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A Human-Centric Approach for Smart Manufacturing Adoption: An Empirical Study

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Abstract

Purpose: This study aims to address the overlooked micro-level aspects within Smart Manufacturing (SM) research, rectifying the misalignment in manufacturing firms' estimation of their technological adoption capabilities. Drawing upon the Social-Technical Systems (STS) theory, this paper utilises innovation capability as a mediating variable, constructing a human-centric organisational model to bridge this research gap. **Research design, data and methodology:** This study collected data from 233 Chinese manufacturing firms via online questionnaires. Introducing innovation capability as a mediating variable, it investigates the impact of social-technical system dimensions (work design, social subsystems, and technical subsystems) on SM adoption willingness. Smart PLS 4.0 was employed for data analysis, and Structural Equation Modelling (SEM) validated the theoretical model's assumptions. **Results**: In direct relationships, social subsystems, technical subsystems, and work design positively influence firms' innovation capabilities, which, in turn, positively impact SM adoption. However, innovation capability does not mediate the relationship between technical subsystems and SM adoption. **Conclusions:** This study focuses on the internal micro-level of organisational employees, constructing a human-centric framework that emphasises the interaction between organisations and technology. The study fills empirical gaps in Smart Manufacturing adoption, providing organisations with a means to examine the integration of employees and the organisational social-technical system.

Keywords: Smart Manufacturing, Industry 4.0, Socio-technical System Theory (STS), Innovation Capability, Human-centered.

JEL Classification Code: M1, L20, N95, O14, O33

1. Introduction

Smart Manufacturing (SM) is reshaping the industrial ecosystem and propelling the manufacturing sector into a new era (Ghobakhloo & Iranmanesh, 2021). Many countries are actively driving the transformation of their manufacturing industries to ensure sustainable development (Li, 2018). Developed nations such as the United States, Germany, and Japan have successfully leveraged digital technologies to establish a new industrial landscape (Li, 2018). These advanced countries have established smart factories integrating Cyber-Physical Systems (CPS) and the Internet of Things (IoT) to achieve seamless production and network connectivity integration. Utilising big data analytics enables faster and more accurate correction of errors during production. Deploying industrial robots

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reduces the exposure risk for workers, enhances operational efficiency, and promotes the optimal utilisation of human capital within enterprises (Sahoo & Lo, 2022).

However, the adoption of SM in developing countries, especially in China, has not been ideal. Despite being a major player in the manufacturing industry, the adoption rate of relevant SM technologies in China is not high. In some manufacturing enterprises, substantial investments are made in SM technologies, only to decide later to abandon their implementation (CAIC & Lenovo, 2023). The reasons may stem from the fact that some companies, due to their traditional approaches in management or production processes, are resistant to change and lack innovation capabilities (Dixit et al., 2022; Sony & Naik, 2020). Moreover, these perceptions affect how management designs manufacturing strategies and operational processes to adopt SM (Kusiak, 2018).

Therefore, as research delves into the micro-level intricacies of organisational structure, conventional wisdom may impede the acceptance of SM by workers, fueled by concerns about technological replacement resulting in unemployment (Marcon et al., 2022). Nevertheless, certain studies indicate that implementing SM technologies shifts employees' required skill sets from singular to diversified (Fernando et al., 2022). These systemic changes pose socio-technical challenges as they involve the transformation of individual social relationships and the interaction between technical aspects during the adoption of new tools, technologies, and management practices (Bag & Pretorius, 2022; De Felice et al., 2018)

Given the intricate nature of these changes, scholars find it necessary to research to understand how to systematically address the human factors supporting the adoption decisions of SM. Such a need aligns with the STS theory. The STS theory offers a comprehensive optimisation approach, enabling enterprises to respond dynamically and multidimensionally to the challenges posed by new technological environments (Dixit et al., 2022). However, similar studies have explicitly identified a gap in the current application of the STS theory in technology adoption. This gap arises because decisions to adopt SM are often technology-driven (Frank et al., 2019b), leading decision-makers to overlook the social and organisational factors within the manufacturing system. As discussed in previous research, realising technological transformation in enterprises is contingent upon maintaining alignment across various aspects of the organisation, such as human resources, tools, and resources (Cimini, 2020). Therefore, the STS theory emerges as a more suitable theoretical framework for evaluating whether the internal conditions of an enterprise are conducive to the adoption of SM (Arcidiacono et al., 2022).

2. Literature Review and Hypothesis Development

2.1. Social Subsystem

The social subsystem is an essential part of the STS theory, which includes both formal and informal communication. It significantly shapes the speed and efficiency of technological knowledge dissemination within an organisation (Patnayakuni & Ruppel, 2010). Usually, the system contains employees, managers, and aspects of resource allocation and technological efficacy, collectively influencing diverse facets of organisational (Zemlyak et al., 2022). Previous research suggests that when employees are confused or anxious about absorbing new technologies, organisations will encounter obstacles when adopting new management methods or technical systems (such as SM). Furthermore, individual employees' attitudes toward new technologies are believed to impact their peers' technological experiences, as peer interactions often involve mutual communication and imitation. Therefore, the relationship between social subsystems and SM adoption can be seen as a significant link.

Additionally, the supervisory relationships between managers and employees influence the adoption of SM. However, the outcomes of this influence may exhibit inconsistency. Aben et al. (2021) posit that information asymmetry and excessive pressure supervisory relationships may fail to promote adoption, and inhibit willingness to adopt new systems (Klein, 1987). Conversely, some scholars argue that supervisory relationships can effectively enhance work performance (Norawati et al., 2022), thereby influencing the rules of the organisational social subsystem. Under pressure conditions, supervisory relationships can expedite the diffusion of SM through effective resource management and organisational institutional mechanisms, ultimately augmenting the organisation's willingness to adopt SM.

H1a: There is a positive relationship between social subsystem and innovation capability.
H1b: There is a positive relationship between social subsystem and SM adoption.

2.2. Technical Subsystem

Elements of technical subsystem are tangible and directly observable (Sony & Naik, 2020). Adopting SM, such as IOT or a machine learning system, typically involves a continuous application within a system, encompassing the entire production process or specific departments, necessitating employee collaborative efforts (Prause, 2019; Verma & Mumbai, 2019). According to Nikas et al. (2007), factors related to the technical subsystem positively influence the adoption of advanced technologies. Because employees can access real-time information during the production process, facilitating collaborative technology usage among different departments enhances overall production smoothly (Vereycken et al., 2021). Moreover, by seamlessly integrating with existing infrastructures, the technologies associated with SM not only assist enterprises in better utilising traditional technologies but also foster a smooth transition, underscoring the positive role of the technology subsystem in SM adoption (Patnayakuni & Ruppel, 2010).

Ahmad et al. (2021) point out a positive relationship between technical subsystem and innovation capability. Furthermore, some studies suggest that the technology tacit knowledge would transfer to explicit knowledge by practice (Sanford et al., 2020). Thus, IT knowledge could be transmitted to employees using knowledge, techniques, equipment, and facilities. However, Li (2022) contends that by 2025, half of the workforce will require reskilling, which leads to the adoption of unfamiliar and challenging technologies beyond the employees' skill levels, which may yield contrasting results. Collaboration between technologies, departments, and teams may lead to data leakage and information asymmetry. Another opinion is that many activities have become monotonous due to excessive specialisation and automation, leading those who quickly complete these tasks to feel fatigued (Zemlyak et al., 2022). Therefore, based on the above discussion, at the technological level, SM might not necessarily enhance the firm's technical subsystem as envisioned, potentially increasing work resistance and psychological pressure for employees.

Furthermore, research indicates that when organisational management assesses employees' abilities to adapt to the enterprise's technical subsystem, decision-makers are more likely to adopt SM (Marcon et al., 2022). Thus, we propose the following hypotheses.

H2a: There is a positive relationship between technical subsystem and innovation capability.

H2b: There is a s positive relationship between technical subsystem and SM adoption.

2.3. Work Design

Makarius et al. (2020) argue that with the continual blurring of boundaries between human employees and intelligent technology in modern society, it might be time to redefine traditional work design and processes for better guidance on the future work experience of employees. However, research in this area is still lacking. Cagliano et al. (2019) emphasise that existing studies on technology in the Industry 4.0 era lack empirical research on the technological impact on micro-level organisational characteristics. For instance, through scenario reasoning, Jones et al. (2018) discuss the specific interactions of IR 4.0 with a particular SM. They aim to provide insights into human-machine interactions, overlooking the influence of the micro-level on organisational decision-making. Therefore, we can observe that the number of low-skilled manual jobs is decreasing (Goswami & Daultani, 2022). This implies that businesses will require more operators with diverse skills—individuals capable of working with advanced digital tools. According to (Marcon et al., 2022), the adoption of new technologies often implies a shift in worker roles towards tasks requiring creativity and social intelligence. This evolution suggests a positive association between work design and the adoption of SM.

However, the transition is not without challenges. Ensuring technologies evolve in tandem with the organisation's formal structure is paramount, thereby mitigating potential disruptions in the work organisation (Cagliano et al., 2019). A well-structured work design facilitates this transition to the Industry 4.0 context and successfully integrates the technology into existing operations (Meindl et al., 2021). However, work design does not evolve following technological advances. In that case, organisations risk exacerbating job dissatisfaction and hampering productivity.

Despite these potential negatives, the implications of work design for SM adoption are largely positive if managed well. Enhanced work designs encompassing principles like goal-driven processes, the interconnection between people and machines, information transparency, decentralised decisions, and integrating ideas from various hierarchical levels expedite new technology adoption (Lee & Norfarah, 2023). Based on the above discussion, wellwork design can bring a positive relationship with SM adoption, aligning with the principles of STS theory.

H3a: There is a positive relationship between work design and innovation capability.

H3b: There is a positive relationship between work design and SM adoption.

2.4. Innovation Capability

Enhancing innovation capability symbolises the enterprise's IR 4.0 digital transformation (Arshad et al., 2023). This is a pivotal factor in ensuring sustainable development for the enterprise; hence, scholars should pay ample attention while researching SM adoption (Dixit et al., 2022). The STS theory highlights the dynamic interaction between technology and society within the organisational environment. The alignment of innovation capability with the core principles of STS theory reveals a continuous state of change and acceptance of novelty within organisations (Castela et al., 2018). An organisation's innovation capability encourages employee engagement in decision-making, leveraging their knowledge, experience, and values, elevating decision quality and promoting sustainable development (Al Taweel & Al-Hawary, 2021).

An organisation's driven and change-oriented culture fosters innovation, effectively mitigating resistance to adopting SM among decision-makers and ordinary employees (Park & Choi, 2019). When managers perceive that technology can optimise production processes, improve product quality, and maximise the utilisation of human resources, they are inclined to reform existing technologies. Finally, innovation capability mirrors an organisation's dedication to continuously improving and optimising technology, aligning with the core principles of the STS theory that emphasise the dynamic interplay between technological and social systems (Castela et al., 2018). Organisations employ their innovation capabilities to consistently enhance their technological systems to adapt to their trade partners' changing requirements (Mendoza-silva, 2021). Indeed, when an organisation exhibits innovation capability, it naturally adopts SM as products undergo evolution or client preferences change.

Hence, as highlighted earlier, organisations that are open to change are more likely to embrace SM, which leads to the formulation of the subsequent hypotheses.

H4: There is a positive relationship between innovation capability and SM adoption.

In an organisation, the positive development of the social subsystem, effective implementation of the technical subsystem, and sound work design will collectively drive the enhancement of innovation capability. This improvement in innovation capability will further stimulate the occurrence and increase of SM adoption. The research framework of the present study is depicted in Figure 1, which is derived from the preceding thorough discussion of relationships.

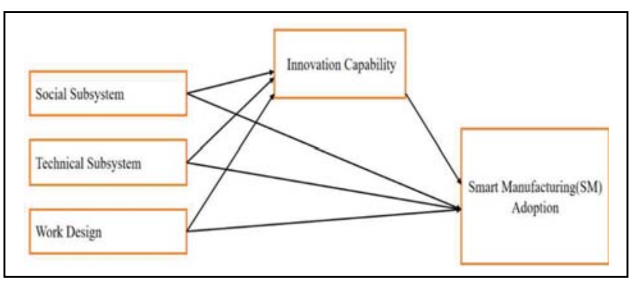


Figure 1: Research Framework (Source: Self-created)

3. Research Methods and Material

3.1. Research Design

This study adopts an explanatory research approach to explore the interconnections and potential causal relationships of various factors. The participant selection process involves straightforward random sampling. To enhance respondent convenience, we conducted an online survey using the widely recognised web platform Questionnaire-Star (Wenjuanxing, http://www.wjx.cn), commonly used for online questionnaire surveys in China (Wu et al., 2020). To ensure the content validity of our survey instrument, we initially distributed the questionnaire to two groups: experts from Chinese manufacturing enterprises and scholars from relevant academic fields. The questionnaire uses a 5-point Likert scale with anchors ranging from one (1) for strongly disagree to five (5) for strongly agree, comprising 21 questions related to five constructs. The data from manufacturing enterprises will be analysed using Smart PLS 4 software and the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. This approach is designed to elucidate causal relationships within the theoretical model, grounded in empirical data. The significance of these efforts lies in their contribution to identifying factors influencing SM adoption within the manufacturing industry.

All measurement items are derived from existing and well-established research. Only slight modifications to the measurement items based on expert opinions to better align them with the focus and objectives of SM. The Independent variables of this study are adapted from Zemlyak et al. (2022), the innovation capability as the mediating variable is based on Dixit et al. (2022) and a dependent variable is derived from Chatterjee et al. (2021). Table 1 illustrates that item details for all items and factor loading indicate strong causality for all reliability scores.

Table 1: Constructs and Measurement of the Study

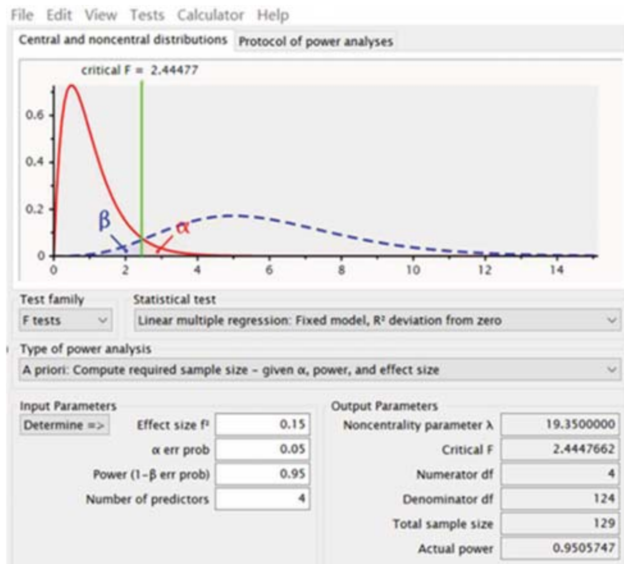
Items	Questions	Factor Loading
SM adoption	I think that SM is advantageous for our firm.	0.871
	I am in favour of SM based manufacturing and production system.	0.855
	I would like to use SM to its full potential.	0.849
	I think using SM will enhance our organisation’s productivity.	0.883
INO	Our organisation accept orders for new customised products.	0.811
	Our organisation frequently introduce new products and services.	0.655
	Our organisation are willing through new channels conduct business.	0.765
	Our organisation always try to improve the existing products.	0.804

Items	Questions	Factor Loading
	Our organisation try to accommodate minor changes of partner demands.	0.696
	Our organisation try to reduce the cost to compete in the existing markets.	0.707
SOSY	Supervisory relationships with the employees would enhance the use of SM.	0.787
	Peer group interaction is important for SM.	0.789
	Proper governance resources are important for adopting SM.	0.822
	SM requires effective processing and business aspects.	0.818
TECHSY	SM would help people work together on interrelated activities.	0.845
	SM use would help effective use of knowledge, techniques, equipment, and facilities.	0.859
	Employees and their social relationships would be improved by SM.	0.753
WD	The adoption of SM would help ensure employees' job descriptions achieve their mission.	0.802
	Employees' job duties would be achieved easily with SM.	0.820
	Employees' performance would be enhanced by adopting SM.	0.845
	Work systems would be effectively defined through SM.	0.755

3.2. Sample and Data Collection

Data were collected from Suzhou Industrial Park in China, representing the apex of SM adoption in the country. Located in the eastern region of Jiangsu Province, Suzhou significantly contributes to China's GDP, ranking first nationally. Suzhou Industrial Park, an early adopter of SM, solidified its distinction by contributing 12% to the national industrial production value. In 2022, the industrial output in Suzhou Industrial Park reached 176.191 billion Yuan, with the high-tech sector accounting for a remarkable 73.9% of the industrial output. Suzhou's manufacturing industry transformation thus serves as a benchmark for the advanced state of SM within the broader Chinese manufacturing landscape.

To ensure respondent convenience, an online survey was conducted (Wu et al., 2020), and all participants voluntarily completed the questionnaires, fully understanding the principles of anonymity and ethical guidelines. The respondent representing the company was either the IT manager or the person in charge of the company's IT strategy. Out of the 483 distributed questionnaires, 317 were returned. Responses from companies that had already implemented SM technologies were excluded, resulting in a complete sample of 233 responses, with an effective response rate of 48.24%. According to Hair, Hult et al. (2017), the expected sample size for this study is 129, and the 233 responses exceed the minimum sample size required by G*power (129). Therefore, the sample size for this study falls within a reasonable range (see Figure 2).



Source: Self-created
Figure 2: Result of G*Power

3.3. Common Method Bias

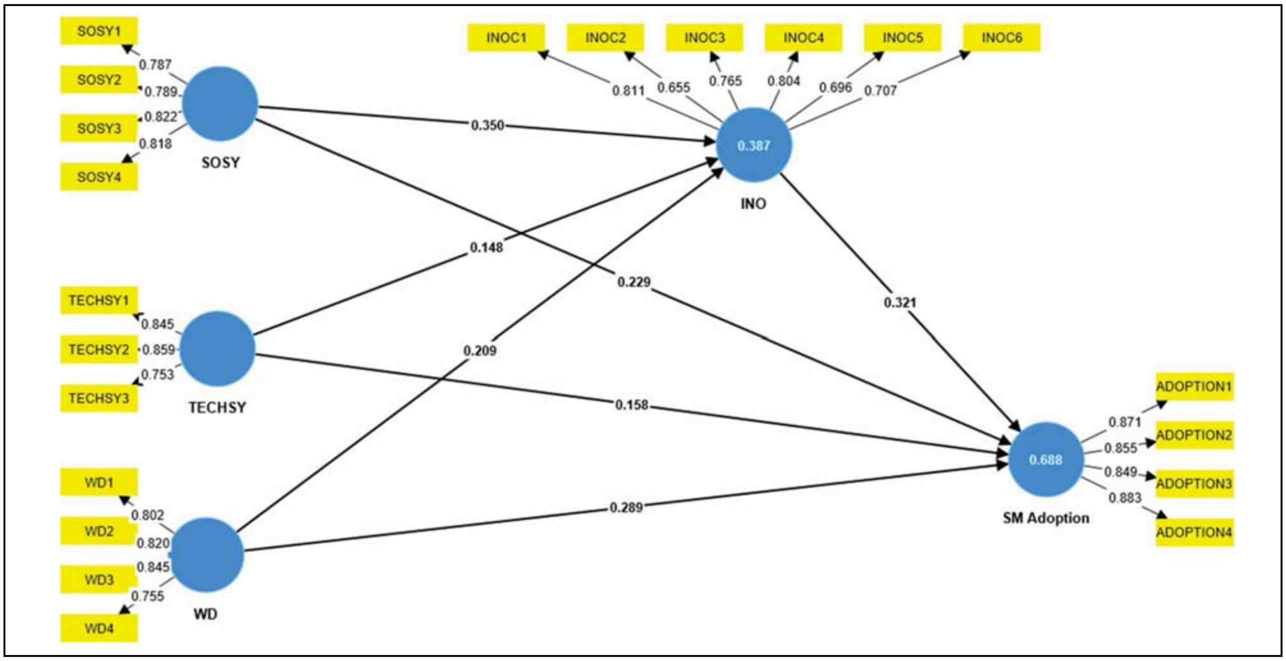
Due to the use of psychological measurement scales in the survey questionnaire and with data primarily sourced from single respondents, two approaches were employed to examine potential bias. The first approach was procedural, involving pretesting with professionals and scholars in the field to ensure the accuracy of language and the quality of responses, thereby enhancing the reliability of the questionnaire. In terms of questionnaire structure, the variables, including the dependent, independent, and control variables, were strategically placed at a considerable distance from each other to prevent respondents from presuming causal relationships due to psychological influences while answering questions. Secondly, as this study employed an online survey, a preliminary explanation was provided on the questionnaire's landing page when the survey link was sent, informing respondents that the questionnaire was anonymous and participation was voluntary. Therefore, the conclusion can be drawn that there are no issues with common method bias.

4. Data Analysis and Result

According to Hair et al. (2017), PLS-SEM analysis comprises two main steps: the measurement model and the structural model. The initial step, the measurement model analysis, serves as the foundation of the entire analysis, with its primary purpose being the evaluation of the effectiveness and reliability of measurement tools.

4.1. Assessment of Measurement Model

In this study, all variables exhibit reflective measurement properties, a method adopted from earlier related research. In this part, we conduct tests to ascertain the constructs' reliability and validity, including Cronbach's alpha, composite reliability, average variance extracted (AVE) and Variance Inflation Factor (VIF), among other measurement model indicators. Additionally, to ensure that each construct accurately measures its concept, discriminant validity was assessed.



Source: Self-created

Figure 3: Measurement Model

By observing the data in Figure 3, it can be seen that all item factor loadings exceed 0.5. This implies that these items exhibit high internal consistency and are retained in our study. Furthermore, two additional methods, Average Variance Extracted (AVE) and Convergent Reliability (CR), were employed to further assess variables' reliability. Results indicate that the AVE values for all variables are greater than 0.5, suggesting high validity in the measurement process (Hair et al., 2016).

Simultaneously, CR values all exceed 0.7, providing additional confirmation of the variables' strong convergent validity. By evaluating these constructs, they meet the required standards of the research methodology, demonstrating strong convergent validity. The standard measures for detecting multicollinearity involve testing the tolerance and variance inflation factor (VIF). Generally, a tolerance value exceeding 0.2 and a VIF value below 5 are considered acceptable thresholds (Hair et al., 2016). In our study, both tolerance and VIF met these criteria, indicating the absence of multicollinearity issues among the variables. This is reflected in Table 2. Overall, our research methodology exhibits favourable results in assessing the internal consistency of indicators.

Table 2: Relevant Indicators of the Measurement Model

Construct	Item Loading	Cronbach Alpha	CR	AVE	TOL	VIF
SM adoption	0.849-0.883	0.887	0.888	0.747	-	-
INO	0.655-0.811	0.835	0.843	0.550	0.622	1.608
SOSY	0.787-0.822	0.818	0.819	0.647	0.489	2.046
TECHSY	0.753-0.859	0.761	0.790	0.673	0.492	2.031
WD	0.755-0.845	0.820	0.825	0.650	0.465	2.152

This research tested discriminant validity by the Fornell-Larcker criterion, which is the square root of each construct's AVE should be greater than its highest correlation with any other construct (Hair et al., 2014). Table 3 illustrates the finding that the measurement model had reached its discriminant validity. Additionally, the heterotrait–monotrait (HTMT) method was used. Henseler et al. (2015) suggested that if HTMT values are lower than 0.90, it can be seen that the correlation between different constructs is not excessively high than 0.9. Table 4 depicts the funding of this study. All the values for the current study are under a level of 0.9. As a result, the results presented in Tables 3 and 4 demonstrate that the criterion for discriminant validity was met.

Table 3: Fornel-Larcker Criterion

Latent Construct	SM adoption	INO	SOSY	TECHSY	WD
SM adoption	0.864				
INO	0.686	0.742			
SOSY	0.695	0.575	0.804		
TECHSY	0.657	0.507	0.624	0.820	
WD	0.710	0.530	0.633	0.671	0.806

Table 4: Heterotrait-Monotrait Ratio of Correlations

Latent Construct	SM adoption	INO	SOSY	TECHSY	WD
SM adoption					
INO	0.784				
SOSY	0.813	0.689			
TECHSY	0.783	0.618	0.772		
WD	0.825	0.626	0.764	0.842	

4.2. Assessment of the Structural Model

Hair et al. (2019) recommend that internal validity be assessed by examining the determination coefficient (R^2) values of the proposed models. In this study, the R^2 value for SM adoption was found to be 0.688, signifying that the determinants explain 68.8% of the variability in SM adoption.

To assess the significance of path coefficients and test hypotheses, this study utilises two-tailed tests at a 5% significance level using "P-Values" and "T-statistics" to determine their importance (Arshad et al., 2023). The path coefficients and significance levels are shown in Table 5. Notably, the direct relationship and hypotheses H1 to H4 are all supported.

H1a, H2a, and H3a are the direct relationships from independent variables to the mediator. They are supported with a beta coefficient of 0.350, indicating a positive relationship between social subsystem and innovation capability. H2a and H3a, the positive relationship between technical subsystem, word design and innovation capability are supported at beta coefficient 0.148 (P=0.046) and 0.209 (P=0.004), respectively.

H1b, the social subsystem, is positively related to SM adoption (β=0.229, P=0.000), and H2b, the technical subsystem, positively affects SM adoption (β=0.158, P=0.0014). H3b, employee work design also positively influences SM adoption (β=0.289, P=0.000). H4 found that innovation capability significantly impacts SM adoption (β=0.321, P=0.000).

To discuss the mediation relationship from the direct relationship, we can calculate that the influence of work design as well as social subsystem on SM adoption is supported and holds practical significance when innovation acts as a mediating factor. Specifically regarding the mediating role of innovation capability between technical subsystem and SM adoption, it did not show a mediation relationship (β=0.047, P=0.103).

Table 5: Direct and Indirect Hypothesis Testing

No.	Hypothesis	Beta	T-statistics	P-value	Decision
H1a	SOSY→INO	0.350	4.534	0.000***	Supported
H1b	SOSY→SM adoption	0.229	3.928	0.000***	Supported
H2a	TECHSY→INO	0.148	1.996	0.046*	Supported
H2b	TECHSY→SM adoption	0.158	2.468	0.0014**	Supported
H3a	WD→INO	0.209	2.891	0.004**	Supported
H3b	WD→SM adoption	0.289	5.031	0.000***	Supported
H4	INO→SM adoption	0.321	5.617	0.000***	Supported

Note: Significant at * $p < 0.05$, ** $p < 0.01$ and *** $p < 0.001$ (two-tailed test).

5. Discussions and Conclusions

In the current study, we placed a specific focus on investigating the internal factors that influence the adoption of SM from the perspective of social subsystems. This study aimed to consider SM adoption factors from a human-centric standpoint, thereby assisting organisations in smoothly transitioning from the IR 4.0 to the Industry 5.0 era. Moreover, by directing their attention towards the internal organisational subsystems, organisations can dynamically assess the alignment of their employees with technology to design a technological transformation path that best suits employees' growth, ultimately making the organisational workforce more suitable for SM adoption.

This study yields several managerial implications. Executive leadership, including CEOs, CIOs, or IT managers, should emphasise the socio-technical system to assess the internal capabilities for investing in SM, thereby supporting the enterprise's strategic advantage in a highly competitive environment. It is imperative to move beyond blindly adopting technological changes as trends. Given the substantial investment required for SM, managers must meticulously evaluate factors related to employees, from job design to technical skills and the organisation's internal technological subsystems. This assessment helps determine whether the enterprise can plan for and sustain the adoption of SM. Similar to fertile soil yielding good fruit under favourable conditions, enterprises should focus on employee development, guide their involvement in transformation, and prevent potential resistance—essential conditions for successful SM adoption.

According to our research findings, practices such as involving employees in creative production, designing job performance focusing on SM adoption, on-the-job employee development, and fostering the exchange of technical experience among employees can effectively reduce resistance to major technological transformations, thereby promoting SM adoption. Furthermore, enterprises with higher innovative capabilities typically cultivate a positive innovation atmosphere and culture, positively influencing employees, potentially increasing their confidence in new technologies, reducing internal communication barriers, and mitigating obstacles to SM adoption. Therefore, enterprises should consider micro-level factors, ensuring organisational readiness and digital knowledge capabilities, avoiding overly ambitious plans, and enhancing the likelihood of adoption intention and sustained usage when planning for SM adoption and implementation.

Moreover, considering the urgent need for manufacturing industry transformation to maintain China's global competitiveness, the government's significant technological investments in industrial zones require careful consideration. We recommend that the government conduct in-depth assessments within enterprises, selecting those with active engagement and innovative capabilities for financial subsidies and policy preferential treatment. Simultaneously, periodic assessments of employees in relevant enterprises are suggested to ensure the increase of SM adoption intentions and effective implementation.

In a nutshell, this study delves into the crucial roles of the social-technical subsystems and innovative capabilities in SM adoption. Emphasising the importance of these subsystems and innovative capabilities highlights the multifaceted considerations required for an organisation's adaptability to technological change. The contribution of this study is clear: while innovative capabilities are vital, their direct impact on SM adoption within the technical subsystem context might not be as significant. Conversely, the role of technological systems in fostering collaborative cooperation may outweigh their direct influence on innovative capability development.

6. Limitations and Future Study

The limitation of this study is that we only focus on the Suzhou Industrial Park, which is the earliest part of China to get in touch with the SM. In order to enhance the adoption rate, it is imperative to conduct further investigations into SM's technological and organisational aspects. Moreover, it is essential to acknowledge that this study was conducted in a developing country, and findings may not be extrapolated to represent developed regions. As highlighted by Alaskar (2023), when disseminating research outcomes, it is crucial to avoid matters from disparities between developed and developing countries, such as cultural differences. Nevertheless, as a developing nation aspiring for technological progress, China boasts a robust information technology infrastructure.

Furthermore, qualitative methodologies could be utilised in future studies of SM adoption in order to identify additional internal factors. Lastly, this study is not exclusively applicable to organisations that have yet to adopt SM. Even organisations that have embraced SM but are experiencing sluggish progress or suboptimal outcomes can benefit from reviewing their human-centric employee task and communication design using the insights resulting from this study. This approach enables a better understanding and acknowledgement of SM, ultimately contributing additional value to enterprises.

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