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Developing Big Data Analytics (BDA) Utilization Model in Indonesia

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Abstract

This paper intends to develop a model of Big Data Analytics (BDA) utilization in Indonesian context. This is important due to the lack of related research on what factors influencing company to adopt BDA as their strategic and somehow secret weapon to win in nowadays intensified competition among companies in industries. By the model, this paper aims to contribute additional knowledge on what factors influence company to adopt this emerging technology as part of their strategic action in winning the market. Thus, intended questionnaires are distributed to about 206 companies. However, only 124 responses can be gathered and proceed using Part-Least Square (PLS) Structural Equation Modeling (SEM) and TOE Framework by adopting SmartPLS 3.0. By processing those data, two significant insights can be generated. First, BDA adoption in Indonesia is mainly encouraged degree of technology savviness, organizational readiness, and better anticipating environmental changes. Second, Organization readiness is also influenced by technology savviness and environmental changes anticipation. the company needs to master its technology which in Indonesia, compatibility and relative advantage could be significant issue. Thus, for those who want to adopt this emerging technology need to develop technology savviness and organization readiness while anticipate environmental changes.

Keywords— Big Data Analytics, Partial-Least Square (PLS) Structural Equation Modeling (SEM), TOE Framework

1 Introduction

Data has emerged into what it called as Big Data as companies enter the era of industry 4.0 marked mainly through massive digitalization like the use of Fintech (Jonny & Kriswanto, 2020) enabling data to be built up into Big Data. In turn, the plenty volume of this data has challenged the existing analytics method that has eventually been obsolete and replaced by new emerging analytical technology called Big Data Analytics (BDA). This technology has enabled such unstructured data due to huge amount of data to be structured through machine learning and thus, many insights could be generated and used to pursue strategic action to win the market. Due to this ability, this emerging technology has entered area of business intelligence as one of its application fields.

In this field, conventional method used simple summing of a known value as result such as order sales to become year-to-date sales. However, by the existence of big data, it requires refined modelling process to find any value. This process may involve developing hypothesis, building statistics, generating models, conducting validations, and adding new hypothesis. By doing this, designated person in any company could interpret visualization, make interactive knowledge-based queries, develop machine learning adaptive algorithms that give business meaning to the company (Agrawal, 2013).

Due to this capability, many companies started to invest in this technology in order to understand consumer behavior, search fraud, and forecast future by using these big data analytics (BDA) so that they can win the market and defeat their counterparts. Thus, company could make better decision-making not in static way but real-time. This may make the company becomes more agile in anticipating environmental changes.

Previous studies still have lack in investigating what factors influence companies to utilize this technology in order to win the market and therefore may be an interesting topic to be investigated in order to gain useful insights for encouraging adoption of this technology (Agrawal, 2015), (R.G. Fichman, 1999) and (Zhu et. al., 2006). Therefore, being motivated by this intention, the main objective of this paper is to investigate what factors influence company to adopt BDA technology in their strategic action to win market while defeat their competitors especially in Indonesia as one of emerging countries in Asia. This paper is based on technology, organization and environment (TOE) framework proposed by reference (Agrawal, 2015).

Although this framework has said to be superior theoretical in studying adoption behavior, however, there is lack in its interrelationship between technology to organization and environment to organization as found in the model as proposed by reference (Awa et. al, 2017). Therefore, a proposed conceptual model is proposed and used as shown in figure 2.

2 Literature Review

Based on TOE framework, there are several elements that should be considered when adopting BDA adoption as elaboration in the following sessions.

2.1 Technology

In this element, there are three factors need to be considered when investigating what factor influences BDA adoption.

First, Complexity. This factor is considered in to order to measure technology savviness of the company (Rogers, 1995). It consists of challenges of customization and high costs (Tsai et. al., 2010). The challenges may include the need of better coordination like data transmission when adjusting BDA backend system and existing IT systems. Meanwhile, High costs when adopting this technology may include high investment or maintenance costs related to skilled manpower and IT infrastructures. For measuring this factor, at least 2 questions are to be asked to respondents whether their company sees BDA adoption is a complex thing for them and whether adopting this technology could be regarded as a complex thing in their lists.

Second, Compatibility. This factor considers whether the technology compatible with existing practice in the company (Rogers, 1995) because the greater compatibility the more likelihood of technology adoption (Cooper & Robert, 1990). For measuring this element, then respondents are asked to see whether BDA technology is compatible to their value, practices, and experiences.

Third, Relative Advantage. This factor has been used in several studies where the more advantage that can be gained from this technology the more likelihood of technology adoption (Jonny & Kriswanto, 2020), (Kuan & Chau, 2001), (Chau et. al., 2008). For measuring this element then respondents are asked whether they expect cost reduction, real-time analysis, and paper-work reduction as its result to promote their competitive advantage in the industry or not.

Based on the above description, two hypotheses can be generated as follows:

H1: Technology impacts BDA adoption

H2: Technology impacts Organization

2.2 Organization

This element considers there are three factors that may influence BDA adoption.

First, Technology Resource Competency. It covers IT infrastructure and capabilities (Zhu et. al., 2006). First factor covers 1) physical IT infrastructure, 2) IT human resources and technical and managerial IT skills, 3) intangible IT-enabled resources such as knowledge management, customer orientation and synergy (Grant, 1991). For measuring this element, then respondents are asked to assess whether their IT infrastructure is supporting, employee's capability is in place, and they have good knowledge regarding to this technology.

Second, Organizational Size. It facilitates technology adoption (Agrawal, 2015). For measuring this element, then respondents are asked to evaluate whether they have sufficient capital, higher return and larger number of employees

Third, Absorptive Capability. It represents the ability to recognize and apply new external information (Agrawal, 2015). For measuring this element, respondents are asked to state whether they actually invest, acquire knowledge, have interest, and regard this as their strategic initiative.

Based on the above description, one hypothesis can be generated as follows:

H3: Organization impacts BDA adoption

2.3 Environment

This element considers there are three factors that may influence BDA adoption.

First, Environmental uncertainty. It indicates the more uncertainty the more opportunities to be pursued (Agrawal, 2015). For measuring this element, respondents state whether their partners suggested, recommended and requested them to adopt BDA technologies.

Second, Competition Intensity. It indicates the degree the company is affected by competitors (Agrawal, 2015). For measuring this element, respondents are needed to give their thought whether they undergo intensified competition to adopt this technology and would face fierce competition if they do not adopt this technology.

Third, Regulatory Support. It represents critical factor for technology adoption (Agrawal, 2015). For measuring this element, then respondents are asked to evaluate whether government, standard and law have influence them to adopt this technology.

Based on the above description, two hypotheses can be generated as follows:

H3: Environment impacts BDA adoption

H3: Environment impacts Organization

3 Methods

3.1 Data Collection

For data collection, a survey is conducted to gain insight from respondents regarding to BDA adoption. Therefore, questionnaires are about to be randomly distributed to companies in DKI Jakarta Province as the biggest Gross Domestic Product's producer in Indonesia (1,989.089 trillion rupiahs out of 11,526.333 trillion rupiahs or 17.26% according to reference (Logaritma, 2020). In order to ensure more representative sampling, the plan was to target members of Indonesian Chamber of Commerce and Industry with 206 members (Kadin, 2021). In the questionnaire to respondent who are the managerial level up in the company, there is a list of questions listed and using five level of Likert scale where 1= strongly disagree, 2= disagree, 3 = neutral, 4 = agree, 5 = strongly agree as follows which has been reviewed by local experts:

T1. Complexity which is measured by T1.1 My company sees complexity of using BDA technology and T1.2 My company sees a complex thing in adopting BDA.

T2 Compatibility which is measured by T2.1 My company's values is compatible with mentality using BDA technology, T2.2 My company's infrastructure is compatible with BDA technology, T2.3 My company's practices is compatible with BDA technology and T2.4 My company's experiences is compatible with BDA technology.

T3 Relative advantage which is measured by T3.1 My company hopes using BDA could reduce costs, T3.2 My company hopes BDA could foster real-time data capturing and analysis and T3.3 My company hopes using BDA could reduce paperwork.

O1 Technical resource competency which is measured by O1.1 My company's IT infrastructure supports BDA-related applications, O.1.2 My company ensures employee's capability with BDA technologies and O.1.3 My company has knowledge of BDA technologies.

O2 Organizational size which is measured by O2.1 My company's capital is more compared to the industry, O2.2 My company's return is higher compared to the industry, and O2.3 My company's employee strength is larger compared to the industry.

O3 Absorptive capability which is measured by O3.1 My company invests funds in BDA technologies, O3.2 My company has knowledge and experience with BDA technologies, O3.3 My company is interested in implementing BDA technologies to achieve competitive advantage and O3.4 My company considers implementation of BDA technologies as strategic initiative.

E1 Environmental uncertainty which is measured by E1.1 My company's partners suggested BDA adoption, E1.2 My company's partners recommended BDA adoption, and E.1.3 My company's partners requested BDA adoption.

E2 Competition intensity which is measured by E2.1 My company undergoes competition intensity to adopt BDA technology and E.2.2 My Company could face competitive disadvantage if BDA is not adopted.

E3 Regulatory support which is measured by E3.1 Government influences the use of BDA, E3.2 Standards support BDA implementation, and E3.3 Legal protection supports BDA implementation.

For measuring BDA adoption, several measures are developed such as BA1. My company want to continually use BDA, BA2. My company expects to use BDA in the future, BA3. My company will frequently use BDA, and BA4. My company recommends the use of BDA to another company.

3.2 Data Analysis

This paper is based on Partial Least Square (PLS) - Structural Equation Modeling (SEM) (Hair, 2014) using several steps as depicted on the following flow chart:

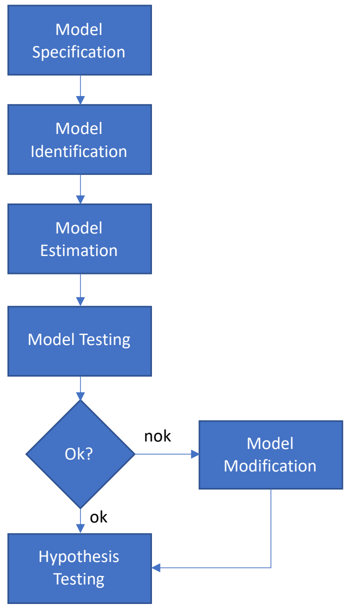

Figure 1: Methodology

From above figure, the steps cover model specification, model identification, model estimation, model testing, model modification and hypothesis testing (Jonny & Kriswanto, 2021).

Model specification. Based on previous studies, a conceptual model is generated as shown in the following figure. This conceptual model has based on TOE framework as stated in reference (Agrawal, 2013) which has been already rejuvenated by reference (Awa et. al., 2017). By this conceptual model, relationship of technology with organization and relationship between environment with organization are added based on previous studies (Awa et. al., 2017) to further investigate whether those relationships are existed in order to gain novel insight and knowledge as the contribution of this paper to the richness of the knowledge regarding to TOE framework. The figure is drawn as basis for PLS-SEM analysis to evaluate those relationships. In this model, there are 4 latent variables in which 2 of them are endogen variables and 3 variables are exogen variables with 31 questions as indicators.

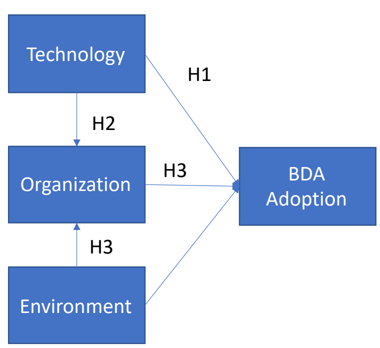

Figure 2: Conceptual model for testing hypotheses H1-4

Model identification. This step evaluates validity and reliability of the model through outer and inner analysis. In outer analysis.

In outer analysis, there are several measurements. First, convergent validity. This measurement is used to see whether indicators used in this model are said to be convergently validated with value more than 0.7. Second, discriminant validity will be used to see whether indicators and latent variables have discriminant validity with value more than 0.7. Third, composite reliability is deployed to see whether latent variables are having composite reliable with value more than 0.7

In inner analysis, there are several calculations. First value of R-square to see portion of exogen variables impacted endogen variables. Second, predictive relevance is calculated to see whether the model can be used for prediction purposes. Third, Goodness of Fit is used to see how fit the model is.

Model estimation. In this step, data from 124 companies are inputted into SmartPLS. The number of data is larger than required 40 responses (4 latent variable multiplies 10 sample data)

Model testing. This is done to evaluate whether the model is good fitted or not through test of Goodness of Fit (GoF) where the model can be said robust if the value is more than 0.38. If it is below than model modification should be done. If it is already robust, then hypothesis testing could be done.

Model modification. If the model is not fitted, the modification is taken placed to ensure its fitness. Then analysis can be done.

Hypothesis testing. After gaining robust model, hypothesis testing can be conducted to gain insights from this research.

4 Result

For data collection, questionnaires have been distributed to about 206 companies as member of Indonesian Chamber of Commerce and Industry to those who are at managerial position level up. From this number, only 124 questionnaires (only 49,6%) have completed using five level of Likert scale where 1= strongly disagree, 2= disagree, 3 = neutral, 4 = agree, 5 = strongly agree. According to reference (Hair, 2014), this response rate is considered good because it is voluntarily for respondents to submit their questionnaire through e-mail which is averaged at 25%-30%. Their profiles are shown in the following table.

Category	Sub Category	Number	Percentage
Company's age	<10	8	6
	11-20	68	55
	21-30	17	14
	>=30	31	25
Number of employees	<500	33	27
	501-1500	27	22
	>=1500	64	52
Size of Company (billion rupiahs)	Small (<0.2)	0	0
	Medium (0.21-10)	113	91
	Large (>10)	11	9
BDA implementation	Yes	93	75
	No	31	25
Period of implementation	<1	112	90
	>=1	12	10

Table 1: Respondents' Profile

From the above table, most of the respondent's company are about 11 to 20 years old (55%) followed by 25% of more than 30 years old, 14% in between 21-30 years or, and 6% in less than 10 years old.

In number of employees, most of respondents have more that 1,500 employees by 52% followed by 27% less than 500 employees and 22% in between 501 to 1.500 employees. For the size of company, it can be understood that most of respondents are from medium enterprises with 91% with remaining 9% in large enterprises.

Regarding to BDA implementation, 75% said to have implemented the emerging technology while 25% are still not exposed with this technology. When respondents are asked the period of implementation, 90% claimed only within 1 years and remaining 10% claimed to have implement the technology in more than 1 year.

4.1 Outer Model Tests

Outer model tests consist of convergent validity and discriminant validity.

4.1.1 Convergent Validity

To evaluate whether indicators from the model are convergently valid, two tests are conducted. First test is based on value of outer loadings. As shown in the below table, it can be seen the value of outer loading for each indicator of the model as follows:

	BDA Adoption	Environment	Organization	Technology
BA1	0.943			
BA2	0.900			
BA3	0.876			
BA4	0.709			
E1		0.729		
E2		0.869		
E3		0.511*		
O1			0.813	
O2			0.721	
O3			0.895	
T1				0.584*
T2				0.807
T3				0.847

Table 2: Value of Outer Loadings

From the above table, indicator E3 and T1 are under the required value of 0.7 (*). Thus, these two indicators are deleted from the model. Therefore, there are 11 remaining indicators from 13 indicators.

Second test is based on value of Average Variance Extracted (AVE) as shown in the following table. This table shows the value of AVE for each latent variable as follows:

Latent Variable	AVE
BDA Adoption	0.742
Environment	0,682
Organization	0,660
Technology	0,749
Average	0,708

Table 3: Value of Average Variance Extracted (AVE)

From the above table, it can be concluded that all latent variables are above the required value of 0.5. Therefore, those latent variables are said to have convergently valid.

4.1.2 Discriminant Validity

Evaluating whether both indicators and latent variables have discriminant validity requires two tests. First test is based on value of cross loadings as shown in following table:

	BDA Adoption	Environment	Organization	Technology
BA1	**0.944**	0,626	0,746	0,738
BA2	**0.901**	0,505	0,656	0,729
BA3	**0.877**	0,532	0,693	0,666
BA4	**0.705**	0,413	0,441	0,516
E1	0,321	**0.730**	0,392	0,417
E2	0,628	**0.912**	0,555	0,460
O1	0,593	0,433	**0.819**	0,673
O2	0,488	0,380	**0.712**	0,439
O3	0,718	0,589	**0.895**	0,660
T2	0,630	0,530	0,671	**0.863**
T3	0,712	0,382	0,609	**0,868**

Table 4: Value of Cross Loading

The above table shows that loading value of each indicator to its latent variable is larger than its crossing loading value. Thus, all indicators have discriminant validity.

Second test is based on value of Fornell-Larcker Criterion as detailed in the following table:

	BDA Adoption	Environment	Organization	Technology
BDA Adoption	**0.861**			
Environment	0.608	**0,826**		
Organization	0.748	0,585	**0,812**	
Technology	0.776	0,526	0,739	**0,866**

Table 5: Value of Fornell-Larcker Criterion

Above table indicates that square root AVE value for each latent variable is larger than its crossing correlation value. Thus, all latent variables have discriminant validity.

4.1.3 Composite Reliability

To conduct this indicator, the following table shows the value of composite reliability generated from SmartPLS 3.0:

Latent Variable	Composite Reliability
BDA Adoption	0.919
Environment	0,809
Organization	0,852
Technology	0,857

Table 6: Value of Composite Reliability

Above table shows that the value of Composite Reliability for all latent variables are above required value of 0.7. Therefore, it can be said that the model is reliable.

4.2 Inner Model Tests

First, this done by looking at the value of R square of the model as shown in the following table:

Latent Variable	R Square
BDA Adoption	0.694
Organization	0,600
Average	0,647

Table 7: value of R Square

Above table indicates that for 60% of Organization is influenced by Technology and Environment with 40% remaining is influenced by other variables, meanwhile 69.4% of BDA Adoption is influenced by Technology, Organization and Environment by other variables. Second, above test is followed by calculating the value of predictive relevance (Q2) as follows:

Q^2=1-(1-R_1^2)(1-R_2^2)
Q^2=1-(1-0,694)(1-0,600)=0,8776

Because the value is above required value of 0.5 then it can be concluded that the model has predictive power on the relationships built among latent variables. Third, the last test is done by calculating the Goodness of Fit (GoF) of the model as follows:

$$GoF = \sqrt{(\overline{AVE})(\overline{R^2})} = \sqrt{(0{,}708)(0{,}647)} = 0.677$$

From the above calculation, it can be seen that the value of GoF is larger than 0,67 then the model can be said to be strongly robust.

4.3 Hypothesis Testing

For testing hypotheses of the model, the path coefficient and T-value are generated and analyzed using SmartPLS 3.0 as described in the below sections. First, the below figure is derived from SmartPLS 3.0 in order to generate correlation value among relationships built in the research model.

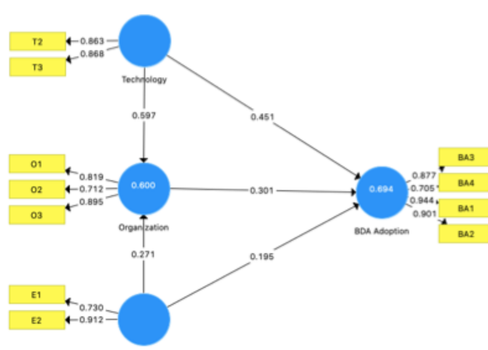

Figure 3: Path Coefficient

From the above figure, it can be confirmed that BDA adoption is influenced mainly by Technology (r=0.451), Organization (r=0.301) and Environment (r=0.195). Meanwhile, Organization is also mainly influenced by Technology (r=0.597) and Environment (r=0.271).

Furthermore, these latent variables are also supported by their indicators respectively. First, in Technology, Compatibility (T2) and Relative Advantage (T3) are strongly needed. Second, all indicators naming Technological Resource Competency (O1), Organizational size (O2), and Absorptive Capacity (O3) support Organization. Third, Environment is indicated by Environmental Uncertainty (E1) and Competition intensity (E2).

Second, T-value is also generated from SmartPLS as shown in the following figure:

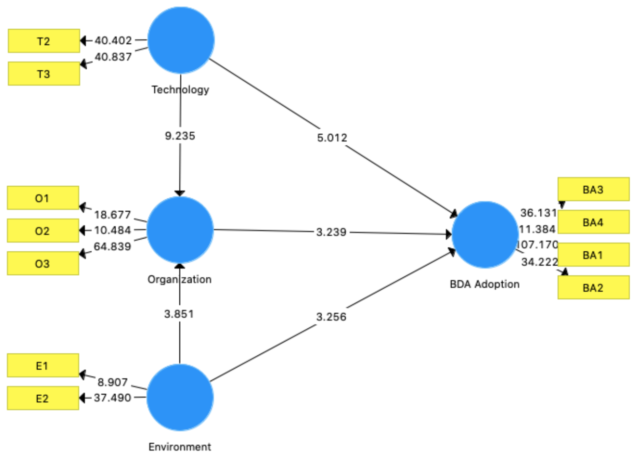

Figure 4: T-Value

Above figure has shown that all latent variables relationships have statistically significancy due do all higher T-value than required of T-value of 1.96.

Third, values generated from SmartPLS are summarized in the following table:

	Original Sample	Sample Mean	Standard Deviation	T-Satistics	P-value
E->B	0,195	0,197	0,060	3.256	0.001
E->O	0.271	0.271	0,070	3.851	0.000
O->B	0.301	0,297	0,093	3.239	0.001
T-B	0.451	0,253	0,090	5.012	0.000
T-O	0,597	0.600	0,065	9.235	0.000

Table 8: Value of Cross Loading

From the above table, it can be understood that 1) Environment positively influences BDA adoption (P-value=0.001), 2) Environment also positively influences Organization (P-value=0.000), 3) Organization positively influences BDA adoption (P-value=0.001), 4) Technology positively influences BDA adoption (P-value=0.000), and 5) Technology positively influences Organization (P-value=0.000).

5 Discussions

In this paper, a model is generated in order to give knowledge on how Big Data Analytics (BDA) is utilized in Indonesian environment. This model is considered robust and has generated valuable insights for any company that wishes to get the best advantage in this emerging technology.

First, this paper gives insight that in order to be able to adopt BDA, the company needs to master its technology which in Indonesia, compatibility and relative advantage could be significant issues.

Second, BDA adoption is also influenced by how well the company understand and anticipate its environment where environmental uncertainty and competition intensity may encourage company to adopt BDA. However, this finding may contrast with literature (Jonny and Kriswanto, 2020) in which regulatory support is found to be most influential factor affecting BDA adoption. This is very interesting since the same factor is not found in this paper.

Third, BDA adoption also depends on the maturity of the organization where technology resource competency, organizational size and absorptive capacity may need to get significant attention from its management. This readiness as an organization is also influenced by technology savviness and anticipative mode to its challenging environment.

Fourth, based on this research, it can be said that most of Indonesian companies are late adopters regarding to adopting this technology as their strategic weapon in gaining competitive advantage for the company to win the fierce competition in their industry.

6 Conclusion

Big Data Analytics has emerged as an important tool for company to win the competition in the industry. This has encouraged many companies to adopt this technology as part of their strategic action. Previous studies still have lack of understanding on what factor impacts the utilization of this technology. Therefore, this paper contributes by presenting a robust model to promote insights gained from this model.

As managerial implication, there are two suggestions can be adoption to pursue BDA adoption. These suggestions are drawn from this research to give companies the previous insights when implementing BDA technology in their organization.

First, Companies need to nurture its technology savviness, organizational readiness and environmental changes anticipation in order to successfully adopt BDA technology.

Second, for promoting organization readiness, the company also need to pay attention to technology savviness and environmental changes adoption. This research has clearly put organization in the center focus to increase the success odd in implementing the technology so that the company could gain upmost competitive advantage in the industry.

However, this research still has at least several limitations such as:

First, it is due to small number of participating companies. By gaining larger number of participating companies, new insights might be reached, and it will contribute to richer knowledge in this field of knowledge.

Second, additional factors should be added as the advancement of knowledge management. This can be done by carefully review literatures that are about to be publish to gain more insights especially on paying attention to factors that can promote the success of this technology adoption.

Third, for the future research, because there is none of small enterprises involved in this research, then it will be better to include them in the research.

Therefore, for future research, these limitations can be considered to pursue better understanding about factors impacting BDA adoption.

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