The Adoption of Big Data Analytic on Performance: Integrated Model

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Abstract:- Based on the technology-organization-environment framework and the resource-based view theory, the study proposes an integrated model to analyze determinant factors and effects of Big Data Analytic adoption in Indonesia's creative industry of SMEs. We used a questionnaire survey to collect data while using the quantitative method. The research model was validated using responses from 119 SMEs in Indonesia's creative industry, and structural equation modeling by Smart PLS is used. Two significant findings emerged from this study. We discovered that relative advantage, organizational readiness, top management support, and government regulations all have a significant impact on Big Data Analytic adoption. The study's findings also show a strong and positive relationship between Big Data Analytic adoption and firm performance. Finally, it was discovered that knowledge management had a mediating effect on the relationship between Big Data Analytic adoption and firm performance. The data revealed how businesses could increase their use of Big Data Analytics to improve firm performance. The current study adds to the small but growing body of literature on the factors that influence technology acceptance. The study's findings can be used as a resource by scholars and practitioners interested in big data adoption in developing countries.

Keywords:- *Component; Big Data Analytics; Performance; TOE Framework; RBV Theory; Creative Industry; SMEs.*

I. INTRODUCTION

With the rapidly developing of big data in recent years, practitioners and researchers must consider how to incorporate the adoption of advanced technologies into their competitive strategies. Big data in business decision-making has recently received a lot of attention [1, 2], and the number of companies investing in big data analytics to improve their competitive advantage and performance is increasing. Furthermore, big data analytics (BDA) are frequently regarded as a critical corporate asset, with decision makers focusing on gaining timely insights and generating a high level of income [3-5]. Big data are the interactions between employees and customers that are recorded in a company's system and provide actionable, accurate, descriptive, and interpretive results [6]. Because of the sizable amount of big data generated at a high rate and the diversification of information assets, offering personalized information and knowledge remains difficult [7, 8].

Big data has become one of the most commonly used technologies/services for businesses to obtain and retain a competitive advantage. Big data is defined broadly as "a collection of subject-oriented data comprised of information from a specific time period that aids management decision-making" [9]. According to International Data Corporation (IDC) [10], the global market for big data was valued at USD 66 billion in 2020 and is expected to grow at a USD 157 annual rate until 2026. Many businesses believe that big data adoption is crucial and has enormous potential. Regardless of the theoretical benefits of BDA implementation, numerous studies have revealed that not all businesses are adopting big data. For example, Choi et al. [11] reported that there is a suspicious notion that 80% of organizations will fail when attempting to leverage big data if they do not have well-defined strategic goals. Most firms' use of big data has recently been comparatively lower [1, 12]. Many businesses have not progressed beyond the early adopter stage [13]. Despite the fact that big data adoption is becoming more popular as an effective tool for new business industry formation and business optimization, only a few firms have already applied it and achieved the expected results [14, 15].

Big data is broadly recognized as one of the pillars of future technology/service, providing organizations with enormous business value [16]. Despite the fact that BDA has numerous benefits, few studies have been conducted on how businesses can engage it and generate commercial value from it. As a result, there is confusion about how organizations approach the process of BDA adoption and value creation [1, 9]. Extensive prior research has also suggested that many industries would be unable to take advantage of the opportunities that BDA could provide. Numerous researchers have questioned the idea that BDA can help companies enhance their performance. [1, 9]. As a result, there may be a lack of knowledge and conflicting opinions about how firms can use BDA to profit from this type of investment. Furthermore, enterprises such as SMEs in the creative industries have not sufficiently investigated the potential of BDA. In this study, we look at how BDA adoption can benefit SMEs. As a result, more research is needed to identify the benefits and drawbacks of BDA adoption in terms of business performance. [13].

However, although research has been conducted on BDA in various sectors, it has presents contradictory results regarding the impact of BDA on organizational performance, for example prior research on the subject indicates that using big data as a strong foundation to improve performance benefits organizations [14, 16]. Most people report a positive

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relationship between big data success and business impact [17]. Big data has been used by larger companies to achieve a variety of goals, include but are not restricted to estimating emerging trends and analyzing consumer behavior and experience to investigate opportunities for improvement [18]. Others consider its impact on organizational performance to be diffusing (19, 20, 21). Despite the increasing number of research studies examining BDA and its effect on performance, the main obstacles to BDA adoption among SMEs are a lack of knowledge and resource limitations for big data (22, 23, 24, 25) systematically reviewed BDA research and discovered that research on the drivers of BDA adoption among SMEs are rare, and little attention has been given within SMEs using the TOE framework. (26). As a result, in this study, we use a technological, organizational, and environmental (TOE) paradigm to investigate factors influencing big data adoption in the creative industry of SMEs. Because of its flexibility in assisting in understanding the degrees of technology adoption across firms, the TOE model is suitable for this scenario [13, 27, 25].

Furthermore, while several studies have been conducted to examine BDA adoption during the strategy and techniques (pre-adoption) and formal adoption phases [28, 25], little attention has been paid to post-adoption challenges and consequences, especially in the context of emerging market economies [3,13,17,25]. The existence of a global during the post-adoption phase and its effect on business performance, especially in a developing country such as Indonesia, represent a crucial and appropriate concern for research as part of a strategy to thoroughly examine the effects of BDA adoption on SMEs in creative industries.

In addition to investigating the post-adoption phase of BDA, the current study investigates the contingent effect of knowledge management, which has been used as a contingency variable in previous studies. According to [29], there are reportedly such little studies into BDA knowledge management and its integration in to the knowledge management, despite the obvious need for a well-constructed and coherent method. To put it another way, few research studies have tried to shed some light on the relationship between knowledge management processes and organizational performance [30]. Similarly, while some research provides empirical evidence for the relationship between BDA and knowledge management processes, as well as the mediating effect of knowledge management processes between BDA and organizational performance [31, 32, 33], other research presents more critical views [34, 35, 36]. According to some studies, BDA and knowledge management do not always result in improved organizational performance or that knowledge management processes have a partial mediating effect between BDA and organizational performance [37]. Meanwhile, other studies [38] find positive associations between each other, and some have suggested validating the mediating role that knowledge management processes could even interact in relation to performance and innovation [39], in this particular instance, BDA.

As the BDA appropriate environment, scholars and practitioners should understand how BDA adds value and has an impact on businesses. As a result, the goal of this study is to address this quandary by introducing and evaluating a fully integrated BDA adoption and causality tests from the creative industry sector's perspective. The following significant study objectives emerge from the preceding discussion:

- To analyze the determinant factors of BDA adoption;
- To identify the effect of BDA adoption on organizational performance; and
- To examine the moderating impact of knowledge management on the relationship between BDA adoption and organizational performance.

II. LITERATURE REVIEW

A. Theoretical Foundation

The TOE (Technology-Organization-Environment) model was first introduced by [40]. The TOE model was then further developed by [41]. The TOE Framework is a set of factors that predict the adoption rate and barriers of hospital information systems. This framework shows that adoption is influenced by technological developments [42], organizational conditions, business and organizational reconfiguration [43], and industrial environment [44]. In other words, the TOE model incorporates a schematic of technological characteristics, organizational factors, and elements of the macro environment [45]. TOE identifies three contexts that affect the adoption and implementation of corporate innovation, namely: the technological context, which illustrates that adoption depends on technology both from outside and from within the company, such as compability (both technical and organizational), complexity, triability (trial/experimental), and observation (visibility/imagination); organizational context, describing the company's business scope, top management support, organizational culture, managerial structure complexity measured from centralization, formalization, differentiation, quality of human resources, and problem size; environmental context related to facilities and factors inhibiting company operations such as competitor pressures, customers, socio-cultural issues, government encouragement, and technological infrastructure such as consulting services through ICT [46].

Likewise [47] stated that the TOE Framework identified three aspects of the context that affect the process of a company adopting and implementing technological innovations: technological context, organizational context, and environmental context. The technological context considers available technology important to the company, both internal and external, which may be useful in increasing organizational productivity. Organizational context is defined in terms of the resources available to support the acceptance of innovation. These criteria include company size and scope, centralization, formalization, and the complexity of the managerial structure as well as the quality and availability of the company's human resources. Environmental context represents the setting in which a company does business, and is influenced by the industry itself, its competitors, the company's ability to access resources provided by others, and interactions with government

The TOE framework has been used to explain intercompany adoption. Understanding of e-business adoption in European countries [48], A multi-perspective framework [49], Cloud computing [50], ERP solution (46), Smart City Readiness Mode [51] and Big Data Analytics [26]. In each study the three elements of technology, organization and environment have been shown to influence the way organizations identify the need to seek out, and adopt new technologies. In each of the empirical studies that tested the TOE framework, researchers used slightly different factors for technological context, organizational context, and environmental context. Different types of innovation have different factors that influence adoption. Likewise, differences in cultural and industrial contexts will also have different factors. Thus research studies employ a variety of factors for technological, organizational, and environmental contexts.

The Resource Based View (RBV) theory was first pioneered by [52]. The RBV theory views that the company's resources and capabilities are important to the company, because they are the main or basis of the company's competitiveness and performance. Based on this resources based theory, an organization can be assessed as a collection of physical resources, human resources, and organizational resources [53]. The indicators for measuring the RBV strategy consist of two indicators, namely: resources and capabilities [54]. The RBV defines a firm's performance in terms of its primary resources [55]. Actual and intangible assets such as information, knowledge, and business procedures and routines are examples of company resources [56]. As a result, valuable, uncommon, one-of-a-kind, and non-substitutable resources can provide organizations with a competitive advantage by creating value and improving firm performance [55]. These advantages can be sustained over long periods of time, allowing the firm to protect itself from resource imitation, transfer, or substitution [57]. Empirical research has validated this hypothesis [13, 17]. Data are increasingly viewed as an essential intangible resource that can be applied to enhance organizational performance in the BDA context [58, 59].

This study employed an integrated model of TOE and RBV. Concerning the first method, prior research indicates that the TOE framework is an excellent starting point for investigating BDA adoption [13]. The TOE framework identifies three different types of factors that influence how businesses use technology. First, perceived innovation features such as compatibility, complexity, trialability, observability, and relative advantage are defined by the technological context. According to a meta-analysis conducted by [60], relative advantage is the most common significant and relevant positive factor to be analyzed in this research. Second, the organizational context indicates the number of slack resources that are available internally. Top management support and organizational readiness have been identified as the most important factors in technology adoption, which is also addressed in this study. Third, "environmental context" refers to "the domain in which a practices that perpetuate its industry and business, rivals, and government contacts." The method is consistent with Rogers' method [61], which emphasizes technological characteristics and organizational factors as drivers of advanced technologies diffusion.

Another research technique has broadened the TOE framework by taking into account the impact of technology usage. Businesses create benefits and influence, according to RBV logic, by combining different resources that are either economically difficult to replicate or valued throughout other businesses [17, 59]. Furthermore, the impact of resources is determined by an organization's ability to leverage an invention rather than the innovation itself. [57]. Thus, the extent to which an innovation/technology is applied in important operations of business value chains determines the impact of innovation. Nonetheless, this concept has been used in very few DBA studies. As a result, we focus on the adoption and impacts of BDA in this study, filling a gap in the literature. To summarize, the TOE paradigm has influenced the majority of previous studies in explaining the drivers of technology adoption. Similarly, based on previous research, the RBV has been applied to forecast the consequences of technology adoption.

The integration of TOE and RBV technological factors can provide a comprehensive study framework. Researchers present a conceptual model (Figure 1) based on the TOE model in this study, attempting to draw on the large number of studies on BDA and TOE variables for technology adoption. A variety of TOE characteristics have influenced technology adoption. Researchers look into technological (relative advantage and compatibility), organizational (top management support and organizational preparedness), and environmental factors (government regulations) in this study. ".

A. Research Framework and Hypotheses

The association of the TOE model will be adapted in this study to describe the antecedents of BDA adoption. As a result, researchers created a theoretical framework based on the TOE framework and RBV theory, which was then turned into a research framework. The variables in this study were classified as technological, organizational, and environmental contexts. The technological characteristics (factors) that determine the degree of BDA relevance to SMEs are relative advantage and compatibility. Organizational readiness and top management support are organizational characteristics (factors) that indicate a SMEs readiness to implement BDA. Furthermore, government assistance is an environmental characteristic (factor) that describes the amount to which SMEs receive assistance as an external requirement for BDA adoption. Nevertheless, because an additional objective of this study is to examine the effect of BDA adoption on company performance, the causality of RBV theory will be examined, as proposed in various previous studies. Taking the foregoing into account, the RBV theory is used in this work to validate the existence of a relationship between BDA adoption and company performance. According to the RBV, the much more substantial and widely spread the adoption of BDA, the greater the chances of a business making a valuable, almost special, and long-lasting impact. As a result, researchers argue in this article that there is a theoretical relationship between BDA adoption and company performance.

Based on various studies, this conceptual framework focuses on the use of BDA. For example, [62] conducted a study in Korea to identify the critical components of BDA acceptance. The study's findings divided the adoption variables into three categories: technology factors, organizational factors, and environmental factors. Similarly, [63] investigated the decision to implement BDA in Lebanese firms using the TOE and contextual theory. The results indicated that technological factors such as complexity and security influenced BDA adoption positively. Besides that, the findings showed that organizational characteristics such as prior IT expertise and manager endorsement influenced the decision to accept BDA significantly. The following is a more detailed explanation regarding the relationship between existing factors based on research that has been conducted.

The technological clearly stated the exogenous and endogenous features of technology that are required for its acceptance. Relative advantage is one such factor [13, 26, 53]. The perceived benefits of new technologies in terms of specific organizational performance have a significant impact on organizational adoption intentions [64, 65]. The level to which technology perceived as outstanding is accepted relative to other aspects of existing technology used in industries, as well as the benefits it brings to the organization, is referred to as relative advantage [61, 66]. According to [13], organizations are prepared to adopt technology if the benefits are worth the disadvantages of current technology. [26] also demonstrated that technological factor data demonstrated that relative advantage significantly influences BDA adoption. As a result, the hypothesis is formulated:
H1. The relative advantage has a significant effect on BDA adoption.

The degree to what new systems/technologies are related with an organization's existing systems/technologies is referred to as compatibility [67]. Compatibility has been determined to be one of the most important factors influencing technology adoption [61], and empirical studies indicate that it was among the in this regard [56]. However, according to [26], data from technological factors show that compatibility is not significantly associated with BDA adoption. As a result, the following hypothesis is proposed: most important factor in determining on big data [64,68]. To support an advantageous compatibility-big data adoption relationship, companies can enhance the flexibility of their procedures and policies
H2. The compatibility has a significant effect on BDA adoption.

Top management support and organizational readiness were identified as factors influencing BDA adoption in the current study. Top management support is defined as the degree to which managers recognize and accept the new system's technological capabilities (BDA) [13]. Prior research has found that senior management support is an important predictor of appropriate innovation adoption [67,69]. [26] also demonstrated that data from organizational Context factors revealed that management support significantly drives BDA adoption. As a result, the following hypothesis is proposed:
H3. Top management support has a significant effect on BDA adoption

The ability and desire of a company to adopt new technologies is referred to as organizational readiness. It denotes a company's ability to manage and spend in the adoption of new technologies, which includes technical IT ability and expertise [13]. Academics believe that organizational readiness is required for BDA adoption in industry analytics and big data [64]. [13] discovered that organizational readiness has a strong and positive relationship with the adoption of new technologies in the context of small businesses, and that organizational readiness is one of the most important factors or requirements for BDA adoption. Similarly, [26] demonstrated that organizational Context data demonstrated that organizational readiness significantly drives BDA adoption. As a result, the following hypothesis has been proposed:
H4. Organizational readiness has a significant effect on BDA adoption.

One of dimension for environmental context is government regulation. The literature has shown that government plays a vital role in the technology adoption [60]. According to the TOE, governmental restrictions are external components that have the capacity to influence big data adoption. More precisely, government laws may restrict or encourage enterprises to embrace innovative technology [60,70]. The acceptance of big data by firms may increase if government regulations, policies, legislation, and standards support and encourage the adoption of new technology [71]. According to previous research [13,71], organizations that face a high degree of government pressure and restrictions are more likely to use cloud technology [72]. According to an initial review of big data adoption research, government legislation in the form of incentives and assistance increases big data adoption and acceptability. So did [26] also prove that Technological factor data showed that relative advantage significantly drives BDA adoption. As a result, we suggest that:
H5. Government regulations have a significant association with big data adoption.

BDA and its application in order to achieve higher organizational performance is grounded in resource-based theory [77], which states that a firm's performance depends on the extent to which it simultaneously possesses valuable, rare, imperfectly imitable, and appropriately organized resources [78,79]. In line with the resource-based theory, BDA is considered a resource that provides competitive advantages by being valuable and possessing key capabilities that generate superior organizational performance [80]. Therefore, the following hypothesis is proposed:
H6. BDA adoption has a significant positive impact on firm performance.

According to [29], there is reportedly such little studies into BDA knowledge management and its integration in to the knowledge management, despite the obvious need for a well-constructed and coherent method. To put it another way, few research studies have tried to shed some light on the relationship between knowledge management processes and organizational performance [30]. Similarly, while some research provides empirical evidence for the relationship between BDA and knowledge management processes, as well as the mediating effect of knowledge management processes between BDA and organizational performance [31, 32, 33], other research presents more critical views [34, 35, 36]. According to some studies, BDA and knowledge management do not always result in improved organizational performance or that knowledge management processes have a partial mediating effect between BDA and organizational performance [37]. Meanwhile, other studies [38] find positive associations between each other, and some have suggested validating the mediating role that knowledge management processes could even interact in relation to performance and innovation [39]. Therefore, the following hypothesis is proposed:

Hypothesis 7. The adoption of BDA positively influences knowledge management

Hypothesis 8. Knowledge management positively influence organizational performance

Hypothesis 9. Knowledge management has a mediating effect between the adoption of BDA and the organizational performance.

A conceptual framework (refer to Figure 1) was developed as a result of a study of previously investigated factors and was used as a guideline during the research process. The three contexts of elements in Figure 1's model are technological, organizational, and environmental.

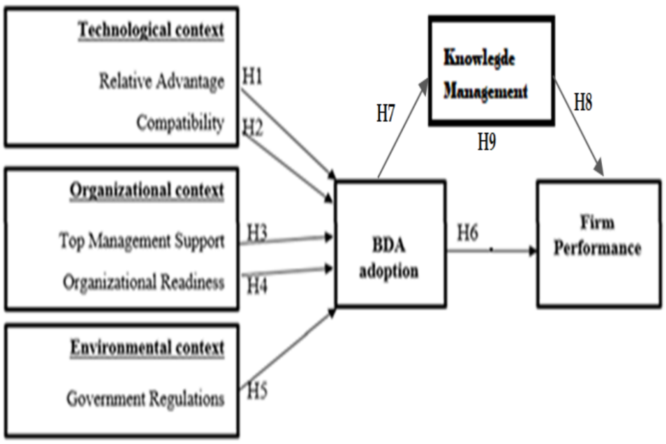

Fig 1. The proposed conceptual model.

III. PREPARE METHODOLOGY

This research used quantitative method, so a questionnaire was utilized to collect data in this research. The questionnaire distributed to the respondents which is got from sample of population. The respondents were creative industry of SMEs owners or managers, as they are the people who know the most about the research topic and are more likely to have accurate perceptions of BDA adoption in creative industry of SMEs because they usually play an important role in decision-making tasks. Therefore, in the present research, we applied the simple random sampling method in the Indonesia's creative industry of SMEs. Approximately 200 questionnaire surveys were distributed, and 119 were returned.

The questionnaire consists of items that were adapted from previous research in the literature. In the TOE model, the exogenous factors were split into technological, organizational, and environmental characteristics variables, and the items evaluating big data adoption. Two constructs were included in the technological factors: relative advantage and compatibility. The items were collected from [13, 26]. In addition to the items mentioned above, the organizational elements of Top management support and organizational readiness were assessed using items from [13, 26]. In contrast, the environmental variables of government support were measured using items from [26, 60, 71]. Furthermore, knowledge management items were adopted from [29]. In the present study, we used five-point Likert-Scale, with responses ranging from one (strongly disagree) to five (strongly agree). The Cronbach's alpha (α) for all constructs surpassed 0.70, indicating a high level of dependability, as per [73].

For hypothesis testing, the partial least square structural equation modeling (PLS-SEM) method was employed in this work. PLS is a multivariate statistical method that enables the estimation of numerous associations in a given model between one or more exogenous factors and one or more endogenous factors. According to the explanations above, PLS-SEM methods were used to evaluate the proposed hypotheses and analyze the acquired data because this research model incorporates nine latent components, which add to the complexity of the suggested model. This research is exploratory in nature and employs the TOE framework, and the RBV. Integration necessitates the employment of a path modeling approach in response to the suggestion of various researchers that the PLS-SEM technique utilized in the study is an extension of an existing theory or prediction-oriented in nature. This approach was used to validate the reliability and validity of the variables before analyzing the structural model.

IV. RESULTS AND INTERPRETATION

A. *Measurement Model Assessment*

The Assessment of measurement models is a precondition and the initial stage in producing findings in PLS-SEM. Assessment focuses on investigating the reliability and validity of measures. The assessment of the measurement model in PLS-SEM changes based on whether the measurement model contains formative or reflecting measurements. The reflecting measurement approach often assumes that the indicators originate from the concept (interchangeable) and that all indicators assess the same causal reality. In contrast, the formative measurement approach assumes that indicators generate a construct of interest. Thus, formative indications are not interchangeable and are discarded as variable indicators. Owing to these differences, each measurement model contains different criteria. The major issues associated with the reflective measurement paradigm are composite reliability, construct convergence, discriminant validity, and factor loadings.

Nevertheless, the nature of the measures for all variables in the current study is reflective. All study factors (variables) were approximated using reflective measurements derived from previous similar studies and handled as individual items. Thus, the internal reliability values of the scales were examined applying composite reliability, along with Cronbach alpha values. The values of Cronbach alpha ranged between 0.720 and 0.849 (Table 1), so it can be said that all of these constructs are reliable. Meanwhile, based on the Average Variance Extracted (AVE) which is value to determine whether the requirements of convergent validity have been met, so, all constructs have met the requirements of convergent validity because the AVE values are all > 0.50

Table 1. The Result of Constructs Reliability and Validity.

	Cronbach's alpha	composite reliability	Average Variance Extracted (AVE)
Relative advantage	0.824	0.898	0.762
Compatibility	0.721	0.835	0.631
Top management support	0.787	0.825	0.697
Organizational readiness	0.756	0.814	0.656
Government regulations	0.720	0.826	0.545
BDA adoption	0.808	0.876	0.732
Knowledge Management	0.772	0.845	0.538
Firm performance	0.809	0.866	0.523

B. Assessment of the Structural Model

Following the study of the measurement model, the structural model was evaluated in the PLS-SEM analysis. testing each relationship which is carried out using the evaluation of estimated path coefficients which is an evaluation to find out how good the causality relationship of each independent construct is to the dependent construct predicted in the model. An independent variable is said to have a good causal relationship, if it has a statistic of more than a critical value of 1.96 (for a 5% significance level). Evaluation of the estimated path coefficient in this study is using smartPLS with a bootstrapping procedure. The results of the evaluation of path coefficient estimates are then used as a basis for decision making in hypothesis testing. Visualization of the final model of mediation accompanied by path coefficients and statistics with the SmartPLS bootstrapping procedure is shown in Figure 2 below.

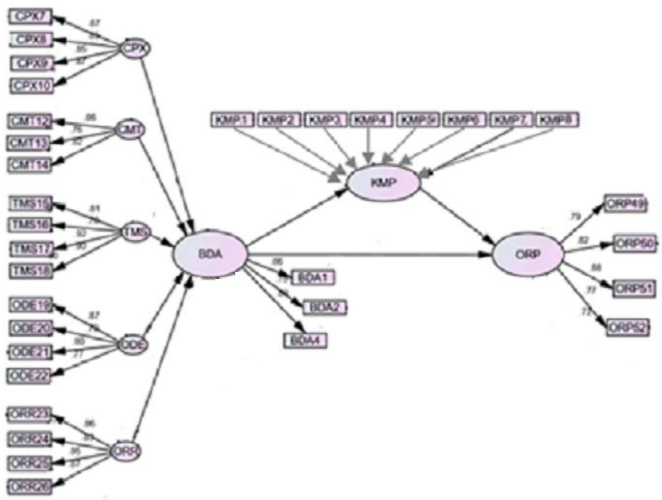

Fig 2. Bootstrapping

In this research there are 9 hypotheses to be developed. To carry out the hypothesis test, 2 criteria are used, namely the value of path coefficient and the t-statistic. The value criterion for the path coefficient, that if the value is positive then the effect of a variable on other variable is unidirectional. If the value of path coefficient is negative, then the influence of a variable on other variables is in the opposite direction. The hypothesis of research can be accepted if the value of t-count (t-statistic) > t-table at an error rate (α) of 5% is 1.96. The following table is the results of the calculation of the hypothesis in the research:

Table 2. Hypothesis constructs.

Hypothesis	Original Sample	T-value	P-Values	Decisions
Direct relations				
relative advantage -> BDA adoption	0.205	2.675	0.003	Accepted
Compatibility -> BDA adoption	0.106	1.184	0.124	Rejected
Top management support -> BDA adoption	0.212	2.843	0.015	Accepted
Organizational readiness -> BDA adoption	0.203	2.028	0.004	Accepted
Government regulations -> BDA adoption	0.279	2.981	0.032	Accepted
BDA adoption -> Knowledge Management	0.362	3.286	0.002	Accepted
BDA adoption -> Firm performance	0.237	2,685	0.000	Accepted
Knowledge Management -> Firm performance	0.206	2.786	0.025	Accepted
Mediating				
BDA adoption -> Knowledge Management -> Firm performance	0.275	2.125	0.033	Accepted

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The structural model for hypothesis testing, in which eight hypotheses are accepted and one is rejected (See Table 2). Relative advantage has significant impact on BDA adoption (β= 0.056, t– statistic=2.675>1.96, p=0.003 < 0.05), so the first research hypothesis (H1) that relative advantage influences BDA adoption is accepted. Compatibility has a no significant impact on BDA adoption (β = 0.106, t–statistic=1.184<1.96, p=0.124 > 0.05), thus, the second research hypothesis (H2) is rejected. Top management support has significant impact on BDA adoption (β = 0.212, t–statistic=2.843>1.96, p=0.015 < 0.05); thus supporting the third research hypothesis (H3), which asserts that Top management support positively influences BDA adoption. Organizational readiness has a significant impact on BDA adoption (β = 0.203, t– statistic=2.028>1.96, p=0.004 < 0.05), supporting the fourth research hypothesis (H4). Government regulations has significant impact on BDA adoption (β = 0.279, t– statistic=2.981>1.96, p=0.032 < 0.05); thus, the fifth research hypothesis (H5) is accepted.

BDA adoption has a significant impact on Knowledge Management (β = 0.362, t– statistic=3.286>1.96, p=0.002 < 0.05), supporting the sixth research hypothesis (H6). BDA adoption has a significant impact on organizational performance (β = 0.237, t–statistic=2.685>1.96, p=0.000 < 0.05); thus, the seventh research hypothesis (H7) is accepted. Knowledge Management have a significant impact on organizational performance (β = 0.206, t–statistic=2.786>1.96, p=0.025 < 0.05), supporting the eighth research hypothesis (H8). Finally, for the evaluation of the ninth hypothesis (H9), confirming that Knowledge Management have a mediating effect between BDA adoption and organizational performance (Sobel's statistic = 2.125, p = 0.033)

C. Discussion

Considering that BDA currently lacks a theoretical foundation from an organizational standpoint, one of the goals of this study was to examine the effect of BDA adoption on company performance (perceived antecedents and impact) from an organizational standpoint. Therefore, we proposed an integrated model based on the TOE to outline BDA adoption and the theory of RBV to explore the influence of BDA adoption on perceived impacts. Based on the findings of the statistical analysis, we identified relative advantages, Top management support, organizational readiness, competitive pressure, and GRs as major antecedents of BDA adoption among the TOE factors.

Technological factor data showed that relative advantage significantly drives BDA adoption, whereas compatibility had an insignificant effect. Thus, the major influence of relative advantage on big data adoption is aligned that reported in prior research indicating a strong effect of relative advantage. This study finding seems to be consistent with studies by [25] and [13], which indicated that relative advantage has a significant effect on BDA adoption. Because the benefits of big data are the primary motivators or drivers for SMEs to embrace BDA, they tend to have a significant impact on its adoption. However, the negligible influence of compatibility on big data adoption contradicts previous findings by [62]. This study finding seems to be consistent with studies by [25] and [13] which indicated that compatibility, has an insignificant effect on BDA adoption. This limited influence might be described by the adaptability level of SMEs processes and practices, which may be easier for SME than for large firms. As SME are adaptable, compatibility between their practices and the BDA system is not an issue encountered in the decisions-making process.

The outcomes of this study reveal the significance of top management support and organizational readiness variables with respect to big data adoption. Prior research has repeatedly shown that top management support is a key component of adopting various types of technology [13, 26]. Given the decision-making role of owners and managers in small hotels, they must create a supporting ecosystem to ensure adoption success. Managers promote organizational changes through value communication and vision clarity to subordinates. In summary, top management support may facilitate technology/service learning and dissemination throughout the firm and plays an important role in the stages of adoption. Furthermore, research dedicated to technology adoption [13] has consistently substantiated the important the association between organizational readiness and big data adoption.

In terms of the environment, Government regulations were found to have a substantial impact on big data adoption. The relationship between Government regulations and big data adoption discovered in this study aligns with previous research [13]. Similarly, government regulatory assistance and financial assistance can help enterprises overcome inadequate technical and financial capabilities for big data adoption. Government legislation makes it easier for hotels to make adoption decisions, especially when firms lack resources.

Results of our empirical analysis provide stimulating evidence with respect to the significant role of BDA acceptance, which was found to significantly affect knowledge management and business performance. The findings reveal that the breadth of BDA implementation is associated with an increased influence on knowledge management and business performance. This finding is consistent with RBV theory predictions and various actual investigations with respect to other types of technologies and applications in which intense use of a technology/service leads to an increased degree of impact and value.

Lastly, the interaction model was evaluated in order to examine the proposed hypotheses. As expected, the major influence of knowledge management on BDA adoption and business performance was verified. In conclusion, the current study findings offer evidence of a moderating effect of information sharing on the relationship between BDA adoption and businesses performance. The results of this study also demonstrated that Technology (relative advantage), organizational (top management support and organizational readiness) and environmental (Government regulations) elements are the most significant antecedents of BDA adoption in the context of SMEs. In addition, the

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results confirm that BDA adoption can enhance the performance of SMEs.

V. CONCLUSIONS

This study aims to explain the determinants of IoT adoption using the TOE model. All of the research hypotheses are supported and significant by data analysis. This study shows that IoT adoption can be increased by considering Technology (relative advantage), organizational (top management support and organizational readiness) and environmental (Government regulations) factors. This shows that managers can benefit from IoT adoption; the ability to make choices and devise plans that will increase the desire for IoT adoption given existing factors.

Further, the present study also provides various contributions to both academics and practitioners. We merged the technology–organization–environment framework (TOE) and the resource based view theory (RBV) in an effort to comprehend the antecedents of BDA adoption and its potential implications for firm performance. Furthermore, we evaluated the relevance of the suggested framework in the domain of BDA practices among hotels in emerging nations. The study results validate firm performance for organizations that undertake commitment as key qualities that assist them in effectively and efficiently undertaking their everyday duties in order to achieve their objectives. Validation allowed us to discover the most relevant setting in terms of TOE and RBV for BDA implementation and effect in the creative industry.

For practitioners, this study highlights critical elements that support increased BDA adoption and how it correlates with company effectiveness, which eventually translates into improved business performance. The study results can support SMEs of creative industry managers or owners in increasing their firms' capabilities, allowing firms to implement BDA in their operational processes to access leverage (such as by enhancing firm performance and competitiveness). The efficient application of BDA reduces the operating costs of firms, decreases operational risks, and allows SMEs of creative industry to generate creative goods in the current dynamic and competitive business climate

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