The Impacts of Environmental Context on Technology Adoption and Their Invariance Analysis in Chinese Supply Chains

Zengwen Yan[1] and Kaining Ge[2]
[1]School of Intelligent Finance and Business, Xi'an Jiaotong Liverpool University, Suzhou, China
[2]Management School, University of Liverpool, Liverpool, U.K.

Keywords: Technology Adoption, Regulatory Environment, Business Innovation Environment, Technology Performance, Technology–Organisation–Environment Framework.

Abstract: Industry 4.0 technologies are increasingly used by corporations worldwide, but their successful adoption remains problematic. In particular, the manufacturing and logistics industries in China have achieved more promising outputs, supported by the adoption of emerging technologies in their supply chains. It is important to research whether environmental context provides a conducive atmosphere for the corporate adoption of these technologies. The study employs structural equation modelling (SEM) with data collected through 1,441 questionnaires from the manufacturing and related industries across mainland China. This paper focuses on and discusses how environmental context affects technology adoption (TA) and post-performance based on the technology–organisation–environment (TOE) framework. The study finds that in China, the regulatory environment (RE) does not directly affect technology adoption and performance (TAP); rather, the business innovation environment (BIE), greatly affected by the RE, influences TAP. This study enriches the content on environmental context, examines the robustness and generalizability of the results.

1 INTRODUCTION

In the contemporary landscape of global industry and technology, the concept of 'Industry 4.0' emerges as a pivotal force reshaping the dynamics of production and supply chain management. Xu et al. (2018) posited that the 'Industry 4.0 project is considered a major endeavour for Germany to establish itself as a leader of integrated industry'; achieving this goal predominantly hinges on technology adoption (TA), which is still in its nascent stages. This necessity is widely recognized across industries, especially in manufacturing and logistics, to maintain continuous production and reliable supply chains amid economic uncertainties. Digital transformation through TA enhances supply chain resilience and visibility (Narwane et al., 2023), highlighting TA's importance in reducing risks and losses.

This study initiates its examination of TA in supply chains through a technology–organisation–environment (TOE) framework, identifying gaps from existing literature. Notably, the research on TA's environmental contexts is limited (Lin, 2014), somewhat vague and broad, despite extensive studies on its organizational and technological aspects (Yeh and Chen, 2018). This research, therefore, focuses on the environmental dimension of TOE. Second, it highlights the scant attention to environmental factors, especially the regulatory environment (RE), a crucial and original TOE element impacting TA and performance (TAP) that has been overlooked for years (Schwarz and Schwarz, 2014; Yeh and Chen, 2018). This paper aims to bridge this gap by focusing on RE, comparing it with the business innovation environment (BIE) regarding TAP (Zhu et al., 2003). Last, it addresses the call for testing findings from developed economies in developing ones, examining Chinese enterprises to glean insights into TA within the Chinese context, responding to calls for broader geographic research applicability (Adomako and Danso, 2014).

2 LITERATURE REVIEW

2.1 Theoretical Background

The TOE framework developed by Tornatzky et al. (1990) is commonly used, with the aim of facilitating

Yan, Z. and Ge, K.
The Impacts of Environmental Context on Technology Adoption and Their Invariance Analysis in Chinese Supply Chains.
DOI: 10.5220/0012622200003717

In *Proceedings of the 6th International Conference on Finance, Economics, Management and IT Business (FEMIB 2024)*, pages 104-111
ISBN: 978-989-758-695-8; ISSN: 2184-5891

the adoption of technological innovations; its technological, organisational and environmental contexts were identified to ascertain whether a firm can successfully implement a technological innovation. Besides, the TOE framework, with a validated theoretical foundation, provides valuable insights for TA across companies, consistent empirical studies support the usefulness of the TOE framework and it is argued that environmental context contributes more to the adoption of information technology than technological and organisational contexts (Pan and Jang, 2008). The environmental context refers to the external situations a corporation may encounter, for example, the government's regulatory policies, the BIE created by the local community and the corporation's industry competitors (Tornatzky et al., 1990).

2.2 Environmental Context of the Technology–Organisation–Environment Framework

Prior research on environmental context lacks clarity (Schwarz and Schwarz, 2014). RE significantly impacts TAP, with mixed findings on its effect. Zhu and Kraemer (2005) found that government regulations play a key role in encouraging firms to adopt new technologies, with supportive regulations or business laws providing incentives and fostering trust in e-business. In China, governmental regulations and support notably shape business operations, and in emerging markets, the blend of Information Technology adoption and political ties greatly affects firms' performance (Luo et al., 2023). Thus, enhancing understanding of the environmental context's role in TA is a primary goal of this research, as depicted in Figure 1.

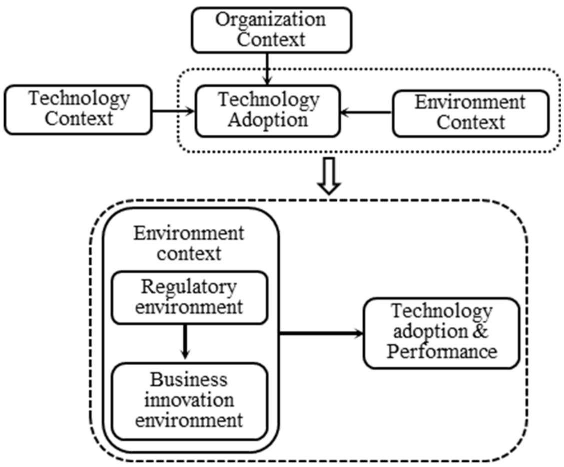

Figure 1: Focus and potential contribution of this study.

3 HYPOTHESIS DEVELOPMENT

3.1 Regulatory Environment and Business Innovation Environment

From a broad perspective, the notion of RE should encompass the political climate and governance authority, as well as policy matters of a region. Enhancing the RE in the marketplace establishes institutional protections for BIE, safeguarding their accomplishments and economic gains. This, in turn, boosts their innovative drive, with the enhancement of RE seen as pivotal for the BIE's survival and growth (Li et al. 2023). Opara et al. (2017) found that the RE significantly influences the BIE in Alberta, Canada, highlighting that political leadership and a supportive policy milieu are essential for a thriving BIE. The RE is deemed crucial for BIE to secure a competitive edge, especially benefiting from robust public safety and security, intellectual property rights protection, and an efficient judicial and legal framework. These factors help minimize the BIE's regulatory compliance costs and waste.

Generally, regulations contain strong controlling purposes of facilitating new targets—innovation being core among these—but the link between the RE and the BIE is indirect because it depends on the types of regulations and targets, which is reflected in the study of the livestock industry by Lin et al. (2023). A business-friendly RE allows an innovation environment to incubate and hatch because government activities pave the way for innovation by preparing a suitable external context, for instance, firms in countries with flexible employment laws raise a competitive edge over those in stricter regulatory nations, affecting the easiness of access to credit (Moro et al., 2022); as the BIE is rooted in the RE.

H1: The more friendly and welcoming the RE, the more dynamic the BIE.

3.2 Regulatory Environment and Technology Adoption and Performance

Prominent studies have concluded that TA is shaped by three sets of factors, one of which is regulatory policies. The influence of the RE on TA is significant and the level of TA is consistent with specific regulatory policies (Javier and Frank, 2006). In fact, TAP is encouraged by regulatory incentives, indicating that advanced technology is important for corporations in many ways, but is still not widespread for several reasons.

Kobos et al. (2018) claimed that a connection exists between regulatory constraints and TA, although the effects created by regulatory factors vary with the nature of each technology. Wang and Feeney (2016) adopted a stakeholder perspective to explore the regulatory behaviours of government, arguing that a positive connection exists between the RE and TAP, and that government and corporations share common interests as external and internal stakeholders, respectively. Opara et al. (2017) argued that political support contributes to TAP in Alberta, with government policies in that area playing the key role in TAP. Ouyang et al. (2019) empirically tested the supportive role of TA regulations in the hotel industry and found that the effect of such regulations may vary in size and scale. Peng et al. (2023) highlight the vital role of policies supporting IT capabilities, differentiated green innovation, and environmental regulations in boosting green tech innovation and corporate performance. Thus, the regulative institutions are the primary stimulus for corporations concerning their technology-related activities.

H2a: There is a positive relationship between a well-regulated environment and TAP.

3.3 Business Innovation Environment and Technology Adoption and Performance

Innovation plays a pivotal role in giving corporations a competitive advantage, both in the external business environment and in their internal innovation capability (Damanpour and Schneider, 2006). The BIE reflects changes in customer needs and future trends for business in relation to improving technological capability—the BIE is closely related to the adoption and performance of technology because there is a high degree of uncertainty associated with corporations' potential success (Tidd, 2001). Indeed, complexity and uncertainty affect organisational structure and intentions for TA. Prajogo and Ahmed (2006) argued that to enable TA, an active business context is required to incorporate practices for implementation and this context represents the enabling stimulus factor for TA. Corporations operate within a certain environmental context, the impulses of which lead them to further innovation, including TA. TAP responds to the BIE, which offers opportunities and resources—such as information and technology—and constraints, such as regulations and restrictions. Khanagha et al. (2013) argued that an ideal BIE should provide appropriate learning patterns and sufficient competences and resources, which can contribute to TA. Similarly, Persico et al. (2014) contended that providing a platform is essential to introducing technology, and changes should be gradual to achieve long-lasting effects. Corporations in a high-level BIE are more likely to introduce technology and obtain the expected performance (Pan and Jang, 2008).

H2b: The BIE is positively related to TAP for corporations, and the openness and dynamics of innovation in the business environment contribute to corporations being more likely to adopt technology and achieve better technological performance.

3.4 Conceptual Model

Apart from verifying the impacts of RE on TAP, and examining the influence of BIE on TAP, this study also investigates the generalisability and applicability of the improvements it has made to the TOE framework. Given that all the hypotheses are supported, whether the indicators of each construct and the model are applicable in different contexts remains doubtful. Thus, this study also conducts an invariance analysis from the perspectives of firm size and location. Figure 2 displays these relationships within the conceptual model.

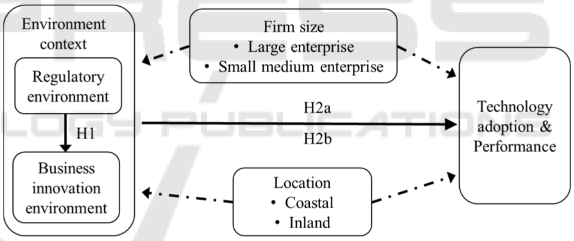

Figure 2: Conceptual model.

4 RESEARCH DESIGN

4.1 Measurements Development and Data Collection

This study applied the existing scales of Zhao (2018) as the framework and then adapted the items to measure the RE (Adomako and Danso, 2014), the BIE (Zhu and Kraemer, 2005) and TAP (Zhu and Kraemer, 2005; Xu et al., 2018). New measurements were developed as well based on the authors' understanding of the constructs concerning the Chinese cultural context and on observations made during interviews and firm visits. Data were collected from municipalities and provincial cities across mainland China for comprehensiveness. 1,441 corporations were studied, and a key informant from each corporation was identified to complete the questionnaire, who ensured the information about the internal and external processes was reliable and insightful.

4.2 Reliability and Validity

The research model was tested using structural equation modelling (SEM) with Amos 24.0, a covariance-based SEM. Considering the nature of this study, the covariance-based SEM was the preferred technique for theory testing and development, as indicated by Fornell and Bookstein (1982). For the TAP construct, the study adopted a second-order mode in the measurement model. In the following two subsections, five representative technology constructs in the first-order measurement model—automation technology (AT), the information management system (IMS), the Internet of Things (IoT), big data (Data) and the logistics platform (Plat)—are analysed along with the RE and BIE constructs; the third subsection discusses the second-order TAP construct.

4.2.1 Reliability Analysis

Construct reliability refers to the degree to which items are free from random errors and, as a result, yield consistent results. According to the criteria suggested by Hair et al. (2010), squared multiple correlations (SMCs) should be greater than 0.36 to indicate the reliability of each item for the latent variable. The values of SMC in the measurement model were all greater than this suggested limit. Further, composite reliability (CR) was analysed following Hair et al.'s (2010) suggestion that the CR value be greater than 0.7 to indicate reliable and consistent data within the same construct (Straub, 1989).

Table 1: Presents the reliability results for each construct.

		SMC	CR			SMC	CR
BIE	BIE1	.643	.836	RE	RE1	.480	.847
	BIE2	.494			RE2	.527	
	BIE3	.533			RE3	.646	
	BIE4	.575			RE4	.674	
AT	AT1	.830	.938	IMS	IMS1	.803	.891
	AT2	.806			IMS2	.671	
	AT3	.865			IMS3	.721	
IoT	IoT1	.835	.919	Data	Data1	.891	.949
	IoT2	.762			Data2	.929	
	IoT3	.774			Data3	.764	
Plat	Plat1	.856	.928				
	Plat2	.806					
	Plat3	.769					

4.2.2 Construct Validity

Straub (1989) argued that successive stages of refinement are necessary for developing an appropriate measurement model. Confirmatory factor analysis was employed to examine construct validity, with two types of validity assessed. Convergent validity examines consistency across multiple operationalisations (Bagozzi et al., 1991). Here, all standardised factor loadings (Std) ranged between 0.6 and 0.95 and were significant ($p < 0.001$), strongly supporting good convergent validity for each construct. The average variance extracted (AVE) (Fornell and Larcker, 1981) was applied to further confirm convergent validity. The AVE value of each construct should exceed the threshold value of 0.5 (Hair et al., 2010).

Table 2: Convergent validity results for the BIE, RE, and technology constructs.

		Std	AVE			Std	AVE
BIE	BIE1	.802	.561	RE	RE1	.693	.582
	BIE2	.703			RE2	.726	
	BIE3	.730			RE3	.804	
	BIE4	.758			RE4	.821	
AT	AT1	.911	.834	IMS	IMS1	.896	.732
	AT2	.898			IMS2	.819	
	AT3	.930			IMS3	.849	
IoT	IoT1	.914	.790	Data	Data1	.944	.861
	IoT2	.873			Data2	.964	
	IoT3	.880			Data3	.874	
Plat	Plat1	.925	.810				
	Plat2	.898					
	Plat3	.877					

Discriminant validity compares the square root of the AVE of a particular construct with the correlation between that construct and other constructs. The value of the square root of the AVE should be higher than the correlation (Henseler et al., 2015).

Table 3: Discriminant validity of each construct.

	AVE	BIE	RE	Data	Plat	AT	IoT	IMS
BIE	.561	**.749**						
RE	.582	.744	**.763**					
Data	.861	.103	.100	**.928**				
Plat	.810	.129	.139	.538	**.900**			
AT	.834	.123	.074	.362	.329	**.913**		
IoT	.790	.110	.094	.453	.531	.420	**.889**	
IMS	.732	.058	.083	.436	.617	.335	.557	**.856**

4.2.3 Rationality of Second-Order Construct

The structure of TAP as a second-order construct was described above. The paths from the TAP construct to four of the five first-order constructs were of high magnitude and significance, according to the suggested limit of 0.7 (Chin, 1998). For the AT construct, the value was quite close to 0.5: the value suggested by Hair et al. (2010) as acceptable. Marsh and Hocevar (1988) proposed that the efficacy of the second-order model be evaluated through the target coefficient (t-ratio) with an upper bound of 1, which is the outcome of the chi-square division between the first- and the second-order constructs. The t-ratio of the proposed model was 0.964, which isreasonably close to 1. This result indicates that the second-order construct captured the key connections among the first-order constructs (Stewart and Segars, 2002). As a result, on both theoretical and empirical grounds, the conceptualisation of TAP as a higher-order and multidimensional construct was justified. In addition, reliability and validity issues for the second-order construct were examined. Table 4 summarises all relevant results.

Table 4: Reliability and validity: TAP construct.

		P	Std	SMC	CR	AVE
TAP	IMS		0.700	0.490	0.789	0.433
	IoT	***	0.695	0.483		
	AT	***	0.478	0.228		
	Plat	***	0.744	0.554		
	Data	***	0.640	0.410		

Note: *** $p < 0.001$

4.3 Model Fitness

The Goodness-of-Fit Index (GFI) and its adjusted version (AGFI), which corrects for the number of indicators per latent variable, assess model fit by comparing the proposed model to observed data, with values above 0.9 indicating acceptability (Hooper et al., 2008). Similarly, the Comparative Fit Index (CFI) evaluates model discrepancy, considering sample size, with values closer to 1 suggesting a better fit; this study's model showed a CFI of 0.98, denoting a good fit (Teo & Khine, 2009). The Root Mean Square Error of Approximation (RMSEA) addresses sample size issues, aiming for values under 0.08 for acceptable fit; the model achieved 0.04 (Hooper et al., 2008; Hair et al., 2010). Lastly, a Chi-square to degrees of freedom ratio between 1 and 5, as seen with 3.325 in this study, signifies a good fit without overfitting (James, 1987). All indices confirmed the model's adequacy.

Table 5: Summary statistics of model fitness.

Chi-square	206.165	GFI	0.978
Degree of freedom	62.000	AGFI	0.968
Chi-square/DF	3.325	CFI	0.98
P value	< 0.000	RMSEA	0.04
Standardised RMR	0.0302		

5 DISCUSSION

5.1 Results

5.1.1 Conceptual Model Results Analysis

A correlation analysis of the data for possible relationships among variables has been conducted, the results in Table 6 reveal that RE is positively related to BIE ($p < 0.001$) and significantly influences BIE, supporting H1: a friendly and welcoming RE leads to a dynamic BIE, and the more friendly and welcoming the RE, the more dynamic the BIE. In examining the effects of the RE and the BIE on TAP, the quantified data show different results. For the relationship between RE and TAP, H2a is rejected ($p = 0.202$), indicating no significant effect of RE on TAP in China, challenging common beliefs about RE's importance in business across Mainland China. That is, the present study found no direct effects on this relationship. For the relationship between the BIE and TAP, the significance value was $p = 0.044$, thus supporting H2b at the 95% confidence level. This implies that the BIE is positively related to TAP for corporations, and the openness and dynamics of innovation in the business environment contribute to corporations being more likely to adopt technology and achieve better technological performance.

Table 6: Results of hypotheses.

RE	BIE	***	H1	Supported
RE	TAP	0.202	H2a	Rejected
BIE	TAP	0.044*	H2b	Supported

Note: * $p < 0.05$, *** $p < 0.001$

5.1.2 Robustness Analysis

There might be other factors affecting the results if the dataset were changed. Thus, the authors re-categorised the data into sub-groups, as per features of the data used for analysis, and selected one sub-group to run the SEM again to test the robustness of the above results. No significant difference was found (Table 7) between the re-categorised data and the above results proving the reliability of the results.

Table 7: Results of re-categorised data (coastal area).

RE	BIE	***	H1	Supported
RE	TAP	0.841	H2a	Rejected
BIE	TAP	0.011*	H2b	Supported

Note: * $p < 0.05$, *** $p < 0.001$

To explore the generalisability of the conceptual model in this study to other contexts, the authors further conducted multi-group invariance analysis in the aspects of firm size and location. Given that the conceptual model can be replicable in each context, a comparison of multi-group SEMs was carried out. Byrne (2016) noted the importance of factor loadings, covariances, and structural regression paths in evaluating the model's relevance for multi-group equivalence, with results detailed in Table 8. The model's fit was confirmed using CMIN/DF, AGFI, CFI, and RMSEA metrics.

To test the invariance of multi-group SEMs, the p value, ΔCFI, and ΔTLI are key, the latter two are frequently employed to assist with the judgment of invariance results. Despite the p value's limitations, Little (1997) and Cheung and Rensvold (2002) highlighted $\Delta TLI \leq 0.05$ and $\Delta CFI \leq 0.01$ as indicators of invariance to be supported, respectively. Table 8 shows the values of p, ΔCFI and ΔTLI confirm the invariance of multi-group SEMs in the context of the firm location. As for the context of the firm size, though the p-value is significant and rejects the invariance from a statistical perspective, the values of ΔCFI and ΔTLI support the invariance of multi-group SEMs in the context of firm size. Therefore, the study supports the conceptual model's invariance and general applicability.

Table 8: Fit goodness and comparison of multi-group invariance results.

	Model	CMIN	DF	CMIN/DF	AGFI	CFI	RMSEA	P	ΔCFI	ΔTLI
Large vs. SMEs	Baseline	279.902	127	2.204	0.958	0.979	0.029			
	Measurement weights	329.217	137	2.403	0.955	0.973	0.031	***	−0.006	0.004
	Structural covariances	330.552	138	2.395	0.955	0.973	0.031	0.248	0	0
	Structural residuals	348.930	140	2.492	0.952	0.971	0.032	***	−0.002	0.002
Coastal vs. Inland	Baseline	296.148	127	2.332	0.956	0.976	0.030			
	Measurement weights	301.629	137	2.202	0.958	0.977	0.029	0.857	0.001	−0.003
	Structural covariances	304.861	138	2.209	0.958	0.977	0.029	0.072	0	0
	Structural residuals	305.282	140	2.181	0.959	0.977	0.029	0.81	0	−0.001

Note: *** $p < 0.001$

5.2 Managerial Implications

Municipal governments should use emerging technologies to boost city competitiveness and innovation, fostering business growth and supply chain development. Government should act as a service provider, supporting a BIE and using online platforms for enterprise services. Industry associations mediate between government and businesses, influencing policy for a dynamic business climate. For technology startups, easy access to venture capital, local education, and industry associations support technology implementation and innovation. Information platforms also play a crucial role in TAP. This study offers insights for policymakers, industry associations, investors, corporate management, and professionals on using emerging technologies to enhance operational efficiency and innovation, benefiting both government and industry by understanding TAP's impact.

5.3 Theoretical Implications

This study reveals three key theoretical implications of testing a conceptual model. Firstly, it shows that TA in supply chains, especially in China, is driven by external corporate environments and faces challenges in practical implementation due to the gap between research and industry practices. It highlights the reluctance in adopting new technologies due to uncertain outcomes. This study provides successful TAP evidence and increases corporations' confidence in implementing emerging technologies in their supply chains. Secondly, it contributes to the TOE framework by focusing on the environmental context's role in TA, a previously underexplored area, and distinguishes between regulatory and business environmental impacts on TA in Chinese supply chains. Further, it suggests a new direction for analysing the BIE as the root cause of TAP. Lastly, it applies findings from developed contexts to developing ones like China, showing that Chinese corporations are affected by government policies similarly to those in mature economies, suggesting a shift towards a more mature market economy in China. This challenges traditional views and emphasizes the evolving role of government regulations in supporting corporate needs in China.

6 CONCLUSIONS

Based on the TOE framework, this study adds to the literature by examining how environmental factors impact TAP from an environmental viewpoint. It finds a connection between the RE and BIE, offering a fuller view of TAP adoption in Chinese supply chains before and after. To prevent TA failure, companies need to fully assess their environments since RE doesn't directly affect TAP success. Instead, BIE, stemming from RE, plays a key role in whether firms can successfully adopt new technologies to boost performance. As emerging technologies are complex, their application in production needs ongoing focus to better TA effectiveness, lower failure rates, enhance performance, and increase competitiveness.

Due to length constraints, more details on measurement development, sample and data collection, and numerical analysis results can be provided by contacting the authors for those interested.

REFERENCES

Adomako, S. and Danso, A. (2014), “Regulatory environment, environmental dynamism, political ties, and performance: study of entrepreneurial firms in a developing economy”, *Journal of Small Business and Enterprise Development*, Vol. 21 No. 2, pp. 212–30.

Bagozzi, R. P., Youjae, Y. and Phillips, L. W. (1991), “Assessing construct validity in organizational research”, *Administrative Science Quarterly*, Vol. 36 No. 3, pp. 421–58.

Byrne, B. M. (2016), *Structural equation modeling with Amos: basic concepts, applications, and programming,* 3rd edn, Routledge, New York, NY.

Cheung, G. W. and Rensvold, R. B. (2002), “Evaluating goodness-of-fit indexes for testing measurement invariance”, *Structural Equation Modeling*, Vol. 9, pp. 233–55.

Chin, W. W. (1998), “Issues and opinion on structural equation modeling”, *MIS Quarterly*, Vol. 22 No. 1, pp. vii–xvi.

Damanpour, F. and Schneider, M. (2006), “Phases of the adoption of innovation in organizations: effects of environment, organization and top managers”, British Journal of Management, Vol. 17 No. 3, pp. 215–36.

Fornell, C. and Bookstein, F. L. (1982), “Two structural equation models: LISREL and PLS applied to consumer exit-voice theory”, *Journal of Marketing Research*, Vol. 19 No. 4, pp. 440–52.

Fornell, C. and Larcker, D. F. (1981), “Evaluating structural equation models with unobservable variables and measurement error”, *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39–50.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E. and Tatham, R. L. (2010), *Multivariate data analysis: a global perspective*, Pearson-Hall International, Upper Saddle River, NJ.

Henseler, J., Ringle, C. M. and Sarstedt, M. (2015), “A new criterion for assessing discriminant validity in variance-based structural equation modeling”, *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp. 115–35.

Hooper, D., Coughlan, J. and Mullen, M. (2008), “Structural equation modelling: guidelines for determining model fit”, *Electronic Journal of Business Research Methods*, Vol. 6 No. 1, pp. 53–60.

James, C. A. (1987), “An approach for confirmatory measurement and structural equation modeling of organizational properties”, *Management Science*, Vol. 33 No. 4, pp. 525–41.

Javier, C. and Frank, W. (2006), “Information technology adoption and political regimes”, International Studies Quarterly, Vol. 50 No. 4, pp. 911–33.

Khanagha, S., Volberda, H., Sidhu, J. and Oshri, I. (2013), “Management innovation and adoption of emerging technologies: the case of cloud computing”, *European Management Review*, Vol. 10 No. 1, pp. 51–67.

Kobos, P. H., Malczynski, L. A., Walker, L. T. N., Borns, D. J. and Klise, G. T. (2018), “Timing is everything: a technology transition framework for regulatory and market readiness levels”, *Technological Forecasting and Social Change*, Vol. 137, pp. 211–25.

Li, X., Tang, J. and Huang, J. (2023) ‘Place-based policy upgrading, business environment, and urban innovation: Evidence from high-tech zones in China’, *International Review of Financial Analysis*, 86.

Little, T. D. (1997), “Mean and covariance structures (MACS) analyses of cross-cultural data: practical and theoretical issues”, *Multivariate Behavioral Research*, Vol. 32, pp. 53–76.

Luo, G., Serrão, C., Liang, D., & Zhou, Y. (2023) ‘A Relevance-Based Technology–Organisation–Environment Model of Critical Success Factors for Digital Procurement Adoption in Chinese Construction Companies’, *Sustainability*, 15(16), p. 12260.

Marsh, H. W. and Hocevar, D. (1988), “A new, more powerful approach to multitrait-multimethod analyses: application of second-order confirmatory factor analysis”, *Journal of Applied Psychology*, Vol. 73 No. 1, pp. 107–17.

Moro, A., Maresch, D., Ferrando, A. & Udell., (2022) ‘Funding innovation and the regulatory environment - The role of employment protection legislation’, *Journal of Business Research*, 145, pp. 745-756-756.

Narwane, VS, Raut, RD, Mangla, SK, Dora, M & Narkhede, BE. (2023) ‘Risks to Big Data Analytics and Blockchain Technology Adoption in Supply Chains’, *Annals of Operations Research*, 327(1), pp. 339-374.

Opara, M., Elloumi, F., Okafor, O. and Warsame, H. (2017), “Effects of the institutional environment on public–private partnership (P3) projects: evidence from Canada”, *Accounting Forum*, Vol. 41 No. 2, pp. 77–95.

Ouyang, Z., Wei, W. and Chi, C. G. (2019), “Environment management in the hotel industry: does institutional environment matter?”, *International Journal of Hospitality Management*, Vol. 77, pp. 353–64.

Pan, M. and Jang, W. (2008), “Determinants of the adoption of enterprise resource planning within the technology–organization–environment framework: Taiwan’s communications industry”, *Journal of Computer Information Systems*, Vol. 48 No. 3, pp. 94–102.

Peng, Y., Zhou, J., Lin, M., & Feng, D. (2023) ‘The Impact of IT Capability on Corporate Green Technological Innovation: Evidence from Manufacturing Companies in China’, *Journal of Information & Knowledge Management*, 22(1), pp. 1-24.

Persico, D., Manca, S. and Pozzi, F. (2014), “Adapting the technology acceptance model to evaluate the innovative potential of e-learning systems”, *Computers in Human Behavior*, Vol. 30, pp. 614–22.

Prajogo, D. I. and Ahmed, P. K. (2006), “Relationships between innovation stimulus, innovation capacity, and innovation performance”, *R&D Management*, Vol. 36 No. 5, pp. 499–515.

Schwarz, C and Schwarz A. (2014), “To Adopt or not to adopt: a perception-based model of the EMR technology adoption decision utilizing the technology organization environment framework”, *Journal of Organizational and End User Computing*, Vol. 26, pp. 57–79.

Stewart, K. A. and Segars, A. H. (2002), “An empirical examination of the concern for information privacy instrument”, *Information Systems Research*, Vol. 13 No. 1, pp. 36–49.

Straub, D. W. (1989), “Validating instruments in MIS research”, *MIS Quarterly*, Vol. 13 No. 2, pp. 147–169.

Teo, T. and Khine, M. S. (2009), *Structural equation modeling in educational research*, Sense Publishers, Rotterdam, Holland.

Tidd, J. (2001), “Innovation management in context: environment, organization and performance”, *International Journal of Management Reviews*, Vol. 3 No. 3, pp. 169–83.

Tornatzky, L. G., Fleischer, M. and Chakrabarti, A. K. (1990), *Processes of technological innovation*, Lexington Books, Lexington, MA.

Wang, S. and Feeney, M. K. (2016), “Determinants of information and communication technology adoption in municipalities”, *American Review of Public Administration*, Vol. 46 No. 3, pp. 292–313.

Xu, L. D., Xu, E. L. and Li, L. (2018), “Industry 4.0: state of the art and future trends”, *International Journal of Production Research*, Vol. 56 No. 8, pp. 2941–62.

Yeh, C and Chen, Y. (2018), “Critical success factors for adoption of 3D printing”, *Technological Forecasting and Social Change*, Vol. 132, pp. 209–16.

Zhao, X. (2018), *Logistics technology development report of China 2018—technology assisting logistics*, CEIBS-GLP Supply Chain and Services Innovative Center, Shanghai, China.

Zhu, K. and Kraemer, K. L. (2005), “Post-adoption variations in usage and value of e-business by organizations: cross-country evidence from the retail industry”, *Information Systems Research*, Vol. 16 No. 1, pp. 61–84.

Zhu, K., Kraemer, K. and Xu, S. (2003), “Electronic business adoption by European firms: a cross-country assessment of the facilitators and inhibitors”, *European Journal of Information Systems*, Vol. 12 No. 4, pp. 251–68.