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

Zengwen Yan¹ and Kaining Ge²

¹School of Intelligent Finance and Business, Xi’an Jiaotong Liverpool University, Suzhou, China
²Management 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...
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.

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.

Figure 1: Focus and potential contribution of this study.
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.

![Conceptual model](image)

**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.

<table>
<thead>
<tr>
<th></th>
<th>SMC CR</th>
<th></th>
<th>SMC CR</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>BIE</td>
<td>.643</td>
<td>.836</td>
<td>RE1</td>
<td>.480</td>
</tr>
<tr>
<td>BIE2</td>
<td>.494</td>
<td></td>
<td>RE2</td>
<td>.527</td>
</tr>
<tr>
<td>BIE3</td>
<td>.533</td>
<td></td>
<td>RE3</td>
<td>.646</td>
</tr>
<tr>
<td>BIE4</td>
<td>.575</td>
<td></td>
<td>RE4</td>
<td>.674</td>
</tr>
<tr>
<td>AT1</td>
<td>.830</td>
<td>.938</td>
<td>IMS1</td>
<td>.803</td>
</tr>
<tr>
<td>AT2</td>
<td>.806</td>
<td></td>
<td>IMS2</td>
<td>.671</td>
</tr>
<tr>
<td>AT3</td>
<td>.865</td>
<td></td>
<td>IMS3</td>
<td>.721</td>
</tr>
<tr>
<td>IoT1</td>
<td>.835</td>
<td>.919</td>
<td>Data1</td>
<td>.891</td>
</tr>
<tr>
<td>IoT2</td>
<td>.762</td>
<td></td>
<td>Data2</td>
<td>.929</td>
</tr>
<tr>
<td>IoT3</td>
<td>.774</td>
<td></td>
<td>Data3</td>
<td>.764</td>
</tr>
<tr>
<td>Plat1</td>
<td>.856</td>
<td>.928</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Plat2</td>
<td>.806</td>
<td></td>
<td>Plat4</td>
<td>.898</td>
</tr>
<tr>
<td>Plat3</td>
<td>.769</td>
<td></td>
<td>Plat3</td>
<td>.877</td>
</tr>
</tbody>
</table>

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).

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.

<table>
<thead>
<tr>
<th></th>
<th>Std AVE</th>
<th></th>
<th>Std AVE</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>BIE1</td>
<td>.802</td>
<td>.561</td>
<td>RE1</td>
<td>.693</td>
</tr>
<tr>
<td>BIE2</td>
<td>.703</td>
<td></td>
<td>RE2</td>
<td>.726</td>
</tr>
<tr>
<td>BIE3</td>
<td>.730</td>
<td></td>
<td>RE3</td>
<td>.804</td>
</tr>
<tr>
<td>BIE4</td>
<td>.758</td>
<td></td>
<td>RE4</td>
<td>.821</td>
</tr>
<tr>
<td>AT1</td>
<td>.911</td>
<td>.834</td>
<td>IMS1</td>
<td>.896</td>
</tr>
<tr>
<td>AT2</td>
<td>.898</td>
<td>IMS</td>
<td>IMS2</td>
<td>.819</td>
</tr>
<tr>
<td>AT3</td>
<td>.930</td>
<td>IMS</td>
<td>IMS3</td>
<td>.849</td>
</tr>
<tr>
<td>IoT1</td>
<td>.914</td>
<td>.790</td>
<td>Data1</td>
<td>.944</td>
</tr>
<tr>
<td>IoT2</td>
<td>.873</td>
<td>Data</td>
<td>Data2</td>
<td>.964</td>
</tr>
<tr>
<td>IoT3</td>
<td>.880</td>
<td>Data</td>
<td>Data3</td>
<td>.874</td>
</tr>
<tr>
<td>Plat1</td>
<td>.925</td>
<td>.810</td>
<td>Plat2</td>
<td>.898</td>
</tr>
<tr>
<td>Plat3</td>
<td>.877</td>
<td>Plat3</td>
<td>Plat3</td>
<td>.877</td>
</tr>
</tbody>
</table>
Table 3: Discriminant validity of each construct.

<table>
<thead>
<tr>
<th></th>
<th>AVE</th>
<th>BIE</th>
<th>RE</th>
<th>Data</th>
<th>Plat</th>
<th>AT</th>
<th>IoT</th>
<th>IMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>BIE</td>
<td>.561</td>
<td>.749</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RE</td>
<td>.582</td>
<td>.744</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>.861</td>
<td>.103</td>
<td>.100</td>
<td>.928</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Plat</td>
<td>.810</td>
<td>.129</td>
<td>.139</td>
<td>.538</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AT</td>
<td>.834</td>
<td>.123</td>
<td>.074</td>
<td>.362</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IoT</td>
<td>.790</td>
<td>.110</td>
<td>.094</td>
<td>.453</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IMS</td>
<td>.732</td>
<td>.058</td>
<td>.083</td>
<td>.436</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 is reasonably 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.

<table>
<thead>
<tr>
<th></th>
<th>P</th>
<th>Std</th>
<th>SMC</th>
<th>CR</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMS</td>
<td>0.700</td>
<td>0.490</td>
<td>0.789</td>
<td>0.433</td>
<td></td>
</tr>
<tr>
<td>IoT</td>
<td>***</td>
<td>0.695</td>
<td>0.483</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TAP</td>
<td>***</td>
<td>0.478</td>
<td>0.228</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Plat</td>
<td>***</td>
<td>0.744</td>
<td>0.554</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>***</td>
<td>0.640</td>
<td>0.410</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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.

<table>
<thead>
<tr>
<th></th>
<th>Chi-square</th>
<th>GFI</th>
<th>Degree of freedom</th>
<th>AGFI</th>
<th>Chi-square/DF</th>
<th>CFI</th>
<th>P value</th>
<th>RMSEA</th>
<th>Standardised RMR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>206.165</td>
<td>0.978</td>
<td>62.000</td>
<td>0.968</td>
<td>3.325</td>
<td>0.98</td>
<td>&lt; 0.000</td>
<td>0.04</td>
<td>0.0302</td>
</tr>
</tbody>
</table>

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.

<table>
<thead>
<tr>
<th></th>
<th>RE</th>
<th>BIE</th>
<th>***</th>
<th>H1</th>
<th>Supported</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RE</td>
<td>TAP</td>
<td>0.202</td>
<td>H2a</td>
<td>Rejected</td>
</tr>
<tr>
<td>BIE</td>
<td>TAP</td>
<td>0.044*</td>
<td>H2b</td>
<td>Supported</td>
<td></td>
</tr>
</tbody>
</table>

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).

<table>
<thead>
<tr>
<th></th>
<th>RE</th>
<th>BIE</th>
<th>***</th>
<th>H1</th>
<th>Supported</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RE</td>
<td>TAP</td>
<td>0.841</td>
<td>H2a</td>
<td>Rejected</td>
</tr>
<tr>
<td>BIE</td>
<td>TAP</td>
<td>0.011*</td>
<td>H2b</td>
<td>Supported</td>
<td></td>
</tr>
</tbody>
</table>

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 ΔTLI ≤ 0.05 and ΔCFI ≤ 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.

<table>
<thead>
<tr>
<th></th>
<th>RE</th>
<th>BIE</th>
<th>***</th>
<th>H1</th>
<th>Supported</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RE</td>
<td>TAP</td>
<td>0.202</td>
<td>H2a</td>
<td>Rejected</td>
</tr>
<tr>
<td>BIE</td>
<td>TAP</td>
<td>0.044*</td>
<td>H2b</td>
<td>Supported</td>
<td></td>
</tr>
</tbody>
</table>

Note: * p < 0.05, *** 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


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


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