THE INFLUENCE OF ORGANISATION DIMENSION IN BUSINESS ANALYTICS ADOPTION BY MALAYSIAN SMES

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ABSTRACT: The use of various technologies by business organisations produces data, which later be converted into meaningful insight through the business analytics process. Prior studies based on the DOI, TOE framework, and Dynamic Capability Theory reported that top management support and organisational readiness were the main attributes that influence technology adoption. However, there were inconsistent findings and required further investigation. Thus, this study examines the relationship between top management support and organisational readiness in business analytics adoption. This deductive study used an online survey questionnaire for data collection. The sample was selected using systematic random sampling from a national directory of Malaysian entrepreneurs. The finding based on 241 data showed that top management support and organisational readiness influence business analytics adoption in Malaysian SMEs. Managers, owners, vendors, and policymakers can use these findings to facilitate and spur the adoption of business analytics.

KEYWORDS: *Business Analytic, Technology Adoption, SMEs, Top Management Support, Organisational Readiness*

1.0 INTRODUCTION

Small and medium enterprises (SMEs) are a catalyst for socio-economic transformation and an engine of growth in most countries across the

globe. SMEs provide employability which develops skilled and semi-skilled workers for talent management and utilises the local resources to produce goods and services [1]. SMEs also allow income generation and reduce income disparities across the country. The activities in SMEs improve forward and backward linkages economically, socially, and geographically [2].

However, SMEs face many external and internal challenges in maintaining growth and competitive advantage. SMEs are affected by globalisation and recession, market competitions and intensity, consumer need and behaviour changes, rapid technological development, and regulations by authorities [3]. Apart from that, SMEs lack financial resources, have barriers in knowledge and expertise in information systems or the latest technology and face a saturated product life cycle [4,5]. Nevertheless, SMEs must be more innovative and upgrade all business aspects that require constant efforts and strategies, especially in the digital economy and the Industrial Revolution 4.0 [3].

Data from internal and external sources may ease SMEs in making the right decisions to improve and upgrade their operations. The usage of data for gaining benefits is called business analytics. Most organisations benefit from business analytics in improving the decision-making process, reducing the turnaround time of the decision process, and aligning resources with proper strategies [6]. Studies also reported the benefits of business analytics in labour productivity and business process enhancement [7] and discover insight [8].

However, despite knowing the benefits and opportunities of business analytics, an organisation should also become aware of the challenges. Therefore, proper understanding and evaluation are crucial to successfully executing and employing business analytics [9]. Study regarding helpful guides for companies to adopt business analytics is limited [10]. Moreover, most of the studies related to the adoption of business analytics occurred at large and multinational companies and seldom studied SMEs across the world [11]. SMEs may not have the same capacity as large companies to perform analysis for new data sets; it requires new leveraging technology, tools, and talent [12]. In addition, technology adoption within SMEs also reported having the lowest score despite improvement in other areas measured [13–15]. Thus, it is essential to examine the factors that influence the adoption of business analytics in SMEs.

2.0 LITERATURE REVIEWS

Technology adoption theories have been applied in a wide variety of domains to understand and to predict user's behaviour on adoption or acceptance of the technology [16,17]. The integration of the TOE and DOI are mostly adopted since the models are the most prominent in the technology adoption by the organisation [18]. However, internal resources are more significant determinants of a strategic advantage than external factors; however, many organisations overlook internal resources [19]. The dynamic capabilities theory focuses on surviving in dynamic environments by creating new resources and renewing or changing the resource base [20]. Dynamic capabilities involve routines and processes to reconfigure the resource base to adapt to markets as they evolve [21]. Also, dynamic capabilities enable organisations to integrate, reconfigure, and recombine their resources promptly to adjust to environmental changes and demands [22]. Effective reconfiguration and transformation require an ability to sense relevant environmental changes, constant surveillance of markets and technologies, willingness to adopt best practices and benchmarks.

Thus, this study employed the DOI, TOE and the Dynamic Capabilities Theory as a prominent theoretical foundation. However, this study only focuses on the organisation dimension. The SMEs' conceptual model for business analytics adoption under the organisational dimension was based on the most significant constructs: top management support and organisational readiness [18,23,24].

2.1 Top Management Support

Top management support is a critical success element in adopting technology, especially in the IT area and within SMEs [25]. Generally, top management initiated and decided on adopting technology [26]. Past research empirically supported the significant relationship between top management support and the adoption of emerging technology [16,17,27–29]. However, research reports an insignificant relationship between top management support and technology adoption [30–32]. Thus, the inconsistent findings require further investigation to examine the relationship between top management support and the business analytics adoption in Malaysian SMEs.

In a SMEs setting, the decision-makers are commonly the top management team members. When the decision-makers realise the potential and impacts of technology and innovation on the

organisation, they tend to commit to the adoption and implementation. The greater the top management support, the higher the overall adoption [33]. Thus, this study tested the following hypothesis:
H1: There is a positive significance between top management support and the adoption of business analytics in SMEs.

2.2 Organisation Readiness

Organisational readiness emphasises the flexibility of arranging its financial, human resource, and IT infrastructure to assist digital innovation needs [34]. Organisations with better readiness have better adoption tendencies. Studies reported that organisational readiness influences technology adoption [28,35–37]. However, several findings reported contrary results [30,38,39].

Due to the inconsistent findings, this study fills the gap for further investigation to examine the relationship between organisational readiness and business analytics adoption in Malaysian SMEs. Thus, this study tested the following hypothesis:
H2: There is a positive significance between organisational readiness and the adoption of business analytics in SMEs.

Figure 1 illustrates the conceptual framework of the organisation dimension for this study.

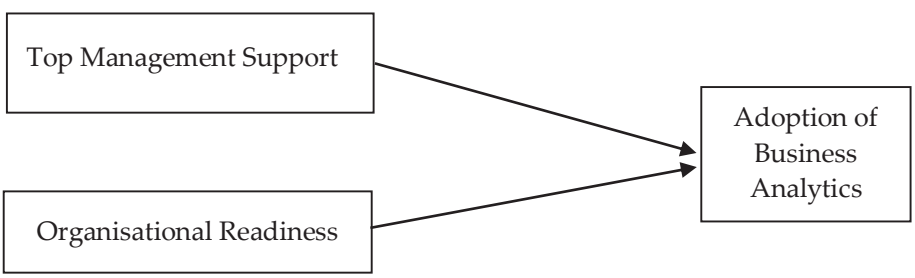

Figure 1: Conceptual Framework of Organisational Dimension in Business Analytics Adoption by SMEs

3.0 METHODOLOGY

3.1 Sample and data collection

This deductive study used an online survey questionnaire for data collection. The population of interest was SMEs in Malaysia. A sampling frame was referred to a directory of national entrepreneurs provided by Malaysia's Ministry of International Trade and Industry. The sample was selected using systematic random sampling.

3.2 Measurement development

The measurement items were measured using 5 points Likert scale; 1 represents strongly disagree to 5 represents strongly agree. The questionnaire was developed in English and then translated into the Malay language. The preliminary survey instrument was first pre-tested for content validation, comprehensiveness, and clarity in meanings by panels from academia and practitioners. Some items had to be reworded to improve their clarity. The instrument was then pilot tested with 30 SME owner-managers to confirm the reliability of the measurement scales. There were four items adopted for top management support [40], eleven items for organisational readiness [33]; eight items for organisational culture[41]; and thirteen items for the adoption of business analytics [42].

4.0 RESULT

4.1 Data screening

A total of 288 SMEs responded to the questionnaire. However, after identifying cases with straight-lining patterns and outliers [43], 47 data were removed. The final data for further analysis was 241. A non-response bias was conducted to determine whether responses of those who have not responded are different from those who have responded [44]. The non-response bias result indicated no significant differences between this study's early and late groups.

This study also collected data from a single source and used a self-administration questionnaire; therefore, this study tested the threats of common method variance (CMV) to avoid biases in the finding [45]. The Herman Single-Factor test was used to test the CMV[46], and the finding revealed that the most significant factor accounted for 47.06%

of the variance, less than 50% cut-off value. Thus, the result indicates that CMV is not critical since no major factor emerges.

Table 1 shows the profile of sampled companies and the respondents' demographic.

Table 1: Profile of Sampled Companies and the Respondents' Demographic

Items	Frequency	Percentage (%)
Gender		
Male	136	56.4
Female	105	43.6
Age	45	18.7
Below 30		
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	10	4.1
Less than 1 year		
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
Number of employees	115	47.7
Fewer than 5 employees		
5- 30 employees	91	37.8
31-75 employees	18	7.5
76- 200 employees	5	2.1
More than 200 employees	12	5.0
Company's sector	3	1.2
Agriculture		
Construction	12	5.0
Manufacturing	55	22.8

Mining and quarrying	1	0.4
Services	170	70.5
Annual sales turnover Less than RM 300, 000	122	50.6
RM 300, 000 - RM 3M	68	28.2
RM 3Million - RM 5Million	16	6.6
RM 5Million - RM 15Million	16	6.6
RM 15Million- RM 20Million	4	1.7
RM 20Million - RM 50Million	8	3.3
More than RM 50Million	7	2.9

The table shows that out of 241 data, the male respondents' proportion (56.4%) is higher than females(43.6%). The age group's highest frequency is 41-50 years old, 81 (33.6), followed by the age group 31-40 years old, 78 (32.4%). The majority of the respondents are Malay, which was 199 (82.6%), followed by Chinese (7.1%), other races (7.9%), and Indian (2.5%). Most of the respondents (63.9%) are the owner-manager of the SMEs, established between 10 to 20 years (27%) and 5 to 10 years (26.1%). Majority of the respondents are from the service sector (70.5%), having an annual sales turrnover less than RM 300 000 (50.6%).

4.2 Measurement model

Measurement model assessment covers testing reliabilities through the squared standardised 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.

Table 2 shows the measurement model of this study. The values follow the recommendation value; the outer loadings and the composite reliability > 0.7 and the AVE > 0.5. Thus, it indicates that the measurement model has demonstrated an adequate convergent validity.

Table 2: Measurement Model and Collinearity Test

Constructs	Items	Loading	CR	AVE
Top Management Support (TMS)	The top management is actively participating in establishing the vision and formulating strategies for business analytics adoption	0.869	0.944	0.808
	The top management is willing to take a risk in business analytics adoption	0.9		
	The top management would provide the necessary resources for business analytics adoption	0.898		
	The top management would provide the necessary support for business analytics adoption	0.927		
Organisational Readiness (ORG_R)	The financial resources are available for business analytics adoption	0.765	0.93	0.55
	The financial budgets would be significant enough for business analytics adoption	0.773		
	It would be easy to obtain financial support from local banks or other financial institutions for business analytics adoption	0.669		
	We would take more seriously business analytics adoption because of the adequate financial support we receive from funders	0.585		
	Business analytics training is provided for employees	0.796		
	New employee(s) with new business analytics skills are hiring	0.743		
	We got expertise in business analytics from external experts	0.654		

	We employ a proper education or work experience staff in business analytics	0.789		
	We have sufficient IT infrastructure for business analytics adoption	0.776		
	We have quality databases management for adopting business analytics	0.799		
	The use of business analytics facilitates by professionals' technical experts	0.772		
Business Analytics (BA) Our company uses business analytics to	enhance employee productivity	0.9	0.98	0.813
	reduce operating costs	0.816		
	reduce communication costs	0.692		
	respond more quickly to change	0.923		
	improve customer relations	0.933		
	create competitive advantage	0.946		
	expand the capabilities of the firm	0.95		
	develop new business opportunities	0.927		
	improve employees' skill level	0.892		
	improve business model	0.933		
	improve management data	0.946		
	improve data accuracy	0.941		
	enable faster access to data	0.928		

Henseler [47] propose assessing the discriminant validity using the correlations' heterotrait-monotrait ratio (HTMT). The value of HTMT should be less than 0.90; otherwise, the HTMT value above 0.90 suggests a lack of discriminant validity. Table 3 presents the discriminant validity using HTMT. Based on the table, the values of HTMT for each construct satisfied the requirement.

Table 3: HTMT of the Correlations

	BA	ORG_R	TMS
BA			
ORG_R	0.581		
TMS	0.694	0.742	

Based on the assessments for the measurement model, the reliability and validity requirements are met for this study. Therefore, the data can be further analysed for the structural model.

4.3 Structural model

The criterion for structural assessment includes the collinearity test, the coefficient of the determinant (R2), the effect size (f2), and the predictive relevance (Q2). The value of VIF for all the constructs satisfied the recommendation value, VIF ≤ 5; thus, there is no collinearity issue in this study.

Bootstrapping procedure is employed to test the hypothesis by creating a large and pre-specified number of bootstrap samples. Hair [48] suggested performing bootstrapping with a larger samples number, such as 5000. An exploratory study mostly assumes a significance level of 10% [48]. Thus, the hypotheses were tested using bootstrapping function at 0.1 significance level, one-tailed test, and 5000 subsamples. Table 4 presents the result of the path coefficient based on bootstrapping procedure.

Table 4: Structural Model

Hypothesis	Relationship	Path Coefficients	P Values	Decision
H_1	TMS -> BA	0.186	0.015	Significant
H_2	ORG_R -> BA	0.148	0.007	Significant

Based on Table 4, top management support is having a positive relationship to business analytics adoption (β= 0.186, t= 1.443, p= 0.015). The value of the coefficient, 0.186 > 0, which shows a positive relationship, the t value, 1.443 ≥ the critical value of 1.28, and p-value, 0.015 ≤ 0.1. The finding does support H1. In addition, organisational readiness is also having a positive relationship to business analytics adoption (β= 0.148, t= 1.468, p= 0.007). The value of the coefficient, 0.148 > 0, which shows a positive relationship, the t value, 1.468 ≥ the critical value of 1.28 and p-value, 0.007 ≤ 0.1. The finding does support H2.

The value of the R2 was 60.9 per cent. The value indicates a moderate, near to substantial to predict the factors of organisation dimension in adopting business analytics. Based on the effect size f2, top management support and organisational readiness have a small effect on business analytics adoption. Apart from that, the value of Q2 was 0.511, indicating that this model has a predictive relevance.

5.0 DISCUSSION

Top management support and organisational readiness correlate significantly with business analytics adoption in the organisation dimension. The owner-managers are a part of the top management in most SMEs. Therefore, they make most of the final decisions. The top management who are willing to take a risk, and provide necessary resources or support, are crucial success factors in adopting business analytics among SMEs in Malaysia.

The organisational readiness in terms of financial, human resources, and infrastructure determine the SMEs to look forward to adopting business analytics, as proved in this study. According to the result in this study, the financial resources, budget, and support from financial institutions or funders give weight to business analytics adoption. Apart from that, SMEs are willing to provide business analytics training for the employees and expertise from external business analytics experts. SMEs are willing to hire a new employee with qualifications and experience in business analytics; thus, indicates that there is a demand for analytics jobs in the market and apparently contributes to a higher employability rate. Sufficient IT infrastructure and quality database management, along with support from professional's business analytics technical experts, also contribute to the agreement of SMEs to adopt business analytics in their business organisation.

The findings offer insights to assist SME owner-managers, government, and policymakers in facilitating business analytics adoption. Even though this research contributes to the practical and theory aspects, the research also has certain limitations. This research only investigates business analytics adoption at one point in time. This cross-sectional survey method does not allow the interpretation of causal inferences between variables. Therefore, a future study may explore longitudinal research to get a more comprehensive conclusion on the business analytics adoption in SMEs. In addition, a future study can look into multiple respondents from each SME to gain more conclusive findings on social desirability. Apart from that, future study can look into post adoption stage of business analytics to measure the impacts and benefits offer on the performance and return of investment. Study on the business analytics adoption from different sectors and industries also may offer meaningful findings.

6.0 CONCLUSION

This study adds to the framework of literature undermined by the theoretical development of the concepts supported in this study and enhances the body of knowledge by testing the underlying theories and contributing to the theoretical understanding of the variables, namely top management support and organisational readiness. The practical contribution of this research lies in the enhancement of technology adoption in SMEs. The finding indicates that top management support and organisational readiness are significantly related to the business analytics adoption in Malaysian SMEs.

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