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Integrating Artificial Intelligence and Strategic Agility for Enhancing Sustainable Innovation in Post-COVID SMEs

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ABSTRACT

This study examines how Artificial Intelligence Capabilities (AI), Strategic Agility (SA), and Organizational Learning (OL) influence Sustainable Innovation (SI) among manufacturing SMEs in China after the mediating role of Knowledge Management (KM) and the moderating role of Top Management Support (TMS). 300 managers from SME groups were subjected to a structured questionnaire, and the data were processed by SmartPLS 4. It has turned out that AI, SA, and OL exert significant positive effects on KM, as the latter strongly predicts SI. KM acts as a mediator between AI, SA, OL, and SI; TMS positively moderates the relationships between AI and SI. The findings complement the dynamic capability theory and provide practical recommendations on how internal capabilities and support from the leadership can be used for sustainability-oriented innovation in SMEs.

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1. Introduction

SMEs in manufacturing have become stagnant against the backdrop of Industry 4.0's upsurge and the impetus behind China's "Made in China 2025" agenda. Leading Chinese companies tend to benefit from sophisticated technologies regularly, but most small manufacturing companies are constrained from doing so effectively because of resource or capability constraints (Wang et al., 2023). In the unrestrained post-COVID environment, with supply chain problems and changing consumer terrains that challenge SMEs to be even more adaptive and enlightened, this technology gap is even more pronounced (Moosavi et al., 2022; Ragmoun & Alfalih, 2025; Wang et al., 2024). In today's environment, Chinese manufacturing SMEs must effectively manage external disturbances by quickly reconfiguring their procedures and resource allocation, which has magnified their strategic challenges.

Although the transformative promise of AI is well recognized, there is little empirical research demonstrating how AI capabilities lead to sustainable innovation in China's manufacturing medium-sized enterprises (MSMEs). Research on Chinese apparel manufacturing suggests that AI will enhance open innovation due to its better knowledge absorption, but it does not relate these to general sustainability goals (Kinkel et al., 2022). Furthermore, there has been very little research on how the relationship between strategic agility and organizational learning, which helps with knowledge management (KM), works, especially in small and medium-sized enterprises (SMEs) that have limited resources and need to manage financial and skill challenges (Arokodare et al., 2023; Mohammad, 2015; Shafiabady et al., 2023). Furthermore, not enough focus has been given to how important support from top management is for promoting AI-enabled innovation in Chinese manufacturing SMEs, and studies in various settings indicate that leadership support is crucial for enhancing the benefits of digital investments.

This study responds to these gaps by proposing and empirically testing an integrative model in which the AI capabilities, strategic agility, and organizational learning are integrated and promote sustainable innovation through KM, where TMS has a moderating role in strengthening the AI innovation relationship. We focus on Chinese manufacturing SMEs, where differences in firm size, regional conditions, and regulatory environments shape the digital innovation strategy. To be clear, our research question can be formulated as: What strategies can Chinese manufacturing SMEs use with AI and strategic agility for enhanced KM and assistance for sustainable innovation, and which situations help TMS augment the advantages of AI investments?

To address this issue, we defined four specific research objectives. We first aim to determine how AI capability, strategic agility, and organizational learning customarily impact KM practices. Second, we will assess how KM influences sustainable innovations, construed as developing eco-efficient products, processes, and business models. Third, we will examine how KM acts as a mediator in AI, organizational agility, and learning processes to sustain innovation. Finally, our study will determine whether TMS is a mediator in the AI-innovation relationship and whether higher leadership motivation augments the effect of AI investments on sustainability.

Our contributions are threefold. Theoretically, we build on dynamic capabilities theory by including AI, usually considered a separate technology, into a larger system that also includes agility and learning, all viewed through the perspective of KM. This advances digital innovation theory in SMEs, which has been fragmented and descriptive (Bhatti & Nawaz, 2020; Khalafi & Rahmati, 2023; Müller, 2019; Ragmoun & Ben-Salhab, 2024). Our study is the first to use SmartPLS to analyses how manufacturing SMEs in China turn AI and agile practices into sustainable innovation through knowledge management, which is an important topic for policy under "Made in China 2025." Practically, we offer actionable insights for SME leaders and policymakers, highlighting which capabilities to priorities and how top management can catalyze AI's impact on green innovation.

We use Partial Least Squares Structural Equation Modelling (PLS-SEM) to analyses survey data from 300 Chinese manufacturing SMEs in Jiangsu, Guangdong, and Zhejiang provinces. This method allows us to understand deeper patterns and examine complex relationships, which meets the stricter standards for quantitative research set by Trocin et al. (2023). As a result, our study lays solid factual groundwork for academics and practitioners who need to guide manufacturing SMEs in China through the digital innovation process.

By focusing on the unique situation of Chinese manufacturing small and medium-sized enterprises facing strong competition, policy changes, and uncertainties after the pandemic, this research shows how AI, flexibility, learning within the organization, and support from leaders work together to promote lasting innovation. Our results can guide leaders seeking to integrate advanced tech and adaptive capacities to reinforce business stability and protect the environment.

2. Literature Review

The post-COVID environment has driven SMEs to use digital resources and progressive approaches to drive sustainable innovation. Specifically, the application of AI, enhancement of SA, and development of OL drive KM, thereby nurturing SI. When top management supports AI initiatives, the association between AI and SI becomes even more robust.

2.1. AI Capabilities and Knowledge Management

Empirical evidence indicates that AI tools, including machine learning, natural language processing, and intelligent automation, improve KM processes in SMEs. Jeble et al. (2018) concluded that predictive analytics capability significantly enhances capturing and reusing organizational knowledge. Mikalef et al. (2018) reported that intelligent question and answer systems make KM workflows smoother. Pagano et al. (2021); Wideda and Alfaliha (2023) proposed that Industry 4.0 AI supports the immediate dissemination of knowledge. As Wamba, Akter, and Guthrie (2020) reported, analytics-informed actions for decision-making advance organizational adaptiveness through better KM. Lee and Mangalaraj (2022) determined that AI-based big-data platforms are a principal approach to encoding tacit knowledge. Based on findings from Polish SMEs, Trocin et al. (2023) concluded that AI integration raises the maturity of KM. Anubala (2023) demonstrated that AI-enhanced predictive analytics in hospitality settings supports better dissemination of knowledge. Al Halbusi et al. (2023) argued that the KM system's effectiveness and sustainability improve due to AI adoption. Based on their studies in several countries, Chaudhuri et al. (2022) found that AI dynamism enhances SMEs' knowledge management processes. Lu et al. (2022) reported in their research that AI-driven knowledge-sharing tools helped small and medium businesses respond better following the pandemic. Taken together, these research results support the argument that strong AI capabilities promote knowledge management, which leads us to conclude:

H1: Artificial Intelligence Capabilities (AI) positively affect Knowledge Management (KM).

2.2. Strategic Agility and Knowledge Management

A knowledge management-oriented culture grows when an organization can sense opportunities, quickly adjust its resources, and respond effectively. Tallon and Pinsonneault (2011) suggested that IT-supported agility promotes more effective knowledge management through constant alignment. Doz and Kosonen (2010) argued that agility integrates dynamic capabilities and competitive advantage by supporting knowledge exchange. Fachrunnisa et al. (2020) showed that digitally agile SMEs perform better in knowledge management and are more innovative. As reported by Mikalef et al. (2018), IT-supported dynamic capabilities improve KM through the practice of organizational learning. The work of Mata et al. (2024) demonstrates that SA combined with open innovation leads to better KM in European SMEs. Rawashdeh et al. (2024) showed that SA contributes to digital knowledge-management maturity, essential for sustainability. Rozak and Fachrunnisa (2021) observed that agility in Indonesian SMEs correlates with higher levels of sophistication in KM systems. Wang and Ahmed (2007) showed that SA is directly connected to organizational knowledge sharing. Abuanzeh et al. (2022) demonstrated that the adoption of knowledge management (KM) is a result of the impact of strategic agility (SA) and that it enhances the performance of small- and medium-sized enterprises. Ahammad et al. (2021) showed that network-based strategic agility enables organizations to transfer knowledge across boundaries. These studies imply that SA is a crucial sign of KM capability.

H2: Strategic Agility (SA) positively affects Knowledge Management (KM).

2.3. Organizational Learning and Knowledge Management

Organizational learning (OL) is the most important foundation supporting effective KM. Jerez-Gómez et al. (2005) suggested that OL capability is important for achieving KM system goals. Tippins and Sohi (2003) argued that organizations that practice OL can better convert IT abilities into improved performance. Easterby-Smith et al. (2009) argued that linking dynamic capabilities to KM depends on the existence of learning routines. Delgado-Verde, Martín-de Castro, and Emilio Navas-López (2011) show that KM innovativeness improves when firms combine strong relational capital with robust OL. Vera and Crossan (2004) pointed out that strategic leaders depend on learning processes to embed KM within the organization. Wang and Wang (2019) demonstrated that the effectiveness of cybersecurity knowledge management (KM) depends on organizational learning routines. According to Durst et al. (2023), the KM adoption rate in Pakistani SMEs largely depends on those organizations' learning orientation. Belkhodja (2022) showed that a family firm's capabilities in learning are important for storing and retaining knowledge. According to Ahmed et al. (2024); Baporikar (2015) cross-border interactions support the adoption of KM in multinational small and medium enterprises. Kavalić et al. (2021) demonstrated that OL influences the durability of KM applications in manufacturing firms. These studies reveal that KM success depends on organizations employing OL mechanisms, especially experimentation, reflection, and shared mental models.

H3: Organizational Learning (OL) positively affects Knowledge Management (KM).

2.4. Knowledge Management and Sustainable Innovation

The main agent for moving SI forward is KM, whose purpose is to create eco-friendly products, processes, and business models. Chen (2008) demonstrated that KM promotes green innovation by organizing and documenting environmental knowledge. Segars (2001) presented knowledge management as the fundamental capability sustaining frequent innovation within an organization. Nonaka and Takeuchi (2019) indicated that the knowledge creation spirals are indispensable for sustainability-oriented innovation. According to Tabrizi et al. (2019), the digital transformation based on firm knowledge management enhances sustainable product development. Based on empirical analysis, Jorna (2007) found that increased maturity in KM supports higher levels of sustainable process innovation. Arsawan et al. (2022) highlighted how using KM mechanisms supports a faster uptake of eco-innovation. Martens and Carvalho demonstrated in 2022 that, by utilizing environmental KM, firms can advance their green product innovation. Nasir et al. (2024) reported that KM practices directly encourage green innovation in Vietnamese small and medium enterprises. Rumanti et al. (2018) found that knowledge sharing driven by KM is predictive of eco-innovation. Cong (2023) proposed a link between integrated KM systems and greater advancements in sustainable product innovation. All ten studies indicate that KM practices, such as knowledge generation, storage, transfer, and application, are essential drivers of SI.

H4: Knowledge Management (KM) positively affects Sustainable Innovation (SI).

2.5. Mediating Role of Knowledge Management

Multiple investigations affirm that knowledge management mediates AI, SA, OL, and SI links. Abbas et al. (2020) employed SEM to establish that KM completes the mechanism connecting dynamic capabilities to innovation. Jorna (2007) confirmed that KM fully explains the effect of digital transformation on innovation outcomes. As shown by (Fachrunnisa et al., 2020), KM links strategic agility to sustainable performance. Zia (2020) proved that KM fully explains how OL affects green innovation. Baquero (2024) identified knowledge management as connecting resource orchestration to eco-innovation. Nyuga and Tanova (2024) reported that knowledge management mediates the connection between SA and SI. Lee and Mangalaraj (2022) suggested that knowledge management is how AI capabilities stimulate innovation. Shaikh and Siponen (2024) demonstrated that KM mediates the link between IT competency and organizational performance. Zong and Guan (2025) illustrated that KM helps explain how digital analytics generates service innovation. Kordab et al. (2020) illustrated that KM partially explains how using AI improves a firm's sustainable performance. Based on this convergence:

H5: KM mediates the AI → SI relationship.
H6: KM mediates the SA → SI relationship.
H7: KM mediates the OL → SI relationship.

2.6. Moderating Role of Top Management Support

Top Management Support (TMS) encompasses strategic sponsorship, resource allocation, and culture reinforcement necessary for successful innovation initiatives. Thong et al. (1996) demonstrated that TMS is key to IS implementation success within small companies. Ifinedo (2012) indicated that TMS is an important moderator of e-business success among SMEs. Ramayah et al. (2014) established a link between TMS and improved IT usage outcomes and positive performance results. According to Ahmed et al. (2016), TMS's presence contributes positively to the achievements of innovation-related projects. Mutegi and Van Belle (2021) showed that TMS supports digital innovation success. According to Chatterjee et al. (2020), the effectiveness of AI adoption depends heavily on TMS. Men et al. (2023) showed that TMS serves as a moderator connecting agility to business results. Wamba et al. (2020) demonstrated that TMS intensifies digital transformation. (Chaudhuri et al., 2022) posits that Knowledge Management mediates the relationship between Artificial Intelligence, Strategic Agility, and Organizational Learning in driving Sustainable Innovation within SMEs. Gazi et al. (2024) further supported that more effective TMS contributes to stronger AI-powered sustainable innovation. Accordingly:

H8: Top Management Support (TMS) positively moderates the relationship between Artificial Intelligence Capabilities (AI) and Sustainable Innovation (SI), such that the relationship is stronger when TMS is high.

3. Methods

A quantitative research design was employed to evaluate the interconnections among AI, SA, OL, KM, TMS, and SI in SMEs of China's manufacturing sector. Information was gathered by giving a structured questionnaire to managers from manufacturing SMEs. A sample of 300 questionnaires was delivered, and subsequently, valid answers were analyzed utilizing SEM in SmartPLS 4.

This study modified the scales based on instruments validated in previous research. The integration of AI in decisions and workflows was evaluated using six items developed by Rialti et al. (2020) and Trocin et al. (2021). Five items measuring organizational responsiveness and flexibility defined the capabilities of SA (Clauss et al., 2021; Doz & Kosonen, 2010). Jerez-Gómez et al. (2005) operationalized organizational learning with four items that examined knowledge sharing and integration practices. KM was evaluated by five items designed to assess how well the company manages and communicates knowledge (Gold et al., 2001; Lee & Choi, 2003). The moderator variable, TMS, was measured using four items that assessed leadership backing for innovation and AI adoption (Thong et al., 1996). The study was conducted by Ramayah et al. (2014). SI was measured using five questions that looked at how much the innovations were environmentally and socially responsible, based on work by Chen (2008) and Lin and Chen (2017). Every construct in the study was measured on a 5-point Likert scale.

Measurement reliability and validity were confirmed through Cronbach's alpha (ranging from 0.861 to 0.948), Composite Reliability (CR, ranging from 0.906 to 0.962, and Average Variance Extracted (AVE, ranging from 0.667 to 0.863). Convergent and discriminant validity assessments (Fornell-Larcker criterion and HTMT ratio) confirmed adequate model robustness. Subsequently, path analysis and bootstrapping procedures with 5,000 resamples were conducted to test direct, indirect (mediation), and moderated relationships among the constructs.

Ethical aspects were managed responsibly at every step during the research. Participation was entirely voluntary, and participants were told about the study's goals and given guarantees of confidentiality and anonymity. All participants gave their informed consent before any data were collected, and no identifying information about them was recorded.

4. Results

This section shows the empirical findings of the analysis done using SmartPLS 4. It includes an evaluation of the validity of the measurement model, explicitly focusing on convergent and discriminant validity, followed by an assessment of the structural model. The results support all the advanced hypotheses, providing an understanding of direct, indirect, and moderating associations between study constructs.

Table 1 presents the convergent validity results for all the constructs used in the research. The outer loadings of all the items are above the recommended level of 0.70, which shows that item reliability is strong. Composite reliability (CR) values are between 0.906 and 0.962, thus indicating a model with high internal consistency. The Average Variance Extracted (AVE) values for the related groups—0.667 (AI), 0.732 (DM), 0.732 (TMS), and 0.863 (TMS)—are above 0.50, which means they have good convergent validity. These findings indicate that all constructs are reliable for estimating latent variables, and the measurement model is suitable for more structural equation modelling.

Table 1
Convergent Validity Test

Constructs	items	Loading	Alpha	CR	AVE
AI	AI1	0.827	0.9	0.923	0.667
	AI2	0.833			
	AI3	0.799			
	AI4	0.787			
	AI5	0.851			
	AI6	0.801			
KM	KM1	0.898	0.935	0.951	0.795
	KM2	0.905			
	KM3	0.89			
	KM4	0.883			
	KM5	0.88			
OL	OL1	0.833	0.861	0.906	0.706
	OL2	0.831			
	OL3	0.844			
	OL4	0.853			
SA	SA1	0.848	0.89	0.919	0.694
	SA2	0.832			
	SA3	0.817			
	SA4	0.842			
	SA5	0.828			
SI	SI1	0.914	0.948	0.96	0.829
	SI2	0.91			
	SI3	0.91			
	SI4	0.914			
	SI5	0.903			
TMS	TMS1	0.922	0.947	0.962	0.863
	TMS2	0.942			
	TMS3	0.924			
	TMS4	0.928			

Tabe 2
Fornell Larcker

	AI	KM	OL	SA	SI
AI	0.817				
KM	0.328	0.891			
OL	-0.035	0.291	0.841		
SA	0.076	0.325	-0.034	0.833	
SI	0.396	0.794	0.412	0.408	0.910

Table 2 supports the discriminant validity following the Fornell-Larcker criterion, as the square root of the AVE values of each construct (diagonal) is greater than its correlations with other constructs. The result implies that there are empirical differences between all constructs. These results are consistent with the advice of Fornell and Larcker (1981), which strengthens the discriminant validity of the measurement model.

Table 3
HTMT Ratio

	AI	KM	OL	SA	SI	TMS
AI						
KM	0.35					
OL	0.087	0.324				
SA	0.099	0.354	0.058			
SI	0.423	0.843	0.456	0.443		
TMS	0.049	0.043	0.031	0.066	0.2	

Table 3 shows the HTMT ratio values, all less than the conservatively determined threshold of 0.85, indicating discriminant validity among constructs. This information is consistent with Henseler, Ringle, and Sarstedt's (2015) findings, who singled out HTMT as a superior criterion for checking discriminant validity in PLS-SEM.

Table 4
Cross Loading

	AI	KM	OL	SA	SI	TMS
AI1	**0.827**	0.326	0.066	0.077	0.373	0.028
AI2	**0.833**	0.247	-0.048	0.104	0.324	0.035
AI3	**0.799**	0.286	-0.084	0.113	0.329	0.009
AI4	**0.787**	0.193	-0.084	-0.017	0.252	0.004
AI5	**0.851**	0.294	-0.015	0.073	0.321	0.03
AI6	**0.801**	0.232	-0.037	-0.005	0.315	0.09
KM1	0.308	**0.898**	0.272	0.284	0.71	-0.013
KM2	0.307	**0.905**	0.275	0.311	0.707	-0.039
KM3	0.256	**0.89**	0.258	0.257	0.694	-0.028
KM4	0.301	**0.883**	0.244	0.291	0.719	-0.002
KM5	0.289	**0.88**	0.247	0.303	0.71	-0.047
OL1	-0.017	0.256	**0.833**	-0.028	0.328	-0.002
OL2	0.005	0.24	**0.831**	-0.058	0.352	-0.024
OL3	-0.065	0.237	**0.844**	-0.005	0.352	0.045
OL4	-0.039	0.245	**0.853**	-0.022	0.353	0.018
SA1	0.024	0.311	-0.06	**0.848**	0.354	0.012
SA2	0.115	0.267	-0.002	**0.832**	0.366	0.026
SA3	0.071	0.256	-0.051	**0.817**	0.319	-0.039
SA4	0.038	0.224	-0.019	**0.842**	0.354	0.097
SA5	0.071	0.292	-0.007	**0.828**	0.306	-0.078
SI1	0.353	0.731	0.36	0.415	**0.914**	0.187
SI2	0.345	0.721	0.376	0.371	**0.91**	0.13
SI3	0.35	0.73	0.356	0.386	**0.91**	0.187
SI4	0.373	0.728	0.371	0.353	**0.914**	0.197
SI5	0.378	0.705	0.412	0.333	**0.903**	0.18
TMS1	0.044	-0.022	0.003	0.007	0.165	**0.922**
TMS2	0.057	0.005	0.03	0.031	0.223	**0.942**
TMS3	0.037	-0.033	-0.017	-0.009	0.157	**0.924**
TMS4	0.006	-0.07	0.018	-0.02	0.16	**0.928**

The results of cross-loading, as shown in Table 4, present a strong indicator of reliability and discriminant validity. Each item has the highest loading on its target construct compared to others, thus indicating a distinct association of indicators with the intended latent variable. For instance, AI1 to AI6 have the highest loadings on the AI construct (0.787–0.851) and considerably low loadings with other constructs, whereas KM1 to KM5 are over 0.88 on KM and below 0.31 on others. This arrangement satisfies the discriminant validity criteria recommended by Chin (1998), which expresses the idea that an item must load more highly on its construct than on any other construct.

Figure 1 is a measurement model showing the relationships between latent constructs and their indicators. All item loadings exceed the recommended cut-off value 0.70, showing strong indicator reliability. Such constructs as AI, SA, OL, KM, TMS, or SI have clear reflective indicators that help sustain convergent validity. The R^2 value of SI is at 0.782, meaning that 78.2% of its variance is accounted for by AI, SA, OL, KM, and the interaction term TMS × AI. The model also shows that KM's performance is explained moderately ($R^2 = 0.295$), which supports the measurement setup for the upcoming structural analyses.

Table 5 provides results of the path analysis, and it supports all the hypotheses (H1–H8). The significant effect of AI ($\beta = 0.315$), SA ($\beta = 0.311$), and OL ($\beta = 0.312$) on KM is found to be statistically significant ($p < 0.001$), supporting H1, H2, and H3. KM does an excellent job at predicting SI ($\beta = 0.598$, $p < 0.001$), favoring H4. Additionally, direct paths from AI, SA, and OL to SI are significant ($p < 0.001$), suggesting partial mediation. The indirect paths (with β values around 0.186–0.189) show that KM plays a role in how AI, SA, and OL are connected to SI. In addition, the moderating effect of TMS for the path of AI → SI has statistical significance ($\beta = 0.083$, $p = 0.001$), confirming H8. Overall, these results back up the proposed model and highlight the key role of KM in mediation and TMS in helping to encourage sustainable innovations in small and medium-sized manufacturing businesses in China.

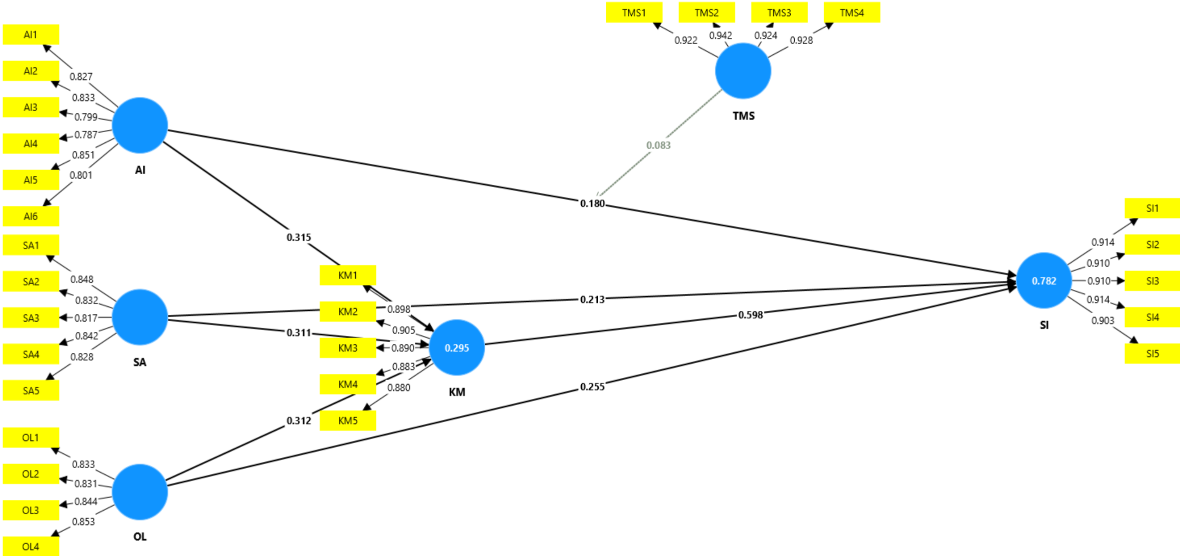

Figure 1: Measurement Model

Table 5
Path Analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values
AI -> KM	0.315	0.315	0.050	6.287	0.000
AI -> SI	0.180	0.180	0.032	5.697	0.000
KM -> SI	0.598	0.596	0.033	18.347	0.000
OL -> KM	0.312	0.313	0.048	6.454	0.000
OL -> SI	0.255	0.255	0.031	8.191	0.000
SA -> KM	0.311	0.312	0.053	5.872	0.000
SA -> SI	0.213	0.214	0.030	7.003	0.000
TMS -> SI	0.206	0.206	0.031	6.701	0.000
TMS x AI -> SI	0.083	0.082	0.026	3.184	0.001
AI -> KM -> SI	0.189	0.188	0.032	5.943	0.000
OL -> KM -> SI	0.187	0.187	0.031	6.071	0.000
SA -> KM -> SI	0.186	0.186	0.033	5.633	0.000

Figure 2 presents the structural model results, demonstrating the hypothesized constructs' interrelationships. All the path coefficients are statistically significant ($p < 0.001$) with quite high t values in parentheses. Knowledge Management (KM) has a central mediating role, with significant effects from AI, SA, and OL going into KM and then to Sustainable Innovation (SI) ($\beta = 0.598$). For SI, the R^2 value is 0.782, which implies that 78.2% of the variance is due to AI, SA, OL, KM, and TMS interaction. The moderating effect of top management support (TMS × AI → SI) is also significant, calling attention to the leadership amplifying action.

5. Discussion

This study looked at how artificial intelligence (AI), strategic agility (SA), and organizational learning (OL) influence sustainable innovation (SI) by considering the role of knowledge management (KM) and the impact of top management support (TMS) in small and medium-sized manufacturing businesses in China. The findings strongly support all eight hypotheses proffered, thus providing theoretical support and practical implications.

First, the strong connection between AI and KM (H1) is consistent with past studies regarding the roles of AI in improving knowledge acquisition, storage, and utilization (Rialti et al., 2020; Trocin et al., 2021). Our results confirm that the application of AI tools for decision-making, automation, and personalization by SMEs will likely make them more capable of organizing and managing internal knowledge. This conclusion also confirms a finding by Wang et al. (2024), who gave AI credit for contributing to the Chinese manufacturing context's digital knowledge platforms.

Second, SA and OL also present significant positive effects on KM (H2 and H3), as explained by the studies of Clauss et al. (2021) and Jerez-Gómez et al. (2005), respectively. Strategic agility facilitates speed in reconfiguring resources and responsiveness, increasing firms' capabilities to capture and distribute knowledge in an uncertain environment. Similarly, organizational learning champions continuous improvement in the sharing of knowledge and collective reflection, thus strengthening KM systems.

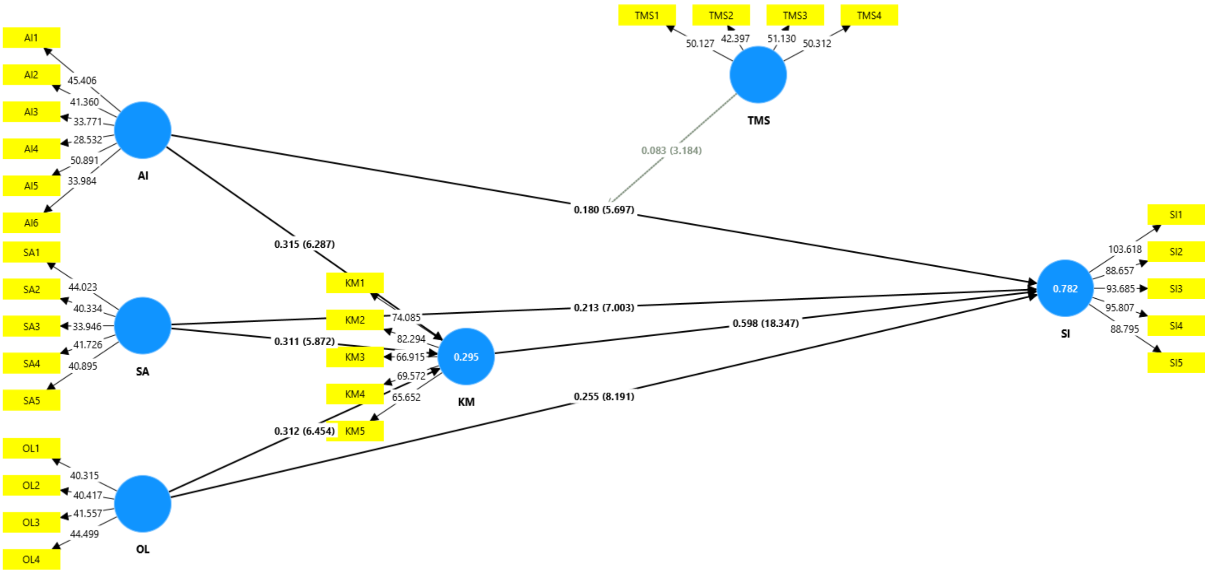

Figure 2: Structural Model

The immediate effect of KM on SI (H4) proved to be strong and significant, as Chen (2008) and Gold et al. (2001) described that firms that practice KM strongly are more likely to promote innovations that are sustainability-oriented in nature. The mediation effects show that KM helps clarify how dynamic capabilities relate to their results and acts as a strategic tool for enhancing capabilities and innovation. This hypothesis aligns with the assertions of Baquero (2024) and Abbas et al. (2020), who considered KM the key mechanism through which learning and technological effort transform into innovation.

Finally, the notably moderated effect of TMS on the relationship between AI and SI (H8) supports the earlier evidence that leadership resources complement digital investment to increase its effects (Chatterjee et al., 2020; Ramayah et al., 2014). In these SMEs, where there is considerable reliance on top management regarding positioning them and allocating resources, it becomes imperative to use such support to transform AI capabilities into sustainable innovations successfully.

These findings empirically show how digital and organizational capabilities and strong leadership work together to support and build theories that drive sustainability-oriented innovation, particularly in the post-COVID Chinese manufacturing SMEs.

6. Conclusion, Policy Implications, and Future Research Directions

This study looked at how artificial intelligence capabilities (AI), strategic agility (SA), and organizational learning (OL) affect sustainable innovation (SI) in small and medium-sized manufacturing businesses in China, with knowledge management (KM) helping to explain these effects and top management support (TMS) influencing them. Using data from 300 managers of small and medium-sized enterprises (SMEs), the SmartPLS-based structural equation modelling results confirmed all eight hypotheses being tested. AI, SA, and OL improved KM significantly, thereby having a very significant positive impact on SI. Additionally, KM was able to mediate the relationship between the independent variables and SI effectively, proving its strategic role in the innovation processes. The moderation analysis showed that TMS strengthens the link between AI and SI, highlighting how important leadership is for boosting technological skills. Such findings support the dynamic capability theory and offer a comprehensive model explaining how competencies and leadership can contribute to sustainability-oriented innovation in post-COVID settings. The study can be used to enhance theory, as it can combine technological, strategic, and organizational capabilities to fit in a single KM structure. It also provides practical information for SME leaders and policymakers seeking to foster environmentally oriented innovation using digital and knowledge-based transformations.

Policy makers should put in place targeted support programs that will improve the readiness of AI and the strategic agility of SMEs. Capacity-building initiatives, tax incentives for green innovation, and digital training for leaders of SMEs can make KM and leadership more effective in sustainable development. These are necessary steps toward addressing China's innovation-based economic and environmental priorities. Future studies can examine sector-level differences, pitting manufacturing against service SMEs, or regional disparities about China. It is further recommended that longitudinal studies be used to determine causal relationships over time. Moreover, introducing such external environmental factors as regulatory pressure or market turbulence may add to a greater understanding of sustainable innovation dynamics within SMEs.

Authors Contribution
Tabish Nawab: Solely conceived, designed, and conducted the research, analyzed the data, and wrote the manuscript.

Conflict of Interests/Disclosures
The authors declared no potential conflicts of interest regarding the article's research, authorship, and/or publication.

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