Data Analytics Adoption on Operational Performance

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Contributor: Luther Yuong Qai Chong, Thien Sang Lim

Data analytics serves as a tool for firms to transform data into meaningful information and subsequently make an informed decision. Firms that successfully integrate DA will reap results through improved predictive capabilities and enhancing operational performance.

Keywords: data analytics adoption ; operational performance ; resource-based view ; technology– organization–environment model ; theory of perceived risk

1. Introduction

The era of knowledge-driven economies has altered how firms compete [1][2], prompting them to utilize data analytics (hereafter DA) as a 'game-changer' to improve performance [3]. Data analytics serves as a tool for firms to transform data into meaningful information and subsequently make an informed decision. Firms that successfully integrate DA will reap results through improved predictive capabilities and enhancing operational performance [4][5]. Without DA, it is challenging for managers to learn from the past or future. In essence, DA improves the assessment of business parameters in dealing with market dynamics.

Previous studies focused on the potential of DA in various aspects, such as improving financial performance [6], marketing efficiency [7], and the decision-making process [8]. Despite DA being frequently associated with improved performance, contradictory evidence is found [6][9][10]. These contradictions may cast doubt on the benefits of DA and cloud the understanding of DA's benefits. Such misunderstandings, especially among smaller firms where resources are often limited, would hinder them from embarking on the process of DA adoption (hereafter DAA). Furthermore, the association between DAA and operational performance remained uncharted in the past.

2. Data Analytics Adoption on Operational Performance

The cornerstone of strategic management involves creating and sustaining business values and performance [9]. The resource-based view (RBV) theory suggests that the firms' performances are influenced by the capabilities to exploit strategic resources [11]—tangible resources, intangible resources, and organizational capabilities [12]. DAA is essential for business development [13], enabling firms to increase their competitive advantages [14][15][16]. Thus, it is justifiable to examine the impact of DAA through the lens of the RBV.

Essentially, data are meaningless if not being converted into information and, subsequently, knowledge. Thus, firms embracing DA can acquire critical knowledge that leads to informed business decision making. In other words, they possess better insight into dealing with issues and challenges from the knowledge gained, which provides them with leverage in competitive advantages. However, for most firms, setting up a DA platform can consume substantial resources. Rationally, firms would usually engage in such endeavors if the expected improved performance or return exceeds the anticipated risks and costs.

Firms' resources and capabilities are two vital RBV elements that received significant attention in empirical studies, especially in technological innovation [9][17]. Previous literature reported the direct and indirect influence of technological capabilities on firms' performance [18][19]. Similarly, recent findings suggested that Information Technology (IT) investment [20][21] enables firms to stay competitive [22]. Even though these works were grounded on the RBV, they focused exclusively on financial or marketing performance. Because of the insufficient evidence from the perspective of the firm's operational performance, which deserves equal attention as financial and marketing performances, this research examined the impact of DAA on operational performance.

The operational performance is measurable from several viewpoints: managing demand, supply chain, customer relationships, and new product development [23]. Demand forecast and supply chain are frequently combined in operations management [24][25] related to DA [26]. This idea is based on the viewpoint that operations and the supply chain are intrinsically linked [27]. Thus, the current research measured operational performance in terms of demand forecast and supply chain. Chae et al. [28] explained that efficiency in data handling and analysis would support management with relevant and quality information, and these aspects are deemed vital to enhance a firm's planning, control, and overall operational performance. The research employed a higher construct for operational performance to ensure a parsimonious and interpretable model [29].

Previously, pull and push factors that may implicate DAA were often investigated separately. Specifically, there are more studies on pull factors than push factors. The disunification of these factors in previous research somewhat impedes understanding the firm's technology adoption. Simultaneously, the motivating and hindering factors are affecting firms' DAA. Hence, this research contributes to the literature by merging the two groups of regressors in a research model.

The technology–organization–environment (TOE) framework posited that the firms' technology adoption, DAA included, is related to external and internal factors [30]. The first context of the TOE encompasses various technologies relevant to firms, including those in the marketplace, regardless of their implementation. Accordingly, three essential factors consistently employed to measure technological aspects are compatibility, complexity, and trialability [30][31]. The second TOE context is organizational, which focuses on the firms' characteristics and resources. Measures used in this context include top management support, organizational readiness, communication process, and organizational structure. The linkage mechanism within firms affects innovation adoption, and the process that connects these subunits tend to promote this adoption further. Notably, other primary factors for innovation adoption include top management support and organizational readiness [6]. The final TOE context is environmental, which refers to the business operating environment directly impacting innovation adoption. This context includes external aspects related to industry structure, the presence of technology providers, and the regulatory system. Observing recent trends [2][6][32], it is opined that competitive pressure and external support are relevant for the current research.

While past studies on technology adoption mainly include the pull factor from the TOE framework, the push factor perspective, on the other hand, can be examined in Bauer's (1960) Theory of Perceived Risk (TPR). The TPR includes a two-dimensional construct of uncertainties and negative consequences. These constructs explain why the decision to act is affected by one's subjective judgments about risk, a critical concern that firms must address. Accordingly, the greater the decision-makers-perceived adverse possibilities related to DAA, the lower the tolerance to undertake these initiatives. Thus, any rational decision makers would be concerned to consider investing in DA and evaluate their readiness to face challenges arising from at least three fronts: erroneous, legal, and ethical. The TPR is closely related to the concept of partial ignorance, in which neither the negative consequences nor the probability of incidence is precisely known. Other than the two dimensions, TPR's flexibility enables researchers to include the types of uncertainties according to the research context [33][34]. Hence, the TPR is widely used in various research areas, and scholars have proposed numerous types of risks, including psychological and social, and related to performance and resources. The current research includes several dimensions under perceived risk: privacy and security, data quality, and resource risk.

Substantial existing evidence was determined using the repeated-indicators approach, where the manifest items of the lower-order constructs are used again for the higher-order constructs. As scholars recommend higher-order constructs examination, the research was motivated to investigate DAA among firms using a two-stage approach. There are two statistical stages under this approach where the lower and higher stages are separated. The former examines the relationship between deals constructs and indicators, while the latter defines the relationship among various constructs. In other words, hypothesis testing will be based on a higher-level construct. There are at least three advantages that arise from the reduction in measurement in lower-order constructs. Firstly, higher-order construct utilization minimizes multicollinearity among indicators [35]. Secondly, the approach prevents indicators from double counting [36]. Thirdly, it allows the higher-order construct to be placed at the endogenous position within a research framework [37]. Overall, instead of specifying relationships between multiple independent and dependent constructs in a path model, higher-order constructs help reduce the number of path model relationships, thereby achieving model parsimony.

3. Discussion

The resultant outcomes of the research demonstrated the significant association of the pull factors under the TOE context with the DAA, in sequence affecting operational performance. It also reaffirmed the role of technological context influence on innovation adoption. With respect to the research hypotheses, all three pull factors representing the technological, organizational, and environmental contexts are positively associated with DAA. From the technological viewpoint, innovation and solution providers must ensure that data analytic system designs are user friendly and easily integrated with systems that are commonly used by industry players. Moreover, the solution providers can provide trial versions to new adopters to promote further innovation adoption. In essence, as firms will assess multiple technological criteria when deciding on DAA, system trialability would allow firms to conduct necessary system evaluation, which is vital to avoid postadoption incompatibility. Meanwhile, firms should have proactive initiative and lend support to encourage the adoption of innovative solutions, including searching for new solutions for data analytics.

Additionally, the research revealed organizational context as an influential pull factor toward DAA, which covers internal and external organizational aspects. Internally, top management support and organizational readiness are vital to DAA. It plays a central role in managing the changes in norms, values, and cultures and facilitating firm members to accept innovation [38] fully. Firms must also pay attention to organizational readiness in terms of resource availability and capabilities. For example, internal fund shortages and inadequacy of human capital would hinder DAA. Roles of external agencies also potentially affect DAA. For instance, financial institutions may offer support through the provision of a unique lending scheme; educational organizations could contribute in terms of developing and nurturing DA talents; governmental agencies may support by offering incentives for DAA. Accordingly, support and cooperation both from the internal and external organizational aspects would encourage a shift towards the DAA sphere. Overall, an inference from the organizational context describes the constructive internal and external attitude that would enhance the DAA.

The obtained results proved the significance of the pull factor under the environmental context. From the viewpoint of competitive pressure, firms may lose market shares if they are not alert and fail to respond to rivals' strategies. Thus, tense competition within the industry induces firms' reactions to adopt new technologies [39]. From the findings and concurring with Gangwar [2], the research exerts critical consideration for external support toward DAA. This form of support prompts firms' DAA, encompassing reinforcement, knowledge sharing, and problem resolution. The experiential learning offered by external parties, i.e., DA solution providers, would promote DAA; hence, more channels must be established for this idea.

The research showed that DAA is associated with TOE pull factors and an antecedent of operational performance. TOE enhances operational performance through DAA, as evident by three mediation analyses showing significant results. Their level of effect on operational performance, indirectly via DAA, varies from one to another. Based on the empirical evidence presented, the technological context of TOE exhibited the most robust effects on DAA and, subsequently, the operational performance, followed by organizational and environmental contexts.

The role of perceived risk on DAA was not established in the research. At the time of the research, the DAA among firms in Malaysia was relatively low [40], and DAA among the firms was still in its infancy. Perhaps, these early adopters may view DA as a game changer, and its adoption would offer more benefits than inherent risk. Thus, they were more focused on the prospects of a successful adoption. Furthermore, it is also fair to assume that early adopters generally are risk takers and thus have a higher tolerance to risk [41]. The unsupported finding on the association of perceived risk with DAA may be viewed as encouraging as there was no evidence to support the claim that perceived risk would repel firms from adopting DA among the firms in the manufacturing and services sectors.

4. Conclusion

Researcher shows that pull factors are more dominant than push factors in associating with data analytic adoption. Although the research covered firms in two economic sectors, it does support the proposition that data analytic adoption plays a strong contribution toward operational performance. From the viewpoint of technological context (compatibility and trialability), it supports the argument that the technological context was positively related to the adoption of data analytics. Meanwhile, organizational context (the top management support and organizational readiness perspective) and environmental support (the competitive pressure and external support perspective) demonstrated a similar link to data analytic adoption. The indirect effects between the three TOE contexts and operational performance, via data analytic adoption as moderator, have also been confirmed. Evidently, initiatives that increase support in terms of technological, organizational, and environmental contexts would promote the adoption of data analytics among firms, which in turn would improve operational performance.

As the TOE and TPR are considered flexible contextual theories, future research can include additional dimensions, which would broaden the scope of interpretation and provide a comprehensive view of the higher-order construct. New research may also explore if the size of firms would influence the relationship between the pull and push factors on the adoption of data analytics. This is because firm size potentially delivers varying challenges in priorities or strategy formulations. As the current research does not distinguish between new and old adopters, examination using multigroup analysis may unravel new insight as firms at different stages of adoption may encounter different challenges in each phase of data analytics. Lastly, future studies may adopt a mixed-method approach to understand how the progression of data analytics adoption affects firm performance.

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