation by buyers [20]. This does not imply that AI enhances culture; rather, it implies that AI enhances the upper bound of competitive return available to a given level of cultural strength by making that strength accessible to buyers who would otherwise be unable to appreciate it. Accordingly, this study proposes:

H1: AI adoption positively moderates the relationship between corporate culture and competitive advantage, such that the positive effect of corporate culture on competitive advantage is stronger among SMEs with higher levels of AI adoption.

The trajectory of the advertising strategy is determined by an alternative competitive logic. This is different from a model where the rules are defined by observability constraints, since the success of advertising within the SME domain is determined by the extent of the resources that could be steered towards decision-makers. Tools of AI fundamentally alter the determinants of this efficiency, shifting the basis of advertising competitions from budgetary size to analytical intelligence [3]. In the context of B2B procurement situations where the aim is to build credibility in front of a niche group of high-value procurement decision-makers rather than visibility in front of a large audience, this change is particularly pertinent for

SMEs that cannot compete on marketing spend [21]. AI applications in B2B marketing have been shown to reshape competitive dynamics by enabling firms to achieve precise audience targeting independently of marketing budget constraints [18]. This implies that not only does the adoption of AI improve the efficiency of advertising, but also that the structural factors through which advertising investments translate into competitive positioning will improve the competitive returns available to SMEs that successfully implement these technologies. Accordingly, this study proposes:

H2: AI adoption positively moderates the relationship between advertising strategy and competitive advantage, such that the positive effect of advertising strategy on competitive advantage is stronger among SMEs with higher levels of AI adoption.

2.5 AI Moderation of the Competitive Advantage-Strategy Relationship

Competitive advantage provides the background to the effective management of strategy, but the conversion of this competitive advantage to strategic effectiveness is conditional upon the quality of the decision-making process through which the firm attempts to act upon the intelligence of the competitive environment. Companies that have a strong competitive position but do not possess the necessary analytical capabilities to effectively leverage this positioning will not benefit from a strong strategic payoff for their competitive position, and it is this disconnect between competitive positioning and strategic execution where the adoption of artificial intelligence has the potential to bridge the gap. Neiroukh et al. found that AI-driven improvements in decision-making speed and quality partially mediate the relationship between AI adoption and organizational performance [16]. The mechanism is applicable for the CA → SM pathway. Even though the firm that developed its competitive advantage has market intelligence about how it fares in relation to its competitors, the capacity to act on this intelligence in relation to developing strategies and decisions may require analysis that an SME manager may not be able to do without technological support.

The use of AI-based tools for strategic analysis increases the strength of analysis through a more systematic treatment of competitive intelligence, a more precise determination of strategic alternatives, and a more reactive response to changing competitive conditions. The strategic momentum of digital transformation in SMEs has been shown to depend critically on the depth of AI tool integration into core processes rather than peripheral business functions [5]. Firms that are successful in the deeper integration of AI tools are better at translating their competitive position into strategic results. Teece argued that sensing and seizing opportunities constitute the core of dynamic capability [13]. The implementation of AI enhances the activities of dynamic capability by enriching the information and analysis base of the firm. Thus, it is imperative to understand that the link between competitive advantage and the effectiveness of strategic management is dynamic rather than static and depends on the degree of the firm's competence in AI with respect to the interpretive and planning processes. Accordingly, this study proposes:

H3: AI adoption positively moderates the relationship between competitive advantage and strategic management effectiveness, such that the positive effect of competitive advantage on strategic management effectiveness is stronger among SMEs with higher levels of AI adoption.

2.6 Moderated Mediation across the Performance Pathway

The moderation hypotheses proposed in Sections 2.4 and 2.5 address specific aspects of the performance chain. H1 and H2 describe the amplifying effect of AI on the translation from resources to advantage, while H3 identifies the enhancing effect of AI on the translation from advantage to strategy. Individually, these components specify the nature of the moderation of particular relationships within the model by AI. The question remaining is whether the moderating effect of AI on the entire chain of causality includes the conditional nature of the indirect effects of CC and AD on SM, mediated by CA, as a function of the level of AI adoption.

If the moderating variable moderates the relationship between the independent variable and the mediator, then the indirect effect of the independent variable on the dependent variable is a function of the moderating variable; the strength of the moderating variable depends on the level of the moderating variable [22]. If the proposed model is applied, the situation where the adoption of AI would improve CC → CA and AD → CA at the initial stage would show a greater indirect impact of both organizational resources on the effectiveness of strategic management through competitive advantage for firms with higher levels of AI adoption compared to those with lower levels. H4 and H5 describe the first-stage moderated mediation effect.

This rationale is extended in H6, which includes the second-stage moderation defined in H3. A moderating factor has been shown to influence both stages of a mediated process [23], producing a dual-stage moderated mediation in which the combined indirect effect is more sensitive to moderator variation than either individual-stage effect alone. AI has further been characterized as a systemic organizational capability that permeates decision-making across multiple levels [17], supporting the argument that its moderating effect operates across the entire process rather than at isolated relational stages. Where the adoption of AI influences the conditions for the development of competitive advantage from resources within the organization and the conversion of competitive advantage to strategic management effectiveness, the entire indirect path from resources to strategic outcomes is magnified by the increasing levels of AI adoption in a compounding rather than additive manner. Accordingly, this study proposes:

H4: AI adoption positively moderates the indirect effect of corporate culture on strategic management effectiveness through competitive advantage, such that the indirect effect is stronger among SMEs with higher levels of AI adoption.

H5: AI adoption positively moderates the indirect effect of advertising strategy on strategic management effectiveness through competitive advantage, such that the indirect effect is stronger among SMEs with higher levels of AI adoption.

H6: AI adoption simultaneously moderates both the first-stage and second-stage relationships in the mediated pathway, such that the full indirect effects of corporate culture and advertising strategy on strategic management effectiveness intensify with higher AI adoption levels.

2.7 Conceptual Framework

Figure 1 shows the conceptual framework. The model is founded on three direct relations that have been empirically established and supported by literature: the relation between corporate culture and competitive advantage, the relation between advertising strategy and competitive advantage, and the relation between competitive advantage and the effectiveness of strategic management. They form the structural base for the model but not the hypotheses for this research. The AI adoption is introduced as a moderating variable, which affects all three trajectories, and the main research interest is about the circumstances under which these established relations are strengthened or weakened at different levels of AI adoption.

The framework is based on the theory of dynamic capabilities and research on AI capability. Dynamic capabilities theory provides a theoretical basis for the link between organizational resources and competitive and strategic effectiveness. Research on AI capability examines the link between AI adoption and the effectiveness of the resource-performance link. H1 and H2 specify the front-end moderation effect on the resource-to-advantage paths, H3 identifies the back-end moderation effect on the advantage-to-strategy relationship, and H4-H6 are extensions of this logic to the entire mediated relationship, suggesting that the effect of AI-conditioned competitive advantage on strategic management effectiveness follows a systematic pattern depending on the level of AI adoption.

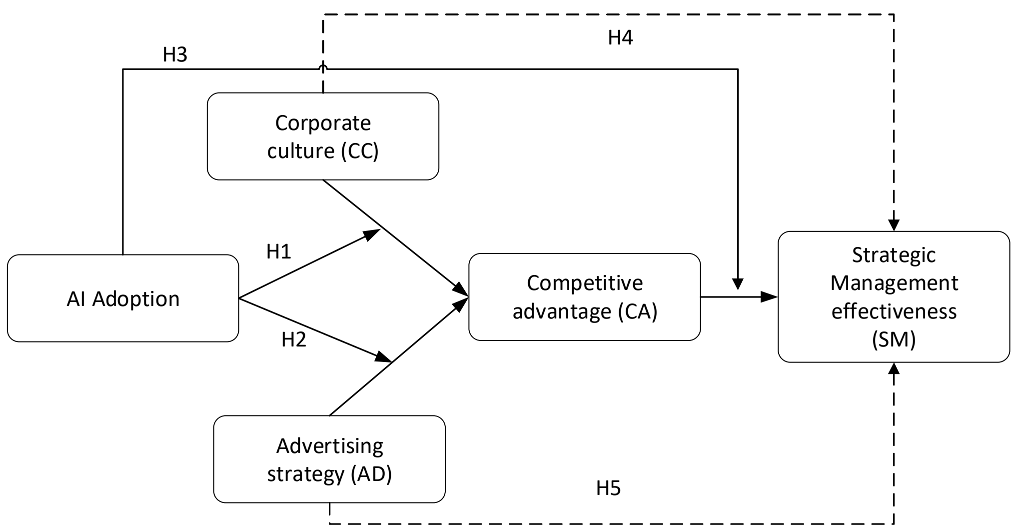

Figure 1. Conceptual Framework

3. METHODOLOGY

3.1 Research Design and Sample

A quantitative approach through a cross-sectional survey design was utilized by targeting SME owners, senior managers, and marketing professionals in the Shandong Province to explore the impact of AI on the relationship between corporate culture, advertising strategy, competitive advantage, and strategic management. The sampling design was stratified random sampling from businesses involved in large-scale project supply chains in three different sectors: manufacturing, services, and technology. The survey was conducted under the umbrella of a broader research project aimed at investigating the organizational resources, digital competence, and strategic performance of SMEs in Shandong Province. The method of carrying out the survey was both online and offline. The online method was achieved through the use of Google Forms and Qualtrics, where the respondents were reached through electronic correspondence, LinkedIn, and business networks. The offline method was achieved through business associations, trade associations, and visiting the premises of SMEs. A total of 310 questionnaires were distributed, and the number of questionnaires returned was 285, giving a response rate of 91.9%. After eliminating 27 questionnaires that contained too much missing data, showed uniform patterns, or had respondents who were not eligible, a total of 255 remained for data analysis after removing three multivariate outliers based on Mahalanobis distance. This research was carried out in accordance with the Declaration of Helsinki. It was a voluntary and anonymous study, and informed consent was obtained from all the participants prior to data collection. Ethical approval was granted by Shandong University Institutional Review Board (Approval No. SDU-IRB-2025-098).

Table 1 shows the demographic information for the sample. In the sample, the majority belong to the manufacturing industry at 37.3%, followed by the services industry at 32.2%, and the technology industry at 30.6%. Small businesses are those businesses with 10 to 49 employees, and this category accounts for 60.0% of the sample. This figure is consistent with the proportion of SMEs found in the general population. This sample included well-qualified individuals with a lot of experience, as indicated by the fact that 77.6% of the sample claimed that they had over ten years of experience, and 87.1% claimed that they had at least a bachelor's degree, thus implying that they were in an appropriate position to assess the constructs in question. The common method bias was assessed by Harman's single factor test, where all 28 items were included. The first unrotated factor accounted for only 21.3% of the total variance, well below the 50% threshold recommended by Podsakoff et al. [24], suggesting that common method bias is unlikely to significantly affect the results.

Table 1. Demographic profile of respondents (N = 255)

Variable	Category	n	%
Gender	Male	148	58.0
	Female	107	42.0
Age group	25-34 years	57	22.4
	35-44 years	99	38.8
	45-54 years	76	29.8
	55 years and above	23	9.0
Education	High school / diploma	33	12.9
	Bachelor's degree	127	49.8
	Master's degree	78	30.6
	Doctoral degree	17	6.7
Work experience	Less than 5 years	14	5.5
	5-10 years	43	16.9
	11-15 years	99	38.8
	More than 15 years	99	38.8
Industry sector	Manufacturing	95	37.3
	Services	82	32.2
	Technology	78	30.6
Company size (employees)	10-49	153	60.0
	50-100	53	20.8
	101-200	35	13.7
	201-249	14	5.5
Geographical location	Urban	159	62.4
	Rural	96	37.6
Years of business operation	5-10 years	57	22.4
	11-15 years	92	36.1
	16-20 years	76	29.8
	More than 20 years	30	11.8
Total		**255**	**100.0**

Note. *Percentages may not sum to exactly 100.0 due to rounding.*

3.2 Measures

All constructs were measured using five-point Likert scales, ranging from 1 (strongly disagree) to 5 (strongly agree), and items were adapted for use in the specific context of the large-scale project supply chain under investigation. Corporate culture was measured using six items [25, 26], encompassing shared organizational values, behavioral norms, cultural cohesion, and adaptive capacity. Advertising strategy was measured using five items [21], covering advertising investment intensity, utilization of digital technologies, multi-channel integration, and strategic communication alignment. Competitive advantage was measured using five items [1, 12], encompassing market positioning, inimitability, reputational positioning, and innovation-based competitiveness. Strategic management effectiveness was measured using six items [8, 13]. These items included strategic goal integration, market responsiveness, organizational flexibility, employee involvement in strategic management, and strategic improvement.

AI adoption was measured using six items [3, 17]. As indicated by the conceptual framework proposed in section 2.3, the measurement of AI adoption was intended to capture the extent to which the respondents' firms adopted AI-based marketing and advertising tools, AI-based systems for competitive intelligence, and AI-based systems for strategic decision support. Items that involved basic automation, conventional digital marketing tools, or basic IT infrastructures without AI components were removed from the scale in order to ensure the clarity of the boundary construct for AI adoption and technology adoption in general. A summary of all measurement constructs used in this particular study is shown in Table 2. The expert panel for content validity for all scales was conducted prior to data collection.

Table 2. Summary of measurement constructs

Construct	Role	Items	Scale source
Corporate culture (CC)	IV	6	Wang &Huang (2022); Xenikou & Furnham (2022)
Advertising strategy (AD)	IV	5	Wu et al. (2024)
Competitive advantage (CA)	MV	5	Barney (1991); Porter (1985)
Strategic management effectiveness (SM)	DV	6	Truong et al. (2025); Teece (2007)
AI adoption	MOD	6	Sahoo et al. (2024); Abrokwah-Larbi & Awuku-Larbi (2024)

Note. *IV = independent variable; MV = mediating variable; DV = dependent variable; MOD = moderating variable. All items measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).*

3.3 Analytical Approach

To test the proposed hypotheses, partial least squares structural equation modeling, using the software SmartPLS 4.0, was employed. The testing process followed a recommended sequential two-stage approach [27]. In the first stage, the measurement model was tested by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. In this case, the indicator loadings were expected to be greater than 0.70. Internal consistency was examined using Cronbach's alpha, composite reliability, and Dijkstra-Henseler's rhoA [28], each of which should be at least 0.70. Convergent validity was checked using AVE, with values of 0.50 or above considered acceptable [29]. Discriminant validity was evaluated using the heterotrait-monotrait ratio of correlations, with values below 0.85 indicating adequate discriminant validity [30].

The second stage was for testing the structural model and the six proposed moderation and moderated mediation effects. Three interaction terms were developed by using the standardized product indicator method for testing the moderating effects of AI adoption on the CC→CA, AD→CA, and CA→SM paths, respectively. Bootstrapping with 5,000 subsamples was used to produce a bias-corrected 95% CI for all path coefficients, interaction effects, and indirect effects. The results were considered significant if the obtained t-values were higher than 1.96 and the CIs did not contain zero [27]. The first-stage moderated mediation of H4 and H5 was performed by using the index of moderated mediation. The results were considered statistically significant if the CI did not include zero [22]. The H6 model was tested as a dual-stage moderated mediation model, where the adoption of AI would simultaneously moderate the two stages of the mediated relationship from organizational resources to competitive advantage, and from competitive advantage to strategic management effectiveness. The study estimated the compound conditional indirect effects at low, mean, and high levels of AI adoption. The effect sizes were also measured using Cohen's f^2, whereby f^2 values of .02, .15, and .35 correspond to small, medium, and large effects, respectively [31].

4. RESULTS

4.1 Measurement Model Assessment

All five constructs satisfied reliability and validity before testing the structural model. As shown in Table 3, indicator loading ranged from 0.709 to 0.876 for all constructs. This indicates satisfactory indicator reliability. Cronbach's alpha ranged from 0.873 to 0.912, and composite reliability ranged from 0.906 to 0.934 for all constructs. All of these reliability coefficients were higher than 0.70. Average variance extracted ranged from 0.623 to 0.714 and was therefore above 0.50. This ensured the convergent validity of these constructs [29]. Among these five constructs, competitive advantage had the highest reliability and convergent validity results, whereas advertising strategy and AI adoption had the lowest results. However, these results were still within an acceptable range.

Table 3. Measurement Model Results and Descriptive Statistics

Construct	Items	Mean	SD	Loading Range	α	CR	AVE
Corporate culture (CC)	6	3.74	0.71	0.724–0.863	0.891	0.921	0.658
Advertising strategy (AD)	5	3.61	0.74	0.718–0.851	0.873	0.906	0.623
Competitive advantage (CA)	5	3.82	0.68	0.741–0.876	0.912	0.934	0.714
Strategic management effectiveness (SM)	6	3.57	0.72	0.733–0.864	0.904	0.927	0.647

AI adoption	6	3.44	0.77	0.709–0.852	0.878	0.911	0.632

Note. *N = 255. All items measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Loading Range = minimum to maximum standardized indicator loading. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. All constructs meet recommended thresholds of α > 0.70, CR > 0.70, and AVE > 0.50.*

Discriminant validity was assessed through the heterotrait-monotrait ratio of correlations, as shown in Table 4. It was observed that the HTMT values remained below the threshold of 0.85; the maximum was observed between competitive advantage and corporate culture, which was 0.738. This shows that each dimension is a unique concept within the model [30]. The range of HTMT values for the adoption of AI varied from 0.612 to 0.658, with the highest value observed for the relationship between AI adoption and competitive advantage, which theoretically supports the proposed moderation effect of AI in the resource-advantage pathway. The descriptive statistics show a large variability between the constructs regarding the perceptions of the respondents, where competitive advantage has the highest average at 3.82 and AI adoption the lowest at 3.44. This indicates that while the sample of firms has a relatively positive perception of their competitive position, the adoption of AI-based tools for decision-making and marketing is relatively low.

Table 4. Heterotrait-Monotrait (HTMT) Ratio Matrix

	CC	**AD**	**CA**	**SM**	**AI**
CC	—				
AD	0.618	—			
CA	0.738	0.691	—		
SM	0.676	0.608	0.699	—	
AI	0.612	0.631	0.658	0.643	—

Note. *CC = corporate culture; AD = advertising strategy; CA = competitive advantage; SM = strategic management effectiveness; AI = AI adoption. All HTMT values below the threshold of 0.85, confirming discriminant validity. Estimates based on bootstrapping with 5,000 subsamples.*

4.2 Structural Model Results

The three structural paths were estimated with AI adoption as a moderating variable, and the results are shown in Table 5. It is clear that all the paths produced a statistically significant positive coefficient, where the confidence interval did not contain zero for all paths. Of the paths for competitive advantage, corporate culture was found to have a greater impact (β = 0.412, t = 6.98, $p < 0.001$), followed by advertising strategy (β = 0.378, t = 6.00, $p < 0.001$). Competitive advantage was found to have a large positive impact on the effectiveness of strategic management, and this relationship was statistically significant (β = 0.389, t = 6.27, $p < .001$). The impact of the three paths was of a medium range. The model accounted for 53.0% of the variance of competitive advantage and 41.2% of the variance of the effectiveness of strategic management. These findings confirm the base structural relationships and provide the necessary foundation for the moderation and moderated mediation analyses that follow.

Table 5. Structural Model Path Coefficients

Path	**β**	**SE**	**t-value**	**p-value**	**95% CI LL**	**95% CI UL**	**f²**
CC → CA	0.412	0.059	6.98	< 0.001	0.296	0.528	0.203
AD → CA	0.378	0.063	6.00	< 0.001	0.254	0.502	0.169
CA → SM	0.389	0.062	6.27	< 0.001	0.267	0.511	0.184

Note. *β = standardized path coefficient; SE = standard error; f^2 = Cohen's effect size; CI LL = confidence interval lower limit; CI UL = confidence interval upper limit. $R^2(CA) = 0.530$; $R^2(SM) = 0.412$. All estimates based on bootstrapping with 5,000 subsamples (bias-corrected 95% CI). All paths significant at $p < 0.001$.*

4.3 Moderation Effects

The moderation effects of AI adoption were also investigated through the use of three different interaction terms based on the standardized product indicator method, and the results are shown in Table 6. The moderation effect of AI adoption on competitive advantage was found to be positively significant (β = 0.191, t = 3.41, p = 0.001, f^2 = 0.092), thus supporting H1. Furthermore, the moderation effect of AI adoption on advertising strategy was also found to be significant (β = 0.168, t = 2.90, p = 0.004, f^2 = 0.076), thus supporting H2. The relationship between AI adoption and competitive advantage revealed a statistically significant positive influence on strategic management effectiveness (β = 0.154, t = 2.80, p = 0.005, f^2 = 0.068), thus supporting H3. The effect size of all three interaction terms was found to fall within the range of small to medium. This was seen as an expected effect for moderation effects in organizational research. Adding these three interaction terms resulted in an increase in explained variance for competitive advantage from 0.530 to 0.551 and for strategic management effectiveness from 0.412 to 0.431.

Table 6. Moderation Effects of AI Adoption (H1, H2, and H3)

Interaction Term	β	SE	t-value	p-value	f²	Decision
CC × AI → CA	0.191	0.056	3.41	0.001	0.092	H1 Supported
AD × AI → CA	0.168	0.058	2.90	0.004	0.076	H2 Supported
CA × AI → SM	0.154	0.055	2.80	0.005	0.068	H3 Supported

Note. *β = standardized path coefficient; SE = standard error; f² = Cohen's effect size. Interaction terms constructed using the standardized product indicator approach. R^2(CA) = 0.551 with moderator included, compared to 0.530 without. R^2(SM) = 0.431 with moderator included, compared to 0.412 without. All significance levels based on bootstrapping with 5,000 subsamples (bias-corrected 95% CI).*

The nature of these interactions is depicted in the simple slope plots provided in Figure 2. In all three plots, the relationship between the predictor and outcome variables is much steeper for the high AI adoption scenario than for the low AI adoption scenario. The moderating effect is strongest for the corporate culture pathway, where the difference in slopes for high versus low AI is greatest, representing a stronger base relationship between corporate culture and competitive advantage than the other pathways. The CA×AI interaction in panel (c) has a slightly smaller difference between the high and low AI slopes compared to the front-end interactions, which is consistent with the slightly smaller effect size found for H3 and the more distal nature of the back-end moderation effect.

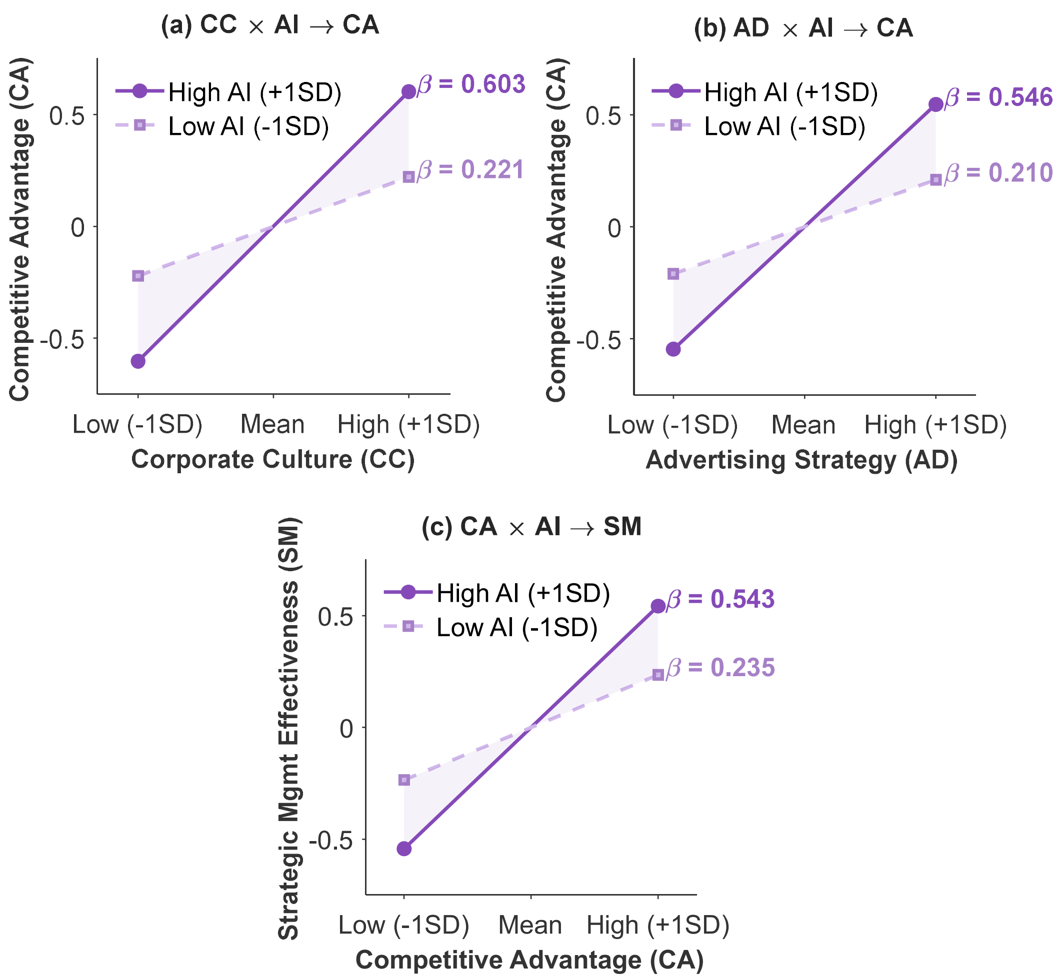

Figure 2. Moderating Effects of AI Adoption

4.4 Moderated Mediation Effects

Moderated mediation was carried out through the index of moderated mediation for H4 and H5, as well as conditional indirect effects at three levels of AI adoption for all three hypotheses. The results are shown in Table 7 and Figure 3.

Table 7. Moderated Mediation Results (H4, H5, and H6)

	Path	AI Level	Indirect Effect	SE	95% CI LL	95% CI UL
H4	CC→CA→SM	Low (−1SD)	0.086	0.032	0.025	0.152
		Mean	0.156	0.034	0.090	0.224
		High (+1SD)	0.235	0.044	0.152	0.324
		IMM	0.074*	0.027	0.026	0.131
H5	AD→CA→SM	Low (−1SD)	0.082	0.029	0.026	0.143
		Mean	0.143	0.032	0.081	0.209
		High (+1SD)	0.212	0.041	0.133	0.296
		IMM	0.065*	0.025	0.021	0.118
H6 (dual-stage)	CC→CA→SM	Low (−1SD)	0.052	0.027	0.011	0.112
		Mean	0.156	0.034	0.090	0.224
		High (+1SD)	0.327	0.048	0.231	0.431
	AD→CA→SM	Low (−1SD)	0.049	0.025	0.009	0.105
		Mean	0.143	0.032	0.081	0.209
		High (+1SD)	0.297	0.046	0.204	0.398

Note. *CC = corporate culture; AD = advertising strategy; CA = competitive advantage; SM = strategic management effectiveness. IMM = index of moderated mediation. CI LL = confidence interval lower limit; CI UL = confidence interval upper limit. All estimates based on bootstrapping with 5,000 subsamples (bias-corrected 95% CI). * IMM confidence interval excludes zero, confirming significant moderated mediation. H6 significance confirmed by confidence intervals of conditional indirect effects excluding zero at all levels.*

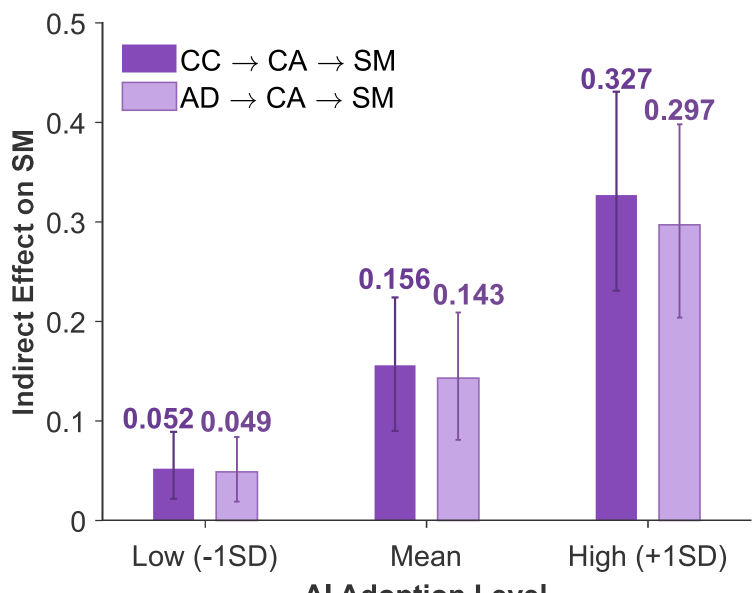

Figure 3. Dual-Stage Moderated Mediation of AI Adoption

As for H4, the indirect effect of corporate culture on the effectiveness of strategic management through competitive advantage was found to increase as the level of AI adoption was higher. The indirect effect was seen to increase from 0.086 at low levels of AI adoption to 0.156 at the mean and up to 0.235 at high levels of AI adoption, and all three conditional effects were statistically significant. The index of moderated mediation was calculated as 0.074, and its 95% bootstrap CI was [0.026, 0.131], excluding zero, thus establishing a first-stage moderated mediation. H4 is supported. As for H5, the indirect effect of advertising strategy is increased from 0.082 at low levels of AI to 0.143 at the mean level and 0.212 at high levels of AI, with all conditional effects being significant. The moderated mediation index is 0.065, and the 95% confidence interval is [0.021, 0.118], which does not contain zero. Therefore, H5 is supported.

The dual-stage moderated mediation hypothesis H6 is an extension of this model. This model examines the simultaneous moderation of both the initial resource advantage relation and the subsequent advantage strategy relation. As depicted in Figure 3, it is evident that the overall indirect effects under high AI adoption conditions are significantly higher compared to those of H4 and H5. This is due to the fact that they reach 0.327 for corporate culture and 0.297 for advertising strategy compared to their counterparts of 0.052 and 0.049 under low AI conditions. This is attributed to the compounding process that occurs through the dual-stage moderation process, where the indirect effect is enhanced through a multiplicative process rather than an additive process. In addition, all the confidence intervals for the conditional indirect effects are non-zero, thereby supporting H6.

In all three hypotheses, the common factor is a situation in which the use of AI always positively impacts the entire performance path from organizational resources, through competitive advantage, and on to the effectiveness of strategic management, with the strongest impacts for higher levels of AI adoption.

5. DISCUSSION

The results provide a coherent explanation for how the introduction of AI affects the conditions through which resources generate strategic returns within the supply chain context of SMEs. The point is not that AI improves organizational performance in some generalized way, but that it does so in specific junctures of the organizational resources-performance trajectory, altering the strength of relationships that would otherwise be bounded by the limits of smaller organizations seeking large-scale project contracts.

On the front end, AI is subject to two different structural constraints. Corporate culture gives a company a competitive edge; however, the attributes of culture are only perceived within an organization and do not necessarily manifest as a verifiable signal for a purchasing decision maker evaluating an unknown supplier. AI evaluation systems address this by providing a structured record of performance where cultural attributes are visible to a buyer who would not have a means of evaluating them [20]. Lu et al. revealed that AI tools can create new competitive opportunities for SMEs under information asymmetry by lowering the threshold for communicating organizational strengths externally [32], a mechanism directly illustrated by the H1 result in the context of supply chain procurement. In the case of advertising strategy, the primary constraint is resource scarcity rather than information invisibility, and AI reshapes competitive dynamics by enabling precise audience targeting that favors analytical capability over budget scale. Consistent with Teng et al., who demonstrated that the advantages of digital transformation are greater for resource-constrained firms [33], the support for H2 illustrates this equalization effect in the context of procurement signaling.

The back-end finding also holds theoretical significance for another reason. Competitive advantage gives firms information on their position from an organizational point of view; however, for this information to be translated into useful strategic direction, firms need analytical capabilities, which SME managers may not have. AI has been shown to enhance the quality of strategic decisions by facilitating the processing of complex competitive environment information [34]. This impact is a direct result of the CA → SM pathway and explains the capability of firms with high levels of AI adoption to effectively leverage their competitive positioning.

The H6 result elaborates this logic along a dimension not included in the H4 or H5 logic by itself. When the AI simultaneously moderates the resource-advantage conversion and the advantage-strategy translation, the effects combine rather than additively accumulate, leading to much greater indirect effects than either stage would produce in isolation. This is consistent with prior evidence that AI capability generates performance benefits that compound across multiple organizational functions rather than remaining confined to isolated processes [35, 36]. H6 provides empirical support for this multiplying effect of AI capability in the SME supply chain. Organizations seeking strategic benefits from AI are unlikely to do so if AI is applied selectively at specific stages of the performance chain.

The study also has some limitations which need to be pointed out. The research design, as well as the use of self-report, are generally considered limitations in survey research on organizations, where the arguments are more a function of theory than actual support, even with procedural controls in place. The sample's geographic concentration in Shandong Province offers greater contextual specificity, which also creates a limitation in terms of generalizability. The construct of AI adoption also subsumes different capabilities into a single construct. Uren and Edwards demonstrated that AI adoption readiness varies significantly by AI type and contextual factors [37] . Future research focusing on specific AI capabilities could offer a more nuanced understanding of the points along the performance curve at which different tools yield the strongest associations with financial returns.

6. CONCLUSION

This study explored the moderating effect of AI adoption on the relationship between corporate culture, advertising strategy, competitive advantage, and the effectiveness of strategic management for SMEs in large-scale project supply chains in Shandong Province. By using the partial least squares structural equation modeling for the respondents totaling 255, the six research hypotheses were supported. AI adoption increases the pathways of competitive advantage for corporate culture and advertising strategy, but in different ways, which reinforce the translation of competitive advantage into the effectiveness of strategic management, and produce compound indirect effects on the entire chain of performance, which far exceed what is possible through a single-stage moderation.

The theoretical implication of this study is the demonstration of the performance implications of AI adoption as a system-level organizational capability, rather than at specific loci along the resource strategy path. The practical implication of this research for managers of SMEs is that the value of the strategic investment in AI is not only additive but also multiplicative in nature, as it pertains to the overall scope of the functions of resource conversion and strategy execution. It is unlikely that firms that have invested in AI on a selective basis will achieve compound returns; instead, the question shifts from which investment stage benefits the most from AI investments to whether the returns from the use of AI across investment stages would be greater than the returns from a single investment stage.

Future studies should also examine whether different typologies of AI capabilities have different moderating effects at different stages of the performance path, as well as whether the cumulative logic found in this research is evident in different regions and industries outside of the Shandong SME supply chain context in which this study was conducted.

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