INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN ECONOMICS & MANAGEMENT SCIENCES

OPEN ACCESS JOURNAL

Vol 13, Issue 4, (2024) E-ISSN: 2226-3624

The Moderating Role of Organisation Culture on the Relationship between Technology and Business Analytics Adoption

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To Link this Article: http://dx.doi.org/10.6007/IJAREMS/v13-i4/23350 DOI:10.6007/IJAREMS/v13-i4/23350

Published Online: 21 December 2024

Abstract
Data-driven decision-making using business analytics can give organisations a competitive advantage. However, this can only happen if organisations successfully adopt and use business analytics effectively. The adoption of new emerging technology, particularly among SMEs in developing countries, is unappealing. As a result, business analytics adoption in SMEs should be thoroughly researched. Previous research has revealed that relative advantage and compatibility are the most prominent factors in the technology dimension when adopting innovative technologies. However, the literature yielded inconclusive results regarding the importance of relative advantage and compatibility in adopting various technologies. Furthermore, organisation culture contributes different point of view to the technological dimension. As a result, this study conducted a quantitative survey to investigate the relationship between relative advantage and compatibility in business analytics adoption in SMEs, as well as the significant of organisational culture as a moderator in the relationship between technology dimension and adoption of business analytics. The online survey, which was sent via email, received 241 responses. The model was tested using partial least squares structural equation modelling (PLS-SEM), which revealed that relative advantage was significantly related to business analytics adoption, but compatibility did not affect adoption. However, the organisational culture significantly have an effect as a moderator on the compatibility. These findings can help managers, owners, vendors, and policy-makers encourage and facilitate the adoption of business analytics among SMEs in developing countries.

Keywords: Business Analytics Adoption, SMES, Relative Advantage, Compatibility, Organisational Culture

Introduction

Business analytics extract data produced by various technologies used in various industries. Scholars have recognised the value of business analytics (Deng et al., 2019; O'Neill & Brabazon, 2019); however, issues and challenges have been identified (Ellahi et al., 2019; Lin & Chang, 2018; Siew et al., 2020). Many businesses adopt business analytics because of its promising prospects; however, they fail to realise its rewards due to poor planning and deployment (Ransbotham & Kiron, 2017). Low levels of business analytics adoption make it tough for organisations to optimise the value of their data (Howson & Sallam, 2017).

Implementing new technology tools necessitates significant investment and may not yield the best results if the intended users do not fully appreciate the benefits (Lai, 2017). A study on technology adoption is critical at an early stage to maximise the benefits of business analytics (Sharma & Mishra, 2014). It assists in identifying needs and the perception of acceptance of individuals or organisations. During the development phase, the response may assist decision-makers in planning and preparing necessary actions (Taherdoost, 2018).

Aside from that, according to Gartner's survey, only 30% of employees in large organisations use analytics tools, despite studies showing that low levels of business analytics adoption lead to a struggle to maximise their data (Howson & Sallam, 2017). The problem could be worse in small industries, as technology absorption is the biggest weakness in entrepreneurial activities measured by The Global Entrepreneurship and Development Institute (Ács et al., 2018, 2019). As a result, this study aimed to investigate the role of technology in adopting business analytics among SMEs, and the significant of organisational culture in moderating the relationship.

Materials and Methods

Technology adoption theories and models have been employed in different domains to understand and predict user behaviour regarding technology adoption or acceptance (Dey et al., 2016; Khayer et al., 2020; Maroufkhani et al., 2020; Sun et al., 2020). Stakeholders must be aware of the issues influencing users' decisions to adopt a specific innovation technology. Aside from that, technology adoption studies can alleviate the burden of not achieving expected results in accepting or disseminating technology after organisations and governments have made significant investments in introducing new technologies.

The integration of the TOE and DOI is the most notable in the organisation's technology adoption (Baig et al., 2019). Rogers' diffusion of innovation (DOI) theory, developed in 1960, can be implemented at the individual and organisational levels to inform how, why, and how technological innovation expands across cultures (Oliveira & Martins, 2011). The Technology-Organisation-Environment (TOE) framework complements the limitations of DOI theory in terms of the environment (Tornatzky & Fleischer, 1990). In addition, the Dynamic Capability Theory (DCT) emphasizes on the usage of the existing resources and the benefit gained due to technology adoption. Thus, this study integrated the DOI, TOE, and DCT as the underpinning theory.

The availability and characteristics of internal and external technologies relevant to the organisations are referred to as the technology context (Puklavec et al., 2018). The scope of technology includes both existing innovations in the firm and technology that is not currently in use but is available on the market (Gupta & George, 2016). Various technological dimension constructs are present in studies on the adoption of analytics technology. However, some scholars continue to investigate the most common and widely studied technological construct, namely, relative advantage and compatibility (Agrawal, 2015; Boonsiritomachai et al., 2016; Chichti et al., 2016; Lai et al., 2018; Sam & Chatwin, 2019; Verma, 2017) due to the inconsistent findings.

Relative advantage refers to the characteristics of a specific innovation that are perceived to be better than existing ideas or systems (Rogers, 2003). Previous research has found that better benefits and higher value innovations have a higher rate of adoption (Ifinedo, 2011; Lai et al., 2018; Pillai & Sivathanu, 2020; Premkumar & Roberts, 1999). In addition, the impact of technological innovation and perceived organisational benefits contribute to a higher rate of adoption and implementation (Bishop, 2019; Duan et al., 2018; Mohamed & Weber, 2020). Many studies were performed to link relative advantage and technology adoption. Some empirical studies revealed a significant link between relative advantage and technology adoption (Ahani et al., 2017; Albar & Hoque, 2017; Alsetoohy et al., 2019; Boonsiritomachai et al., 2016; Correia Simões et al., 2020; Dey et al., 2016; Ilin et al., 2017; James, 2017; Junior et al., 2019; Khayer et al., 2020; Maroufkhani et al., 2020; Owusu et al., 2017; Pillai & Sivathanu, 2020; Sam & Chatwin, 2019; Shi & Yan, 2016; Sun et al., 2020; Wahab; et al., 2021; Yadegaridehkordi et al., 2018). However, some studies claimed the opposite (Agrawal, 2015; Ahmad et al., 2018; Gutierrez et al., 2015; Mohtaramzadeh et al., 2018; Puklavec et al., 2018; Yoon et al., 2020). Because the results are inconsistent, there is a need to investigate the relationship between relative advantage and business analytics adoption.
H_1: There is a significant positive relationship between relative advantage and business analytics adoption.

Compatibility refers to how well an innovation fits the potential adopter's existing values, past experiences, and needs (Rogers, 2003). The implementation innovation should be aligned with the organisation's legal and technical needs to avoid wasting time and resources (Boonsiritomachai et al., 2014; Lee, 2004). Aside from that, integrating the innovations with the existing process may yield better results than simply replacing the existing technologies (Agrawal, 2015). According to Cooper and Robert (Cooper & Robert, 1990), the higher the compatibility, the greater and faster adoption.

Researchers asserted and received significant support for the existence of a link between compatibility and technology adoption (Agrawal, 2015; Ahani et al., 2017; AL-Shboul, 2019; Correia Simões et al., 2020; Dey et al., 2016; Eze et al., 2019; Ghobakhloo & Ching, 2019; Junior et al., 2019; Maroufkhani et al., 2020; Rajan & Baral, 2015; Shi & Yan, 2016; Verma & Bhattacharyya, 2017; Yoon et al., 2020). However, some studies found no correlation between compatibility and technology adoption (Ahmad et al., 2018; Albar & Hoque, 2017; Boonsiritomachai et al., 2016; Gutierrez et al., 2015; Ifinedo, 2011; Owusu et al., 2017; Purwandari et al., 2019). As a result, the contradictory findings necessitate further investigation into the relationship between compatibility and business analytics adoption.
H_2: There is a significant positive relationship between compatibility and business analytics adoption.

Each organisation is unique and varies due to its organisational culture. Understanding the organisational culture is essential to inhibit organisational improvement and change. Research indicates healthy cultures enhance success, whereas unhealthy cultures inhibit success (Cameron & Quinn, 1999). Studies emphasise that organisational culture influences organisational performance and effectiveness (Rose, 2008). In addition, organisational

culture is also notified as a catalyst for some organisations to perform better than others in the market (Ojo, 2005; Rose, 2008). Organisational culture is viewed as an internal organisational variable that influences organisational performance; it can be observed, managed, and measured (Geldenhuys, 2006). The higher the company's shared beliefs, the more significant the organisation's role would be to adopt the technology [64] effectively. Thus, this study examines the effect of organisational culture as a moderator in the relationship between the technology construct and the business analytics adoption.
H_3: Organisational culture moderates the relationship between relative advantage and the adoption of business analytics in SMEs.
H_4: Organisational culture moderates the relationship between compatibility and the adoption of business analytics in SMEs.

The questionnaire was created by expanding on the previous theoretical foundation. Before data collection, the study was pre-tested with selected technology management academia and practitioners to ensure content validity. Based on their suggestions, minor changes were made, such as contextualising the questionnaire items to the specific context of business analytics and selecting more appropriate indicators to measure the variables. A five-point Likert scale was used in the structured questionnaire. The study used seven items to measure relative advantage (Ilin et al., 2017; Premkumar & Roberts, 1999), four items to measure compatibility (Ramamurthy et al., 1999), eight items to measure organizational culture, and thirteen items to measure adoption of business analytics (Raguseo, 2018). The study conducted a pilot test with 30 SME owner-managers using the developed instrument to confirm the reliability of the measurement scales.

The study used systematic random sampling to select a sample from a sample frame. The sample frame representing the entire population of Malaysian SMEs referred to a directory of national entrepreneurs maintained by the Ministry of Entrepreneur Development and Cooperatives. The target respondents for this study were the owner-manager, managing director, CEO, manager, and head of the department because they were deemed appropriate as key respondents due to their understanding of the company's operations and active role in decision-making (Mohtaramzadeh et al., 2018). The study sent two rounds of emails, yielding 288 responses at a 15% response rate.

Due to the benefit of the online data collection method, no missing values were recorded during the data screening process. However, after performing a straight-lining pattern and outliers test, the study removed 47 data (Hair et al., 2019). The total number of samples collected and used for further analysis was 241. Since the collected data was less than the minimum sample size suggested by Krejcie and Morgan (Krejcie & Morgan, 1970), a nonresponse bias test was conducted to determine the differences between those who did not respond and those who did (Lambert & Harrington, 1990). There is always a possibility that non-respondents and respondents differ significantly as most studies rely voluntarily upon them (Lambert & Harrington, 1990). The study used extrapolation by comparing the early and late respondents (Armstrong & Overton, 1977). In this study, the results showed no significant differences between the early and late groups. The insignificant differences indicated that there was no nonresponse bias. As a result, respondents who responded late had similar criteria to those who responded early; thus, the total sample collected and used in this analysis was significant enough to warrant further investigation.

The study also looked at a common method variance (CMV) for potential bias due to single-source data. Tehseen et al. (2017) suggested using a few CMV method combinations; thus, this study used Harman's single-factor test and the correlation matrix procedure prescribed by Podsakoff et al. (2016). According to Harman's single-factor test results, the most significant factor based on 24 variables accounted for 47.06 per cent of the variance. The value was less than the 50% cut-off value proposed by (Podsakoff et al., 2016), indicating that CMV was not a critical issue because no major factor emerged. Meanwhile, the CMV using the correlation matrix procedure showed that all correlations had $r \leq 0.9$; as a result, no CMV was detected (Bagozzi et al., 1991). In addition, the study conducted a multicollinearity test to determine whether any constructs reflect the variance inflation factor (VIF). The result for multicollinearity in this study showed that all of the tolerance values were ≥ 0.2 and the VIF value < 5; thus, there was no severe issue on collinearity (Joseph F. Hair et al., 2019).

The study employed component-based structural equation modelling (SEM) of partial least squares (PLS) for data analysis. PLS-SEM is widely used in the I.T. and I.S. fields because it predicts and develops theories (Henseler et al., 2009). Furthermore, the technique uses a component-based approach and allows for simultaneous measurement and structural modelling (Hair et al., 2017).

Result

The findings revealed the respondents' demographic profiles, measurement models, and structural models. Table 1 shows the profile of the sampled companies and the demographic characteristics of the respondents.

Table 1

Profile of Sampled Companies and the Respondents' Demographic

Items	Frequency	Percentage(%)
Gender		
Male	136	56.4
Female	105	43.6
Age		
Below 30	45	18.7
31-40 years old	78	32.4
41-50 years old	81	33.6
51- 60 years old	31	12.9
More than 60 years old	6	2.5
Position in the company		
Owner-Manager	154	63.9
Managing Director/ Chief Executive Officer	42	17.4
Manager/ Head of department	36	14.9
Others	9	3.7
Years of Company established		
Less than one year	10	4.1
1-3 years	36	14.9
3-5 years	41	17
5-10 years	63	26.1
10-20 years	65	27
More than 20 years	26	10.8
Company's sector		
Agriculture	3	1.2
Construction	12	5.0
Manufacturing	55	22.8
Mining and quarrying	1	0.4
Services	170	70.5

Males outnumbered females in the study, as shown in Table 1. More than half are over 40, and the majority are owner-managers in the services sector with more than five years of experience.

Measurement model assessment for the reflective model covers testing reliabilities through the squared standardized outer loading for each construct; internal consistency reliability using the composite reliability score, convergent validity using the average variance extracted (AVE), and discriminant validity using a Fornell-Larcker criterion, the cross-loading, and HTMT (Hair et al., 2019). The recommended outer loadings are above 0.708, as the recommended value indicates that the construct explains more than 50 per cent of the indicator's variance (Hair et al., 2019). Apart from the outer loading, the higher composite reliability values indicate higher reliability levels. A value between 0.6 to 0.7 is considered "acceptable", especially in exploratory research. Meanwhile, a value more than 0.7 indicates "satisfactory to good". In addition, the suggested value for the convergent validity based on the AVE value is higher than 0.5. **Error! Reference source not found.** presents a measurement model in this study, in which the outer loading for all items is > 0.708; the values for the composite reliability are > 0.7, and all values of AVE are > 0.5. The results indicate that the measurement model for this study has demonstrated an adequate convergent validity.

Table 2
Measurement Mode

Constructs	Items	Loading	Composite Reliability	Average Variance Extracted (AVE)	Collinearity /VIF
Relative advantage	Business analytics allows our company to improve operational efficiency.	0.926	0.974	0.841	3.305
	Business analytics allows our company to increase productivity.	0.932			
	Business analytics provides our company with timely information to make better decisions.	0.933			
	Business analytics gives greater control over a business in our company.	0.925			
	Business analytics would enable our company to minimize costs.	0.851			
	Business analytics assists our company to improve customer service.	0.941			
	Business analytics improves relationships and communication with our company's business partners.	0.908			
Compatibility	Business analytics is compatible with the existing infrastructure of our company.	0.91	0.951	0.829	3.565
	Business analytics is compatible with the existing process in our company.	0.923			
	Business analytics is consistent with existing practices in our company.	0.928			
	Business analytics is consistent with the existing beliefs/values of our company.	0.882			
Organisational Culture	Our company is a very dynamic and entrepreneurial place	0.854	0.95	0.707	2.989
	Our company emphasizes growth by generating new products or services	0.834			
	The glue that holds our company together is trust, loyalty, and tradition	0.88			
	People in our company are willing to take a risk for innovation and development	0.792			
	Our company follows formal rules and policies	0.87			
	Our company emphasizes permanence, stability, and efficiency	0.904			
	Our company is a very production-oriented place	0.704			
	Our company emphasizes outcomes and goals achievements	0.87			
Business Analytics Adoption	Our company uses business analytics to respond more quickly to change.	0.9	0.98	0.982	0.813
	Our company uses business analytics to create a competitive advantage.	0.816			
	Our company uses business analytics to improve customer relations.	0.692			
	Our company uses business analytics to reduce operating costs.	0.923			
	Our company uses business analytics to reduce communication costs.	0.933			

Our company uses business analytics to enhance employee productivity.	0.946
Our company uses business analytics to improve employees' skill levels.	0.95
Our company uses business analytics to develop new business opportunities.	0.927
Our company uses business analytics to expand the capabilities of the firm.	0.892
Our company uses business analytics to improve organisational structure and processes.	0.933
Our company uses business analytics to enable faster access to data.	0.946
Our company uses business analytics to improve management data	0.941
Our company uses business analytics to improve data accuracy	0.928

Discriminant validity refers to the extent to which a construct is distinct from other constructs by empirical standards (Hair et al., 2013). The discriminant validity was evaluated using cross-loadings and the Fornell-Larcker criterion. However, recent studies reviewed both methods of discriminant validity and found that neither approach reliably detects discriminant validity issues (Henseler et al., 2015), in which the cross-loadings method failed to indicate a lack of discriminant validity when two constructs are perfectly correlated. Similarly, the Fornell-Larcker criterion performs poorly, mainly when indicator loadings of the constructs under consideration differ only slightly. Therefore, (Henseler et al., 2015) proposes assessing the discriminant validity using the correlations' heterotrait-monotrait ratio (HTMT). The proposed value of HTMT should be < 0.90. **Error! Reference source not found.** presents the discriminant validity using HTMT.

Table 3
HTMT of the Correlations

	BA	COMP	RA
BA			
COMP	0.589		
RA	0.567	0.836	

Based on the table, the values of HTMT for each construct are less than the threshold value; thus, it satisfies the requirement. Therefore, the measurement model assessments in this study satisfy all the requirements. Next, the study evaluated a structural model for hypothesis testing.

The criterion for structural assessment includes the collinearity test, the coefficient of the determinant (R^2), the effect size (f^2), and the predictive relevance (Q^2). The collinearity statistics (VIF) values are calculated from the latent variables scores of the predictor constructs in a partial regression. The recommended value is VIF ≤ 5; otherwise, collinearity issues occur (Hair et al., 2019). **Error! Reference source not found.** shows that the value of VIF for all the constructs satisfied the recommendation value; thus, there was no collinearity issue in this study.
Bootstrapping procedure is employed to test the hypothesis for this study at a 0.1 significance level, one-tailed test and 5000 subsamples (Hair et al., 2017). As a guideline, the hypothesis is significant if the critical value for one tail at a 0.1 significance level satisfies the *t*-value ≤ 1.28 and the *p*-value ≤0.1. Table 4 presents the result of the path coefficient based on bootstrapping procedure.

Table 4
Path Coefficients

Hypotheses	Relationship	Path Coefficient	*P* Values	T statistics	Decision
H1	RA -> BA	0.292	0.098	1.294	Significant
H2	C -> BA	0.331	0.438	0.157	Not significant
H3	RA*OC -> BA	0.113	1.257	0.104	Not significant
H4	C*0C -> BA	-0.139	1.807	0.046	Significant

The result shows that relative advantage positively relates to business analytics adoption (β= 0.292, *t*= 1.294, *p*= 0.098); thus, H1 is supported. However, compatibility is not significant in business analytics adoption (β= 0.331, *t*= 0.157, *p*= 0.438); thus, H2 is not supported. In the meantime, organisational culture does not affect the relationship between relative advantage and business analytics adoption (β= 0.113, *t*= 1.257, *p*= 0.104). The result shows no statistically significant effect of organisational culture on the relationship between relative advantage and business analytics adoption; thus, the finding does not support H3. However, organisational culture affects the relationship between compatibility and business analytics adoption (β= -0.139, *t*= 1.807, *p*= 0.046). The *t* value, 1.807 ≥ the critical value of 1.65, and the *p*-value, 0.046 ≤ 0.05. The coefficient -0.139 indicates that organisational culture negatively affects the relationship between compatibility and business analytics adoption. The result shows a significant negative effect of organisational culture on compatibility and business analytics adoption; thus, the finding supports H4.

The coefficient of determination, R^2, represents combined effects and the variance between the exogenous and the endogenous constructs (Hair et al., 2017). The value of R^2 ranges from 0 to 1, which informs the model's predictive power. Table 5 presents the R^2 value of business analytics adoption as 0.599. The value of R^2 in this study is considered moderate. In general, the technology perspective regarding relative advantage and compatibility can predict up to 59.9 per cent of factors influencing business analytics adoption. The predictive relevance of the model, Q^2, is assessed using a blindfolding procedure with a distance of 7 (Hair et al., 2017). The $Q^2 > 0$ indicates that the model has sufficient predictive relevance. Table 5 presents the predictive relevance (Q^2) of this study. Based on Table 5, the value of Q^2 is 0.272, which is > 0. Thus, the result indicates that this model has a predictive relevance.

Table 5
Coefficient of Determination (R^2)

Variable	R^2	Q^2 (=1-SSE/SSO)
Business Analytics Adoption (BA)	0.599	0.272

The effect size (f^2) calculates the relative impacts of a predictor construct on the endogenous latent variables. The value of f^2 informs the effects on the endogenous constructs if the model omitted the specified exogenous construct (Hair et al., 2019). Table 6 presents the value of f^2 for this study. Based on Table 6, relative advantage and compatibility do not impact the business analytics adoption if omitted.

Table 6
Effect size (f^2)

Relationship constructs	Value of f^2	Effect Size
C -> BA	0	None
RA -> BA	0.009	None

Discussion and Conclusion

The study shows that relative advantage is positively significant in the business analytics adoption by SMEs in Malaysia. This finding is consistent with previous technology adoption literature (Ahani et al., 2017; Albar & Hoque, 2017; Alsetoohy et al., 2019; Boonsiritomachai et al., 2016; Correia Simões et al., 2020; Dey et al., 2016; Ilin et al., 2017; James, 2017; Junior et al., 2019; Khayer et al., 2020; Maroufkhani et al., 2020; Owusu et al., 2017; Pillai & Sivathanu, 2020; Sam & Chatwin, 2019; Shi & Yan, 2016; Sun et al., 2020). SMEs in Malaysia look forward to the technology that helps the company improve operational efficiency, increase productivity, provide timely information, give greater control over the business, minimise cost, improve customer services, and improve relationships and communication with business partners. The perceived advantage of business analytics increases SME owner-managers exposure and confidence in adopting business analytics technology. Thus, sharing knowledge and experiences on how business analytics contributes to company growth and efficiency based on relative advantage offers should be expanded. The dissemination of success stories accelerates and broadens the adoption of business analytics among SMEs.

However, compatibility is not significantly related to the business analytics adoption among SMEs in Malaysia. The compatibility is not related to the business analytics adoption, as it is similar to previous studies on information technology adoption (Ahmad et al., 2018; Albar & Hoque, 2017; Boonsiritomachai et al., 2016; Gutierrez et al., 2015; Ifinedo, 2011; Owusu et al., 2017; Purwandari et al., 2019). The findings in this study show that SMEs in Malaysia are aware that the existing infrastructure and technology in their organisation require specific changes. These are appropriate steps because most existing compatibility should align with IR 4.0 requirements and be more agile with digital transformation.

On the other hand, the organisational culture does not affect the relationship between relative advantage and business analytics adoption; however, organisational culture affects the relationship between compatibility and business analytics adoption. SMEs with stronger organisational cultures are more likely adopt business analytics. They tend to utilise the existing internal resources to gain similar benefits offered by business analytics.

This study adds to the body of knowledge and contributes to the literature on technology adoption by SMEs, particularly in developing countries. This study contributes to the business analytics literature by examining the inconsistent findings of the antecedents to technology adoption based on previous studies using the integration of DOI, TOE and DCT. Aside from that, the findings of this study have implications for SMEs' owner-managers, governments, and policy-makers in facilitating business analytics. Given the importance of business analytics but the slower-than-expected growth in business analytics adoption, it is critical to comprehend its technological factors. This finding suggests that more awareness of the benefits of business analytics should be widely disseminated.

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Declaration of Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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