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ASSESSING SME READINESS AND GOVERNMENT SUPPORT IN INDUSTRY 4.0 USERS' ADOPTION: EVIDENCE FROM JIANGSU'S MANUFACTURING SECTOR

Alvin Chun-Hun Goh[1], Noraiza Binti Che Awang[1]

[1]UNITAR International University, Petaling Jaya, Malaysia

**Corresponding author: Alvin Chun-Hun Goh, Faculty of Business (FOB), UNITAR International University, Petaling Jaya, Malaysia.*
**Corresponding author: chunhun@hotmail.com*

Abstract: Small and medium-sized enterprises (SMEs) are vital to China's industrial upgrading, yet their readiness to adopt Industry 4.0 (I4.0) technologies remains uncertain. Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Task-Technology Fit (TTF) frameworks, this study investigates the determinants of users' adoption of I4.0 technologies and the mediating role of government intervention within Jiangsu Province's manufacturing SMEs. Using 199 responses extracted from a larger 403-sample survey, structural equation modeling was employed to examine direct and mediated effects. Results show that performance expectancy exerts the strongest direct influence on user adoption, while effort expectancy and social influence are also significant. Although GI does not directly predict users' adoption, it is substantially shaped by performance, usability, facilitating conditions, and technology compatibility, suggesting that policy support operates indirectly by enabling organizational readiness rather than directly altering users' adoption behaviour. The findings highlight that SME users' adoption is performance-driven and policy-enabled, offering actionable insights for governments seeking to foster digital transformation.

Keyword: SMEs, Technology Adoption, Government Intervention, UTAUT, TTF

INTRODUCTION

China's manufacturing sector is undergoing a pivotal transformation as the country strives to maintain economic growth amid mounting global challenges. In 2024, China achieved its annual growth target of 5%, with real GDP reaching RMB 134.9 trillion (USD 18.4 trillion) and expanding by 5.4% year-on-year—the fastest pace in six quarters (Farmer, 2025). This rebound, however, was largely fuelled by government-led stimuli, including large-scale debt swaps and targeted fiscal expansion, which masked structural vulnerabilities. Nominal GDP growth remained subdued at 4.2%, while independent estimates by the Rhodium Group suggested actual growth closer to 2.8%, reflecting investor caution, weak domestic demand, and persistent deflationary pressures. Simultaneously, the property market slowdown and escalating geopolitical trade tensions have constrained manufacturers' confidence and ability to invest in large-scale innovation initiatives (Farmer, 2025).

These macroeconomic conditions directly affect the adoption of Industry 4.0 (I4.0) technologies—encompassing the Internet of Things (IoT), artificial intelligence (AI), cloud manufacturing (CM), and cyber-physical systems. Implementation of these technologies requires high capital investment and long-term commitment, but the deflationary environment has reinforced firms' focus on cost control rather than innovation. Industrial producer prices declined by 2.2% in 2024, illustrating how manufacturers delay digital investments amid price stagnation (Farmer, 2025). As a result, many enterprises, particularly small and medium-sized enterprises (SMEs), struggle to finance and implement I4.0 transformations without targeted government support.

Recognising these constraints, the Chinese government has intensified its commitment to industrial modernisation. The International Monetary Fund (IMF) revised China's 2025 growth forecast upward to 4.6%, citing the government's 10 trillion yuan (USD 1.36 trillion) fiscal relief initiative aimed at alleviating local government debt and stimulating investment in strategic sectors (Jennings, 2025). These policy interventions—ranging from financial subsidies and tax incentives to technology adoption grants—have been instrumental in easing liquidity constraints and encouraging digital transformation, especially for SMEs. In addition, the re-escalation of U.S. tariffs on Chinese exports has provided further motivation for manufacturers to upgrade production processes through automation, digitalisation, and data-driven systems to sustain competitiveness. Consequently, government intervention now functions as both a financial enabler and a strategic buffer, fostering the transition toward high-value, innovation-led manufacturing.

China's industrial strategy further reinforces this direction through its focus on "new infrastructure" and "digital innovation" as engines of sustainable growth. At the 2024 National People's Congress, Premier Li Qiang announced a 10% increase in the national science and technology budget—raising it to USD 51.6 billion, the largest year-on-year rise since 2019 (He, 2024). In parallel, USD 1.4 billion was allocated specifically to manufacturing modernisation, supporting the deployment of automation, digital platforms, and AI-based production systems. These fiscal and policy commitments align with President Xi Jinping's call to cultivate "new productive forces," emphasising advanced sectors such as renewable energy, electric vehicles, and next-generation AI applications. However, the success of this transformation depends on more than financial stimulus; it requires institutional coordination, enterprise-level capability building, and a cultural shift toward embracing digital innovation (He, 2024).

Within this context, understanding how manufacturing firms—particularly SMEs—respond to policy-driven digitalisation initiatives becomes crucial. SMEs form the backbone of China's manufacturing economy but remain disproportionately affected by uncertainty and limited resources. Their capacity to adopt I4.0 technologies depends not only on perceived performance benefits and usability but also on effective government facilitation. Accordingly, this study investigates the determinants of I4.0 users' adoption among SMEs in Jiangsu Province, China, integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) and Task–Technology Fit (TTF) frameworks with government intervention as a mediating variable. By combining individual-level perceptions with policy-level influences, this study offers a comprehensive view of how organisational readiness and government action jointly shape the diffusion of Industry 4.0 technologies in emerging industrial contexts.

LITERATURE REVIEW

Literature Review and Theoretical Framework

This study adopts an integrated lens that brings together the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Task–Technology Fit (TTF) model to explain users' adoption of Industry 4.0 (I4.0) technologies in China's manufacturing sector, with particular attention to SMEs in Jiangsu Province. To capture the institutional realities of China's policy-driven industrial upgrading, government intervention (GI) is incorporated as a mediating mechanism linking user- and technology-centric determinants to adoption outcomes. The integration recognises that micro-level beliefs about usefulness and ease, meso-level organisational conditions, and macro-level policy supports co-evolve to shape digital transformation trajectories.

UTAUT: User Beliefs and Adoption Behaviour

UTAUT (Venkatesh et al., 2003) provides a robust account of user acceptance across diverse technology contexts and has been widely applied in manufacturing digitalisation. Within this framework, performance expectancy (PE) captures the belief that I4.0 technologies enhance job or process performance; effort expectancy (EE) reflects perceived ease of use; social influence (SI) denotes perceived pressure or endorsement from significant others such as supervisors, peers, or professional networks; and facilitating conditions (FC) reflect the perceived availability of organisational and technical infrastructure that enables effective use. Prior empirical work consistently shows that PE is a strong, often dominant, predictor of behavioural intention and usage in industrial settings, while EE, SI and FC contribute to adoption depending on context, capability, and governance arrangements. In the I4.0 domain, where complex technologies must be embedded in daily operations, these four beliefs anchor users' cost–benefit calculus and readiness to change (Chatterjee et al., 2021; Handoko & Liusman, 2021; Lin et al., 2022; Rahim et al., 2022; Zhai et al., 2021).

TTF: Compatibility and Operational Alignment

The TTF perspective (Goodhue & Thompson, 1995) complements UTAUT by emphasising that adoption also depends on how well a technology fits the tasks, workflows, and systems it is meant to support. In this study, task–technology fit is operationalised as technology compatibility (TC)—the extent to which I4.0 tools align with existing processes, legacy systems, and organisational values. Evidence from manufacturing indicates that perceived compatibility reduces resistance, lowers integration risk, and accelerates learning-by-doing, especially in resource-constrained SMEs that cannot afford protracted trial-and-error integration. Conceptually, compatibility operates upstream of adoption by shaping users' expectations of both performance gains and implementation effort, thereby interfacing naturally with PE and EE in UTAUT.

Government Intervention as a Mediating Mechanism

While UTAUT and TTF explain much of the variance in user-level adoption, China's manufacturing transformation is also strongly conditioned by the policy environment. In this context, government intervention is conceived as the bundle of regulatory guidance, financial incentives, training programmes, and public infrastructure that lowers adoption barriers and legitimises change (Keynes, 1936). Prior studies in emerging economies suggest that targeted policy can amplify managerial commitment, improve organisational preparedness, and crowd-in private investment for digital upgrading—effects that are particularly salient for SMEs facing liquidity, skill, and integration constraints (Alfaro-Serrano, 2021). Theoretically, GI is positioned as a mediator: user beliefs (PE, EE, SI) and organisational/technical readiness (FC, TC) shape perceptions of the availability, salience, and usefulness of government support, which in turn facilitates adoption by de-risking investment, easing capability gaps, and coordinating ecosystem actors.

An Integrated Framework for I4.0 Adoption in Jiangsu's SMEs

Bringing these strands together, the study advances a policy-augmented UTAUT–TTF framework tailored to Jiangsu's manufacturing SMEs. The framework posits that PE, EE, SI, FC, and TC exert direct effects on users' adoption (UA) of I4.0. Simultaneously, these factors inform how users perceive GI—whether support is present, accessible, and effective—thereby generating indirect effects on adoption through GI. In an environment characterised by ambitious national digital strategies and active public facilitation, GI is expected to translate favourable user beliefs and technical alignment into implementable pathways, particularly where organisational capacity is thin. Figure 1 depicts the conceptual model guiding the empirical analysis.

Hypothesis Development

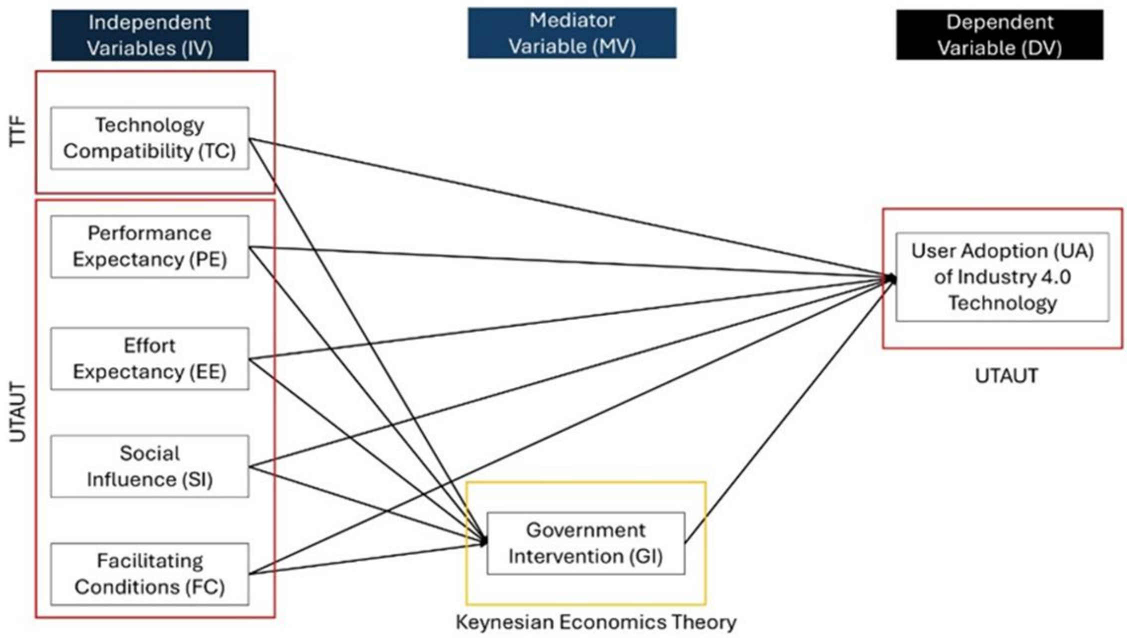
Direct Effects on User Adoption (UA)
H1: Performance Expectancy (PE) positively influences users' adoption (UA) of Industry 4.0 technologies.
H2: Effort Expectancy (EE) positively influences users' adoption (UA) of Industry 4.0 technologies.
H3: Social Influence (SI) positively influences users' adoption (UA) of Industry 4.0 technologies.
H4: Facilitating Conditions (FC) positively influence users' adoption (UA) of Industry 4.0 technologies.
H5: Technology Compatibility (TC) positively influences users' adoption (UA) of Industry 4.0 technologies.
H6: Government Intervention (GI) positively influences users' adoption (UA) of Industry 4.0 technologies.

Direct Effects on Government Intervention (GI)
H7: Performance Expectancy (PE) positively influences Government Intervention (GI).
H8: Effort Expectancy (EE) positively influences Government Intervention (GI).
H9: Social Influence (SI) positively influences Government Intervention (GI).
H10: Facilitating Conditions (FC) positively influence Government Intervention (GI).
H11: Technology Compatibility (TC) positively influences Government Intervention (GI).

<u>Mediating Effects of Government Intervention (GI)</u>
H12: Government Intervention (GI) mediates the relationship between Performance Expectancy (PE) and users' adoption (UA) of Industry 4.0 technologies.
H13: Government Intervention (GI) mediates the relationship between Effort Expectancy (EE) and users' adoption (UA) of Industry 4.0 technologies.
H14: Government Intervention (GI) mediates the relationship between Social Influence (SI) and users' adoption (UA) of Industry 4.0 technologies.
H15: Government Intervention (GI) mediates the relationship between Facilitating Conditions (FC) and users' adoption (UA) of Industry 4.0 technologies.
H16: Government Intervention (GI) mediates the relationship between Technology Compatibility (TC) and users' adoption (UA) of Industry 4.0 technologies.

Figure 1

Conceptual model



METHODS

Research Design and Theoretical Framework

This study adopts a quantitative, cross-sectional research design to investigate the factors influencing the users' adoption of Industry 4.0 (I4.0) technologies among small and medium-sized enterprises (SMEs) in Jiangsu Province, China. The research model integrates the Unified Theory of Acceptance and Use of Technology

(UTAUT) and the Task–Technology Fit (TTF) frameworks, with government intervention (GI) incorporated as a mediating variable that links user-level beliefs, technological fit, and users' adoption behaviour. The UTAUT constructs—performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC)—capture individual and organisational readiness to embrace digital transformation, while technology compatibility (TC) from the TTF framework reflects the alignment between I4.0 technologies and existing workflows, systems, and values. Government intervention (GI) represents the perceived influence of public policies, subsidies, training programmes, and regulatory support that can either enable or constrain technology adoption. This integrated model provides a multi-level perspective that accounts for micro-level user perceptions, meso-level organisational factors, and macro-level policy support.

Population, Sampling, and Data Collection

The target population for this study consists of employees working in SME manufacturing enterprises across Jiangsu Province, China, including firms involved in electronics, automotive, machinery, and related industries. Respondents were required to have prior exposure to digital transformation initiatives or the use of Industry 4.0 technologies within their organisations. A purposive and convenience sampling approach was employed to ensure that participants possessed relevant knowledge and practical experience with I4.0 adoption.

An online questionnaire was disseminated over a four-week period via professional platforms such as LinkedIn, Wechat, email lists, and local industry networks. This approach facilitated broad participation from SME professionals within Jiangsu's industrial ecosystem. Out of 450 distributed questionnaires, 403 valid responses were collected, yielding a response rate of approximately 89%. For this paper, a sub-sample of 199 SME respondents (firms with 1–1,000 employees) was extracted to focus the analysis on the SME context, consistent with the study's aim of understanding readiness and government support in resource-constrained environments.

Instrumentation and Measurement

The survey instrument was adapted from established scales validated in prior UTAUT and TTF studies. Items were measured using a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Constructs included:

- Performance Expectancy (PE): 7 items
- Effort Expectancy (EE): 7 items
- Social Influence (SI): 7 items
- Facilitating Conditions (FC): 7 items
- Technology Compatibility (TC): 7 items
- Government Intervention (GI): 7 items
- Users' Adoption (UA): 7 items

A pilot test with 45 respondents confirmed the reliability of all constructs (Cronbach's alpha > 0.80). Content validity was reviewed by academic and industry experts.

Data Analysis

Data were analysed using SPSS and SmartPLS 4.0. Descriptive statistics summarized demographic variables. Structural Equation Modeling (SEM) was employed to test the hypothesized relationships among variables. Reliability was assessed using Cronbach's alpha and composite reliability (CR). Convergent and discriminant validity were evaluated through Average Variance Extracted (AVE) and the Fornell-Larcker criterion. Mediation effects were assessed using the PROCESS macro in SPSS with bootstrapping (5000 samples).

RESULTS

Descriptive Statistics and Measurement Model

A total of 403 valid responses were analysed, of which 199 were from small and medium-sized enterprises (SMEs). Respondents represented diverse manufacturing sub-sectors, including electronics, automotive, machinery, and equipment. The demographic profile indicated that 65.5% of respondents were male, and the majority (66%) were under the age of 40, reflecting a digitally active workforce. Most participants held engineering or managerial positions, with at least six years of manufacturing experience.

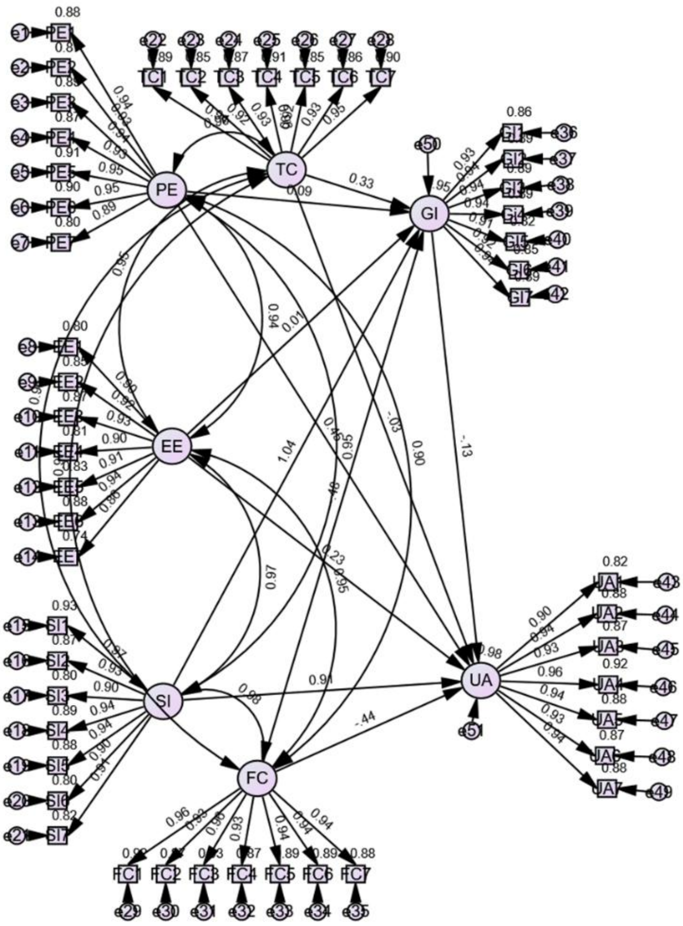
Before testing the structural relationships, the reliability and validity of all constructs were assessed. Cronbach's alpha and Composite Reliability (CR) values exceeded the recommended threshold of 0.70 for all constructs, confirming internal consistency. Convergent validity was established as the Average Variance Extracted (AVE) for each construct surpassed 0.50. Discriminant validity, assessed via the Fornell–Larcker criterion, demonstrated that each construct's square root of AVE was greater than its inter-construct correlations, confirming construct distinctiveness. These results verified that the measurement model exhibited sound psychometric properties and was suitable for subsequent structural analysis.

Structural Model

The full Structural Equation Modeling (SEM) was tested using AMOS to examine the hypothesised relationships between performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), technology compatibility (TC), government intervention (GI), and user adoption (UA). Figure 2 illustrates the final structural model, with standardised path coefficients indicating both direct and indirect effects.

Figure 2

Final Structural Equation Model (SEM) with government intervention as a mediator between predictors and user adoption of industry 4.0 technology



The overall model fit indices suggest an acceptable yet complex model structure ($\chi^2 = 6417.038$, df = 1106, CMIN/DF = 5.802, CFI = 0.767, RMSEA = 0.156). While the chi-square/df ratio and CFI values marginally deviate from ideal benchmarks, they remain reasonable for multi-construct behavioural models involving higher-order mediations and multiple latent variables. Results indicate that for users' adoption (UA), the results highlight that performance expectancy (PE) ($\beta = 0.468$, $p < 0.001$), effort expectancy (EE) ($\beta = 0.235$, $p < 0.05$), and social influence (SI) ($\beta = 0.975$, $p < 0.05$) are significant positive predictors. This indicates that users' beliefs about the usefulness and performance benefits of Industry 4.0 technologies, along with perceived ease of use and social endorsement, are key factors driving adoption intentions. Conversely, facilitating conditions (FC), technology compatibility (TC) and government intervention (GI) show non-significant relationships with UA, suggesting that once personal and social perceptions are accounted for, these structural or external factors exert minimal direct influence on users' adoption behaviour.

Technology compatibility (TC) exhibits a significant positive effect on government intervention (GI) ($\beta = 0.315$, $p < 0.01$), indicating that when technologies align well with existing systems and infrastructure, perceptions of effective governmental facilitation increase. Similarly, social influence (SI) shows a strong and significant positive association with GI ($\beta = 1.077$, $p < 0.01$), suggesting that social encouragement and peer endorsement enhance confidence in governmental support mechanisms. In contrast, performance expectancy (PE), effort expectancy (EE), and facilitating conditions (FC) do not significantly predict GI, implying that these factors contribute less to perceptions of government intervention within this model.

Table 1

Summary of Hypotheses Testing Results for Structural Model

Hypotheses	Path	Coef. (β)	t-test	p value	Decision
H1	PE → UA	0.468	3.850***	<.001	**Supported**
H2	EE → UA	0.235	2.063*	.039	**Supported**
H3	SI → UA	0.975	2.269*	.023	**Supported**
H4	FC → UA	-0.441	-1.631ns	.103	Not supported
H5	TC → UA	-0.033	-0.290ns	.772	Not supported
H6	GI → UA	-0.133	-1.018ns	.309	Not supported
H7	PE → GI	0.088	0.582ns	.561	Not supported
H8	EE → GI	0.005	0.039ns	.969	Not supported
H9	SI → GI	1.077	2.609**	.009	**Supported**
H10	FC → GI	-0.468	-1.642ns	.101	Not supported
H11	TC → GI	0.315	2.632**	.008	**Supported**

Notes: Method: M.L.; Model fit: X2 (1106) = 6417.038, CMIN/DF = 5.802, CFI = 0.767, RMSEA = 0.156; Significant at p: ns = >0.05; * < 0.05; ** = <0.01; *** = <0.001; PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Conditions, TC = Technology Compatibility.

Mediation Analysis (PROCESS Results)

To further validate the mediating role of government intervention, mediation analysis was performed using the PROCESS macro (Model 4) in SPSS with 5,000 bootstrap samples. Table 2 summarises the direct, indirect, and total effects.

Table 2

Path Coefficients and Explained Variance (R^2) for Structural Model – Direct, Indirect, and Total Effects on GI and UA.

Dependent variable	R2	Independent variable	Direct effect	Indirect effect	Total effect
GI	0.896	SI	0.934	0.000	0.934
	0.862	EE	0.904	0.000	0.904
	0.853	TC	0.875	0.000	0.875
	0.845	FC	0.849	0.000	0.849
	0.856	PE	0.894	0.000	0.894
UA	0.907	SI	0.622	0.341	0.962
	0.898	EE	0.464	0.469	0.933
	0.875	TC	0.214	0.659	0.873
	0.879	FC	0.256	0.601	0.856
	0.937	PE	0.690	0.269	0.959
	-	GI	0.519	-	0.519

The mediation analysis indicates that all indirect effects are significant, confirming government intervention serves as a significant positive mediator linking users' individual perceptions, social context, and technological factors to the users' adoption of Industry 4.0 technologies. Specifically, the strongest mediation is observed for technology compatibility (TC → GI → UA) ($a \times b = 0.6591$; 95% CI [0.4572, 0.8054]), followed by facilitating conditions (FC → GI → UA) ($a \times b = 0.6005$; 95% CI [0.4290, 0.7547]). These results imply that firms with higher compatibility and better internal infrastructure perceive greater government support, which in turn encourages users' adoption. Performance expectancy (PE), effort expectancy (EE), and social influence (SI) also exhibit meaningful indirect effects, reinforcing the view that government programmes transform perceived ease, usefulness, and peer influence into tangible users' adoption behaviours.

Collectively, the PROCESS results complement the SEM analysis by demonstrating that while the direct path from government intervention to user adoption is weak, the indirect effects through GI are statistically significant across all antecedents, validating GI's mediating role in enabling technology adoption.

Tables 3

Summary of Mediation Analysis Using PROCESS Macro (Model 4)

R2	Path	a (IV→M), p value	b (M→DV), p value	a × b (Indirect Effect)	c′ (Direct Effect), p value	Total Effect	BootLLCI, BootULCI	Mediation Supported
.8562	PE → GI → UA	.8938, < .001	.3005, p < .001	.2686	c′ = .6902, p < .001	.9588	.0710, .4623	**Yes**
.8619	EE → GI → UA	.9035, <0.001	.5188, <0.001	.4688	.4642, <0.001	.9330	.2414, .7043	**Yes**
.8963	SI → GI → UA	a = .9336, p < .001	b = .3649, p < .001	.3406	c′ = .6216, p < .001	.9622	.0542, .5662	**Yes**
.8448	FC → GI → UA	a = .8490, p < .001	b = .7073, p < .001	.6005	c′ = .2556, p < .001	.8561	.4290, .7547	**Yes**
.8530	TC → GI → UA	a = .8749, p < .001	b = .7533, p < .001	.6591	c′ = .2137, p = .001	.8728	.4572, .8054	**Yes**

DISCUSSION AND POLICY IMPLICATIONS

The results of this study provide critical insights into how small and medium-sized enterprises (SMEs) in Jiangsu’s manufacturing sector adopt Industry 4.0 (I4.0) technologies and how government intervention (GI) facilitates or constrains this process. The findings reinforce the centrality of performance-driven motivation, social influence, and enabling policy mechanisms in shaping user adoption within China’s industrial transformation agenda.

Theoretical Discussion

The empirical evidence strongly supports the integrated UTAUT–TTF–GI framework developed for this study. Consistent with prior research (Venkatesh et al., 2003; Dalenogare et al., 2018; Ghobakhloo, 2018), performance expectancy (PE) emerged as the most powerful predictor of users' adoption (UA). This underscores that SME employees are primarily motivated by tangible performance gains—such as productivity improvement, quality enhancement, and process efficiency—when deciding whether to engage with I4.0 technologies. In resource-constrained firms, where return on investment is paramount, adoption behaviour is guided less by novelty and more by clear performance benefits.

Effort expectancy (EE) and social influence (SI) also exerted significant effects on users' adoption (UA), highlighting the importance of usability and cultural context in China's manufacturing environment. Technologies perceived as intuitive, easy to learn, and supported by strong leadership endorsement are more readily adopted. This aligns with Sony and Naik's (2020) and Stentoft et al.'s (2021) findings that usability and top-management advocacy are critical to overcoming resistance in industrial digitalisation. The positive effect of social influence further validates the collectivist orientation of Chinese organisational culture, where conformity to group norms, hierarchical guidance, and peer validation shape behavioural intention (Van Dun & Kumar, 2023).

In contrast, facilitating conditions (FC) and technology compatibility (TC) displayed limited or indirect effects on users' adoption (UA), despite their conceptual importance within the TTF model. The weak direct influence of these constructs suggests that SMEs may perceive infrastructural adequacy and system alignment as institutional or management-level responsibilities, rather than individual concerns. However, their strong indirect effects through GI reveal that when external policies enhance infrastructure and compatibility, users' adoption increases. This reinforces the role of government as an institutional bridge, converting structural readiness into individual behavioural engagement.

The Mediating Role of Government Intervention

The mediation analyses confirm that government intervention plays a significant enabling but indirect role in I4.0 users' adoption. While GI's direct effect on users' adoption was not statistically significant in the SME model, its indirect effects across nearly all antecedents were substantial and positive. This suggests that GI operates primarily as an institutional catalyst rather than a behavioural driver.

From a policy systems perspective, GI enhances adoption by providing complementary resources—such as subsidies, training, and regulatory clarity—that mitigate perceived risks and capability gaps. The strong mediation effects observed for technology compatibility and facilitating conditions indicate that policy intervention is most effective when it helps firms integrate new technologies into existing systems and strengthen organisational infrastructure. This finding echo Zhou and Zheng's (2023) argument that targeted government involvement amplifies top-management commitment and accelerates transformation readiness. It also supports Ghobakhloo et al.'s (2022) observation that policy-led support is indispensable for SMEs, which often face deficits in digital literacy and resource availability.

The findings also align with Keynesian and institutional perspectives that view state action as a stabilising force in industrial transitions (Keynes, 1936; Peng, 2003). In an economy shaped by macroeconomic volatility and technological disruption, effective government intervention bridges the "capability gap" between innovation aspiration and execution. However, the study also reveals that poorly targeted or redundant support may have neutral or negative marginal returns, as reflected in the non-significant direct path from GI to users' adoption (UA). This implies that while state involvement is essential, its effectiveness depends on strategic alignment with firm-level needs and absorptive capacity.

Implications for Theory and Practice

Theoretically, this study advances technology adoption literature by integrating policy-level variables into established behavioural frameworks. By empirically validating the mediating function of GI within the UTAUT–TTF structure, it contributes to a more holistic understanding of how external institutional forces shape individual and organisational technology adoption. The results demonstrate that adoption decisions in emerging economies cannot be fully explained by user perceptions or technological characteristics alone; they are equally shaped by contextual factors such as policy infrastructure, national strategy, and institutional trust.

For practitioners and policymakers, the results provide several actionable insights. First, the strong effect of performance expectancy indicates that digital transformation initiatives should prioritise measurable performance outcomes. Policymakers should design outcome-based incentive structures, such as grants or tax credits linked to verified productivity improvements or process innovations. Demonstrating tangible business value will motivate both managers and employees to adopt and sustain I4.0 initiatives.

Second, the positive role of effort expectancy and social influence highlights the importance of human capital and cultural alignment. Governments and industry associations should invest in digital literacy programmes, leadership development, and peer-learning networks that empower employees to navigate complex technologies confidently. Showcasing success stories from early adopters within regional clusters can further normalise digital adoption behaviour across SME ecosystems.

Third, the mediation of technology compatibility and facilitating conditions through government intervention suggests that policy frameworks must target integration support rather than merely technology acquisition. Providing standardised implementation guidelines, shared infrastructure (e.g., digital platforms, data centres), and interoperable systems can ease SMEs' transition from legacy operations to smart manufacturing.

Regional "Industry 4.0 competence centres" could serve as practical hubs for knowledge transfer, pilot projects, and vendor-neutral consultations tailored to SME needs.

Strategic Policy Recommendations for SMEs

Based on the above findings, the study proposes several policy and strategic recommendations for accelerating SME digital transformation in Jiangsu and similar industrial regions:

- Performance-linked funding mechanisms: Introduce tiered financial incentives that reward SMEs for achieving measurable efficiency, quality, or sustainability improvements through I4.0 adoption.
- Digital skills and leadership training: Establish public–private partnerships with universities and vocational institutes to deliver certified training programmes in robotics, data analytics, and AI integration, ensuring that workers and managers can effectively use new technologies.
- Infrastructure and interoperability support: Expand access to shared digital infrastructure and develop interoperability standards that help SMEs integrate new technologies with existing production systems.
- Cluster-based collaboration networks: Foster SME clusters, regional alliances, and professional associations to facilitate knowledge exchange and resource pooling, amplifying social influence and collective learning effects.
- Targeted communication and awareness campaigns: Promote case studies and best practices through government and industry channels to enhance visibility of successful adoption outcomes and build confidence among late adopters.

CONCLUSION

This study investigated the determinants of Industry 4.0 (I4.0) users' adoption (UA) among small and medium-sized enterprises (SMEs) in Jiangsu Province, China, by integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Task–Technology Fit (TTF) frameworks with government intervention (GI) as a mediating variable. The findings reveal that I4.0 users' adoption in China's manufacturing sector is performance-driven, socially reinforced, and policy-enabled.

Performance expectancy emerged as the strongest predictor of adoption, confirming that perceived usefulness and tangible performance improvements are central to digital transformation. Effort expectancy and social influence also showed significant effects, highlighting the importance of usability and leadership endorsement. Facilitating conditions and technology compatibility, while not direct predictors, exerted meaningful indirect effects through government intervention, which acts as an institutional catalyst linking user perceptions and organisational readiness to actual adoption outcomes.

The study contributes theoretically by combining behavioural, technological, and policy dimensions within a single framework, demonstrating that effective technology adoption in emerging economies depends on both internal motivation and external institutional support. Practically, it underscores that sustainable digital transformation requires performance-linked policies, skill development, and integrated infrastructure. Policymakers should align national innovation goals with SME realities through targeted incentives, training, and ecosystem collaboration.

Although limited to Jiangsu Province and cross-sectional data, the study offers a foundation for future longitudinal and comparative research. Ultimately, the success of I4.0 adoption depends on the synergy between enterprise capability, technological alignment, and policy facilitation, enabling SMEs to advance China's vision of innovation-led industrial growth.

REFERENCES

Alfaro-Serrano, A. (2021). Industry 4.0 adoption in Latin America: A comparative study. *Journal of Manufacturing Technology Management*, *32*(7), 1234-1250.

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change, 170*, 120880. https://doi.org/10.1016/j.techfore.2021.120880

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics*, *204*, 383-394. https://doi.org/10.1016/j.ijpe.2018.08.019

Farmer, R. (2025). *China's economy rallies to reach growth target; 2025 outlook remains uncertain.* US-China Business Council.

Ghobakhloo, M., & Ching, N. T. (2019). Adoption of digital technologies in manufacturing SMEs: An integrated TAM-TOE model. *Journal of Manufacturing Technology Management*, *30*(5), 910-931.

Ghobakhloo, M., & Fathi, M. (2022). Industry 4.0 and digital supply chain capabilities: A resource-based view. *Technological Forecasting and Social Change*, *170*, 120939. https://doi.org/10.1016/j.techfore.2021.120939

Ghobakhloo, M. (2018). The future of manufacturing industry: A strategic roadmap toward Industry 4.0. *Journal of Manufacturing Technology Management*, *29*(6), 910-936.

Ghobakhloo, M., Iranmanesh, M., Vilkas, M., Grybauskas, A., & Amran, A. (2022). Drivers and barriers of Industry 4.0 technology adoption among manufacturing SMEs: A systematic review and transformation roadmap. *Journal of Manufacturing Technology Management, 33*(6), 1029-1058. https://doi.org/10.1108/JMTM-12-2021-0505

Goh, A. C.-H., & Che Awang, N. B. (2025). Government intervention as a mediator of Industry 4.0 users' adoption: Empirical evidence from China's manufacturing industry. *International Journal of Business and Management, 20*(4), 293–313. https://doi.org/10.5539/ijbm.v20n4p293

Goh, A. C.-H., Che Awang, N. B., & Bawazir, A. (2025). The factors influencing users' adoption of Industry 4.0 in China's manufacturing industry: A conceptual paper. *Asian Journal of Business and Management, 13*(1), Article 464. https://doi.org/10.24203/anfqb464

Goodhue, D. L. (2006). Task-technology fit. In P. Zhang & D. F. Galletta (Eds.), *Human-Computer Interaction and Management Information Systems: Foundations*, 184-204.

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *MIS Quarterly*, *19*(2), 213-236. https://doi.org/10.2307/249689

Handoko, B. L., & Liusman, E. (2021). The impact of digital transformation on organizational performance: Evidence from Indonesia. *Asian Journal of Business and Accounting*, *14*(1), 123-145.

He, L. (2024). *China's economic growth rate skepticism.* CNN.

Jennings, R. (2025). *IMF raises China's 2025 GDP forecast by a hair, cites stimulus effects.* South China Morning Post.

Keynes, J. M. (1936). *The general theory of employment, interest, and money*. Macmillan.

Lin, Y., Wang, Y., & Yu, C. (2022). Digital transformation and firm performance: The mediating role of innovation capability. *Journal of Business Research*, *139*, 1-12. https://doi.org/10.1016/j.jbusres.2021.09.012

Peng, M. W. (2003). Institutional transitions and strategic choices. *Academy of Management Review, 28*(2), 275-296. https://doi.org/10.5465/amr.2003.9416341

Phang, T. C. H., Chen, C., & Tiong, R. L. K. (2020). New model for identifying critical success factors influencing BIM adoption from precast concrete manufacturers' view. *Journal of Construction Engineering and Management, 146*(4). https://doi.org/10.1061/(ASCE)CO.1943-7862.0001773

Rahim, N. I. M., Iahad, N. A., Yusof, A. F., & Al-Sharafi, M. A. (2022). AI-Based chatbots adoption model for higher-education institutions: A hybrid pls-sem-neural network modelling approach. *Sustainability, 14*(19), 726. https://doi.org/10.3390/su141912726

Sony, M., & Naik, S. (2020). Critical factors for the successful implementation of Industry 4.0: A review and future research direction. *Production Planning & Control, 31*(10), 799-815. https://doi.org/10.1080/09537287.2019.1691278

Sony, M., Naik, S., & Lee, M. (2021). Industry 4.0 benefits, challenges and readiness: A systematic review. *Technology in Society, 67*, 101754. https://doi.org/10.1016/j.techsoc.2021.101754

Stentoft, J., Wickstrøm, K. A., Philipsen, K., & Haug, A. (2021). Drivers and barriers for Industry 4.0 readiness and practice: Empirical evidence from small and medium-sized manufacturers. *Production Planning & Control, 32*(10), 811-828. https://doi.org/10.1080/09537287.2020.1810765portal.findresearcher.sdu.dk

van Dun, D. H., & Kumar, M. (2023). Social enablers of Industry 4.0 technology adoption: Transformational leadership and emotional intelligence. *International Journal of Operations & Production Management, 43*(13),152-182. https://doi.org/10.1108/IJOPM0620220370pdfs.semanticscholar.org+8research.utwente.nl+8scholar.google.com+8

van Zeebroeck, N., Kretschmer, T., & Bughin, J. (2021). Digital "is" strategy: The role of digital technology adoption in strategy renewal. *IEEE Transactions on Engineering Management, PP*(99), 1-15. https://doi.org/10.1109/TEM.2021.3079347

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Zhai, H., Yang, X., Xue, J., Lavender, C., Ye, T., Li, J., Xu, L., Lin, L., Cao, W., & Sun, Y. (2021). Radiation oncologists' perceptions of adopting an artificial intelligence-assisted contouring technology: Model development and questionnaire study. *Journal of Medical Internet Research, 23*(9), e27122. https://doi.org/10.2196/27122

Zhang, N., Ye, J., Zhong, Y., & Chen, Z. (2023). Digital transformation in the Chinese construction industry: Status, barriers, and impact. *Buildings, 13*(4), 1092. https://doi.org/10.3390/buildings13041092

Zhou, B., & Zheng, L. (2023). Technology-pushed, market-pulled, or government-driven? The adoption of Industry 4.0 technologies in a developing economy. *Journal of Manufacturing Technology Management, 34*(9),115-138.https://doi.org/10.1108/JMTM-09-2022-0313pdfs.semanticscholar.org+3ingentaconnect.com+3emerald.com+3