Manufacturing Enterprises' AI Capabilities Drive Product Innovation: A Moderated Mediating Model of Organizational Sensing-Responsiveness Capability and Digital Leadership

An Empirical Study of Advanced Manufacturing Small and Medium Enterprises in the Yangtze River Delta and the Pearl River Delta

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Abstract

Against the backdrop of deep fusion between the digital economy and the real economy artificial intelligence has surfaced as a pivotal engine through which manufacturing firms surmount growth ceilings and pursue high quality development. But much existing research still assumes that AI investment automatically leads to innovation output and it ignores the deeper pathways and leadership boundary conditions of the transformation. Based on the resource based view and dynamic capabilities theory, this study proposes a moderated mediation model to intertwine enterprise artificial intelligence capabilities (both technology and talent, and process), organizational sensing responsiveness capability, and digital leadership. 160 advanced technology small and medium manufacturing enterprises were surveyed using a multiple source paired questionnaire, which was completed on an online survey form, from the Yangtze River Delta cluster of Suzhou and the Pearl River Delta cluster of Dongguan. Partial least squares structural equation modeling and subgroup regression gave rise to three key conclusions. AI capability has multiple dimensions that drive innovation in fundamentally different ways: Technological infrastructure and human capital have a strong linear drive, while AI-driven process culture has an inverted concave function, confirming that over-standardization leads to core rigidity. Organizational sensing responsiveness capability is a partially mediating conduit between technological potential and market momentum. Digital leadership is a double-edged moderating force that turns on infrastructure and boosts agility while stifling talent autonomy.

Keywords: Enterprise AI Capability; Product Innovation; Organizational Sensing Responsiveness Capability; Digital Leadership; PLS-SEM

1. Introduction

The rapid spread of advanced computing technologies has given the manufacturing sector unprecedented windows into the past and the future of transformation and upgrading (Haefner et al., 2021). Artificial intelligence with its formidable prowess in data processing and pattern recognition and intelligent decision making has become the fulcrum driving this wave of renewal (Wang Yonggui et al., 2020). The major industrial countries have adopted national strategies to capitalize on this frontier, and the Yangtze River Delta and the Pearl River Delta have developed world class advanced manufacturing clusters (Verganti et al., 2020). While there is growing excitement, a troubling gap is that many businesses invest in AI without a consistent innovation payoff (Raisch et al., 2021). This divergence reveals three gaps in the knowledge. The first gap is about the transformation mechanism, since previous studies have found a positive relationship between the capabilities of AI and innovation performance, but rarely shed light on the organizational processes through which latent capability is converted into tangible product renewal (Mikalef et al., 2021).

The second gap relates to the boundary conditions as the leadership context in which the value of artificial intelligence crystallizes has not been rigorously verified (Benitez et al., 2022). The third lacuna is fragmented perspectives as scholars tend to study technology, people and process separately instead of an integrated system (Wu Xiaobo et al., 2021). This study aims to fill these gaps by developing and examining a moderated mediation model with organizational sensing responsiveness capability as the transmission hub and digital leadership as the situational boundary. The inquiry thus illuminates the way manufacturing companies harmonize technology and process, people and performance, and create a virtuous circle (Chen Jin et al., 2020). The theoretical contribution is three-fold. This study breaks down the nonlinear microfoundations of artificial intelligence driven innovation, and thus transcends the existing linear narrative (Duan et al., 2019). It adds to the boundary theory of digital innovation by revealing the situational moderating effects of leadership (Wei Jiang et al., 2021). It also provides managerial reference for companies and policy makers to optimize the innovation ecosystem (Xu Qingrui et al., 2020). The practical dimension is also relevant as a nuanced understanding of dimensional heterogeneity helps managers to deploy artificial intelligence in a calibrated way.

2. Literature Review

Enterprise artificial intelligence capability is a composite entity, not a single piece of technical equipment. In the last years, subjective scales that are grounded in capability theory have become mainstream and the framework proposed by Mikalef et al. divides the construct into technology and data foundation, human capital and analytics capability, and artificial intelligence driven organizational process and culture (Mikalef et al., 2021). This tripartite decomposition reflects the resource based logic that competitive advantage is derived from valuable, rare and inimitable bundles of resources (Barney et al., 1991). Product innovation in the intelligent era is no longer just novelty in terms of functionality, but more and more in terms of emotional intelligence and connective intelligence, which allows the product to learn the user's preferences and dynamically adapt to them (Cichosz et al., 2020). Nevertheless, scholars warn that the momentum behind artificial intelligence is far from universal and unconditional, and that excessive investments can go astray (Acemoglu et al., 2020). The organizational sensing responsiveness capability is an extension of the tradition of dynamic capabilities, as it is the firm's ability to sense market signals and to reconfigure resources and to make rapid responses (Teece et al., 1997). Previous research shows that information technology capability fosters organizational agility and analytics competency enhances market sensing (Lu et al., 2011).

Digital leadership is the highest level construct that informs the entire transformation, as the strategic direction of the entire organization is stamped onto the behavior of the organization by the dispositions of those at the top echelon (Hambrick et al., 1984). This study differs from the literature that sees leadership as a direct antecedent by seeing digital leadership as a contextual moderator that indicates under which conditions the mediation pathway strengthens (Xie Kang et al., 2020). Digital leadership has also been associated with employee innovative behavior, and team innovation through such mechanisms as psychological empowerment and knowledge sharing (Li Yanping et al., 2020). Other work places digital leadership in the context of the resilience of the organization and organizational agility in turbulent conditions (Zou Bo et al., 2021). Data empowerment views also suggest that data lifecycle management influences enterprise dynamic capabilities and consequently, the outcomes of transformation (Jiao et al., 2021). However, one of the limitations of the literature is that many studies focus on the general effect of information technology skills on organizations without dissecting the intervening capability chain (Li et al., 2016). The present model (Liu Xielin et al., 2021) was motivated by the lack of incorporation of capability and process and leadership in a single moderated mediation model.

3. Theoretical Framework

This study is theoretically underpinned by two interwoven pillars. The resource based view provides the core assumption that differences in resources are the source of differences in performance and it shows that the technology and data base and the human capital reservoir directly drive product innovation (Wernerfelt et al., 1984). Dynamic capabilities theory provides the processual logic that, in a changing environment, value is created only when firms sense and seize and reconfigure, and that static possession of resources is not enough (Teece et al., 2007).

In this context, enterprise artificial intelligence capability serves as the resource base that enables companies to access and analyze large amounts of data, both within and outside of their own organization. This resource base is transformed into agile innovation action through the higher order dynamic capability of organizational sensing responsiveness. Based on this reasoning, the mediating proposition is that the capability of artificial intelligence is able to build sensing responsiveness capability that will trigger product innovation. Together, the contingencies and upper echelon theory explain the moderating role, as any organizational capability is exercised in a leadership context and the strategic will of digital leaders conditions the efficiency of the translation of agility into innovative output (Cortellazzo et al., 2019).

The dialectical concept of too much of a good thing also suggests that some dimensions of artificial intelligence might have an inverted concave curve, where moderate standardization can help make the organization more efficient, but excessive standardization can lead to ossification of the organization (Sun Xinbo et al., 2021). These overlapping premises result in ten hypotheses, including direct effects, mediating effects and moderating effects. The direct hypotheses assume that the technological foundation and human capital have a linear positive effect on product innovation and process culture has a concave inverted effect. The empowerment hypotheses assume that each dimension of AI increases the sensing responsiveness capability. The mediating hypotheses assume that the impact of each dimension is transferred to product innovation through the sensing responsiveness capability. The moderating hypotheses are that digital leadership enhances the direct path from artificial intelligence capability to sensing responsiveness capability and the reverse path from sensing responsiveness capability to product innovation (Sun Xinbo et al., 2021).

Figure 1 Moderated mediation research model

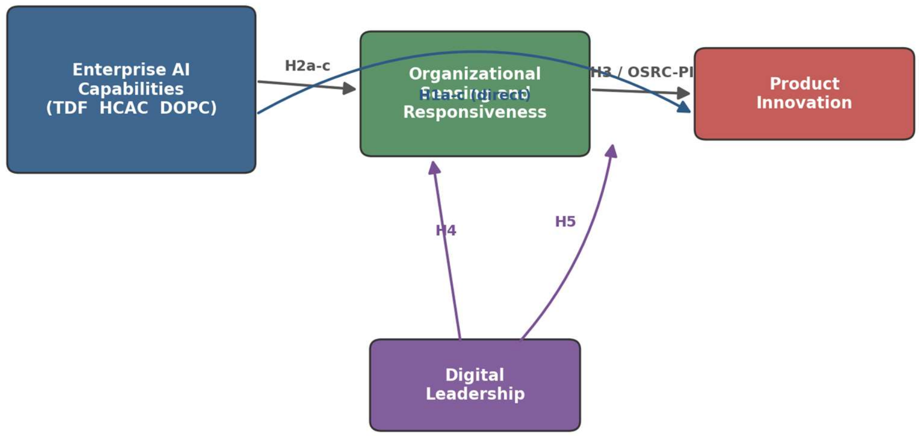

Figure 1 Moderated mediation research model integrating AI capability, sensing responsiveness capability, and digital leadership.

4. Research Methodology

The research design of this study was quantitative deductive to test the theory. Advanced technology small and medium manufacturing enterprises were sampled in the Yangtze River Delta (Suzhou) and the Pearl River Delta (Dongguan), as these clusters represent advanced technology-driven manufacturing. 160 enterprises provided valid responses, 80 from each region. The study used a multiple source paired protocol to reduce common method bias, with paired ratings being provided by the senior executives and middle managers and technical staff within the same firm, each rating a different set of construct blocks. All subjective items were measured on a 7-point Likert scale and adapted from validated scales and localized to the Chinese manufacturing context. Enterprise artificial intelligence capability included technology and data foundation (10 items), human capital and analytics capability (10 items), and artificial intelligence driven process culture (10 items). Product innovation included 15 items, organizational sensing responsiveness capability included 9 items and digital leadership included 9 items (Clauss et al., 2019). The pilot survey sent 80 questionnaires and received 62 valid responses (77.5 percent return rate) and also verified that all scales were above the reliability level. To mitigate heteroscedasticity, firm age and firm size and research intensity were used as control variables and transformed using natural logs. The analytical engine was PLS-SEM since the model included formative logic and mediation and nonlinear quadratic and interaction terms.

Direct effects and mediating effects were explored by conducting a bootstrapping procedure with 5000 resamples and moderating effects were explored by using the interaction term method (Sambamurthy et al., 2003). Prior to structural estimation the study standardized all latent variables and centered the constituent items before constructing quadratic and interaction terms in order to curb multicollinearity. Intraclass correlation values for each of the core constructs ranged from 0.36 to 0.45, supporting within group agreement and allowed individual ratings to be aggregated to the enterprise level. The regional distribution of firm size and firm age and research intensity conformed to the preset target proportions which testifies to a scientific and controlled sampling structure and lends the sample strong representativeness of the innovation driven manufacturing population (Grover et al., 2020).

5. Results

The quality of the measurements was checked prior to structural estimation. The internal consistency was very good with all constructs achieving composite reliability well above the recommended level and all average variance extracted well above 0.50 as reported in Table 1. The square root of each average variance extracted was greater than the interconstruct correlation (Fornell and Larcker criterion) and every heterotrait ratio was below the strict criterion of 0.85 with a range of 0.810 to 0.851, indicating that discriminant validity was maintained. The absence of collinearity was not an issue as all inner variance inflation factors were below 3.3, making common method bias unimportant.

Table 1 Construct reliability and convergent validity

Construct	Composite reliability rho_a	Composite reliability rho_c	AVE
TDF	0.921	0.940	0.759
HCAC	0.919	0.939	0.756
DOPC	0.914	0.936	0.745
OSRC	0.915	0.936	0.745
DL	0.913	0.935	0.741
PI	0.911	0.934	0.738

Note. All AVE values exceed 0.50 and all composite reliability values exceed 0.90.

The structural model presented tremendous explanatory and predictive power. The coefficient of determination for product innovation reached 0.962 which vastly exceeds the strong benchmark and the predictive relevance statistic remained positive throughout. The standardised RMSE was 0.021 and 0.023, well below the acceptable limit and indicates a good agreement between the model and the experimental data.

Table 2 and Figure 2 show the main effect tests. All direct links between the three dimensions of artificial intelligence and product innovation were positive and significant. Human capital and analytics capability had the highest direct impact with a coefficient of 0.302 compared with the technological foundation coefficient of 0.229 and highlighted the importance of leveraging intellectual capital. Each of the three dimensions to sensing responsiveness capability also had a significant impact, with the technological dimension having the highest coefficient (0.419). As shown in Table 3 and Figure 3, the nonlinear analysis indicated that the coefficient of the quadratic term of process culture on product innovation was significantly negative at the value of negative 0.261, which supported the concave inverted hypothesis with the inflection point around 0.351. The simple slope changed from strongly positive (0.705) at low levels to highly negative (negative 0.339) at high levels. In contrast, the quadratic term of technological foundation on sensing responsiveness capability was not significant, suggesting a strong linear instead of concave relationship.

Table 2 Main effect hypothesis tests

H	Path	beta	t	p	Result
H1a	TDF > PI	0.229	3.639	0.000	Supported
H1b	HCAC > PI	0.302	4.360	0.000	Supported
H1c	DOPC > PI	0.183	2.535	0.011	Supported
H2a	TDF > OSRC	0.419	4.753	0.000	Supported
H2b	HCAC > OSRC	0.289	3.382	0.001	Supported
H2c	DOPC > OSRC	0.273	3.031	0.002	Supported

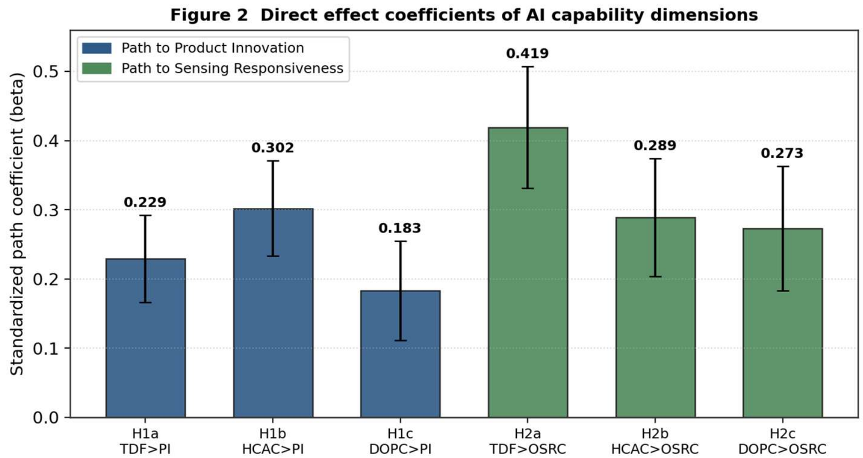

Figure 2 Standardized direct effect coefficients with bootstrap standard error bars.

Table 3 Test of the concave inverted relationships

H	Quadratic path	beta	t	p	U form
H1c	DOPC squared > PI	-0.261	2.827	0.005	Yes
H2a	TDF squared > OSRC	-0.010	0.135	0.892	No

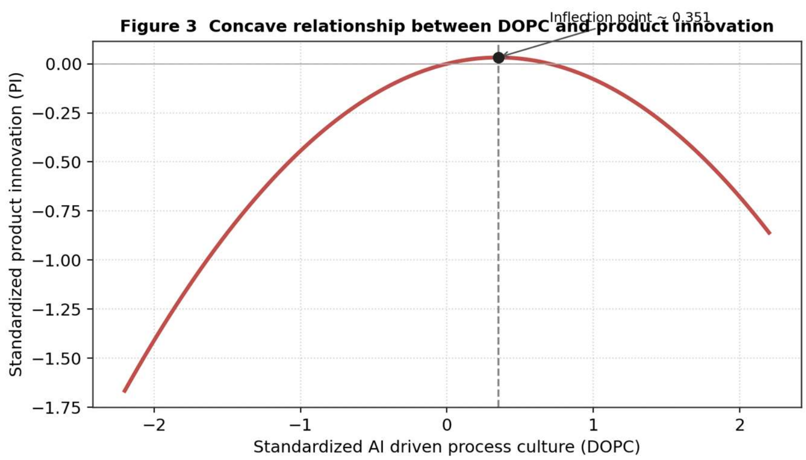

Figure 3 Concave inverted relationship between AI driven process culture and product innovation with inflection near 0.351.

The results of mediation are shown in Table 4 and Figure 4. All three indirect pathways through sensing responsiveness capability were positive and significant and none of the confidence intervals contained zero. The technological foundation pathway had the highest mediation ratio (34.76 percent), followed by the process culture pathway (30.15 percent) and the human capital pathway (21.76 percent). The decomposition validates that one-fifth to one-third of the innovation value of artificial intelligence capability is passed on through the conduit of sensing responsiveness.

Table 4 Mediation effect tests and effect decomposition

Indirect path	Indirect effect	t	p	95% CI	Ratio
TDF > OSRC > PI	0.122	3.322	0.001	0.057 to 0.202	34.76%

Indirect path	Indirect effect	t	p	95% CI	Ratio
HCAC > OSRC > PI	0.084	2.786	0.005	0.032 to 0.149	21.76%
DOPC > OSRC > PI	0.079	2.751	0.006	0.027 to 0.140	30.15%

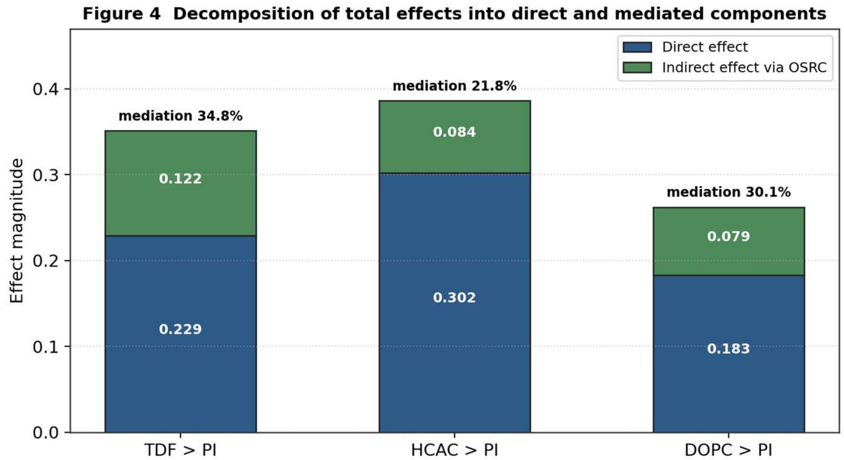

Figure 4 Decomposition of total effects into direct and mediated components with mediation ratios.

The results of the moderation can be seen in table 5 and graph 5. Digital leadership had a positive impact on the transformation of technological foundation into sensing responsiveness capability at a coefficient of 0.387. It nevertheless reduced the transformation of human capital at a high negative coefficient of negative 0.278 that shows an autonomy crowding out phenomenon. Process culture was not significantly affected by its interaction. Digital leadership had a coefficient of 0.097 which is positive and confirms its amplifying role in the downstream path from sensing responsiveness capability to product innovation.

Table 5 Moderating effect tests of digital leadership

H	Interaction path	beta	t	p	Result
H4	DL x TDF > OSRC	0.387	3.140	0.002	Supported
H4	DL x HCAC > OSRC	-0.278	2.921	0.004	Reversed
H4	DL x DOPC > OSRC	-0.142	1.526	0.127	Not supported
H5	DL x OSRC > PI	0.097	2.452	0.014	Supported

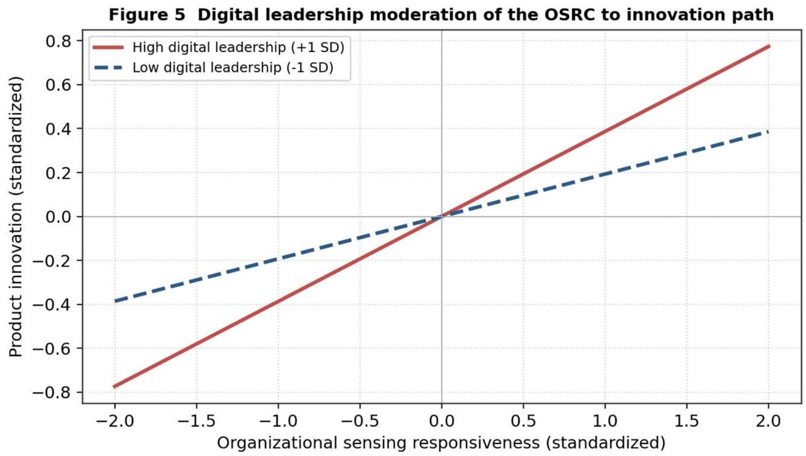

Figure 5 Simple slope plot of the digital leadership moderation on the sensing responsiveness to innovation path.

These conclusions were strengthened by the effect size analysis which revealed that the sensing responsiveness capability path to product innovation had the highest effect size of 0.241, indicating the path has an above average contribution. The technological foundation path to sensing responsiveness capability reached 0.168, surpassing the human capital effect of 0.071, and thus highlighting infrastructure as the material prerequisite for agile transformation. The control variables that had a significant positive impact on both sensing responsiveness capability and product innovation were research intensity, while firm age and firm size did not. This counterintuitive finding suggests that, in the case of advanced technology manufacturing, the perceptual and innovative stance of a firm is more influenced by strategic proactive investment than by the mere survival of the firm.

6. Discussion

The empirical portrait contributes to the theoretical understanding on three levels. The main effect pattern shows that the capability of artificial intelligence is not a single lever since hard infrastructure and human capital follow a linear pattern and process culture follows a concave pattern (El-Kassar et al., 2019). This imbalance supports the too much of a good thing thesis as too much proceduralization undermines the ambiguity and creative slack required for breakthrough innovation (Nadkarni et al., 2007).

The mediation results highlight the dynamic capabilities argument, as they indicate that the potential of AI can only be translated into market outcomes once it is internalized as organizational sensing responsiveness capability (Teece et al., 1997). Thus, sensing responsiveness capability serves as the essential link between resource and performance (Li et al., 2021). The moderation results provide the most nuanced contribution as digital leadership is a double-edged tool. It acts as an amplifier for rigid infrastructure and downstream agility since visionary leaders connect technology and business intent (AlNuaimi et al., 2022). It paradoxically acts as a suppressor of the agile creativity of expert talents, as it can narrow down the discretionary space that knowledge workers need to unleash agile creativity (Zhao Shuming et al., 2021). The activation and amplification and crowding out configuration presents a digital leadership as a force that is not always positive (Zhang Xiao et al., 2023).

The non-significant interaction with process culture indicates that once the algorithmic workflows are institutionalized, they are not easily affected by the leadership (Jiao et al., 2021). It is important to highlight the strategic importance of the amplifying effect on the downstream path, since sensing responsiveness capability in the absence of directionality could turn into blind experimentation. Visionary digital leaders move agile behavior toward high value domains that are aligned with strategic intent, and they maximize the innovation yield per unit of agility (Kane et al., 2019). They also help create a culture of psychological safety and error tolerance that encourages agile teams to make a real leap forward (Shrestha et al., 2021). The overall picture thus helps to account for the wide range of innovation performance of firms with similar AI investments: the real difference is the organizational and leadership structure that envelops the technology, and not the technology itself (Grant et al., 1996).

7. Conclusion

The study breaks down the complex and nonlinear processes by which AI can contribute to product innovation within manufacturing companies and sheds light on the complex relationship between leadership and organizational competence. Three conclusions are salient. The capability of artificial intelligence is a multidimensional composite engine, whose dimensions require differentiated management, since technology and talent require scale expansion, while process culture requires a cultivated equilibrium, which avoids the rigidity trap. The capability to sense and respond to the organization is the key transmission mechanism that transforms the potential of artificial intelligence into innovation momentum and its cultivation is essential. Digital leadership is a contingent boundary condition, with the value depending on the dimensional fit, as it must enable the infrastructure and amplify agility, while also preventing the crowding out of expert autonomy. The practical implication is the need for the two in one: hard infrastructure and soft governance, as managers strive for economies of scale in technology and retain the organizational redundancy in process and culture. There are a number of limitations that suggest further research. The cross sectional design limits causal claims and longitudinal tracing would strengthen temporal claims. Generalizability and sampling across industries would be improved by the regional focus on two clusters, which would increase external validity. Future research may also explore the implications of emerging generative technologies on the sensing responsiveness conduit.

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