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Factors Impacting the Perceived Strategic Value, Evaluation, And Adoption of Big Data Analytics - A Case Study of The Top Ten Revenue Share Contractor Companies in Bangkok, Thailand

Thongchad Chinasi*

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Abstract

Purpose: The purpose of the research was to clarify the causal correlation among Big data analytic adoption environment of Top ten revenue-shared contractors company located in Bangkok with an aimed to arrange an alternative extensively and potentially ensures that the study's findings are valid and reliable, offering valuable insights for organizations, decision-makers and to explore the factors that impact the intention to use perceived strategic value of big data analytics.
Research design, data and methodology: This study uses the questionnaire survey and quantitative method to collect data from target groups. distributed questionnaires to workers who worked in the Top 10 revenue construction company.
Results: The relationships between Casual correlation among big data analytic adoption environment were clearly defined to shape the conceptual framework. This research gathers data from organizations experienced with big data analytics. The research outcomes confirmed the theories and relationships between the factors impacting big data analytics adoption.
Conclusions: The conclusion of research provide valuable insights into the factors that influence big data analytics adoption, highlighting the importance of managing complexity, ensuring compatibility, fostering organizational readiness, securing top management support, and conducting thorough evaluations to realize the strategic value of big data analytics. These insights can guide organizations in developing strategies to effectively adopt and utilize big data analytics for improved performance and competitive advantage. In order to maximize the highest utility, organizations need to ensure that new analytics technologies are compatible with existing IT infrastructure and business processes. This involves conducting thorough compatibility assessments before adoption and making necessary adjustments to current systems to facilitate seamless integration. Compatibility ensures that big data analytic tools can be effectively utilized without disrupting existing operations.

Keywords: Contractor; Big Data adoption; Construction industry; Building Information; Technology compatibility

JEL Classification Code: M15, O30, O31, O32, O33

1. Introduction

1.1 Background of The Study

In 2019, Thailand's construction industry generated a revenue around THB 1 trillion (approximately USD 30 billion) (GlobalData, 2020). The construction industry's contribution to Thailand's GDP was about 8.2% in 2019 (World Bank, 2020). Thailand's construction industry is one of a crucial profession contributing significantly to its revenue especially in contractor companies. These companies are responsible for various activities, including construction, infrastructure development, and renovation projects. They create jobs and stimulate economic growth

1 Thongchad Chinasi, Managing Director - Hook Architects, Thailand. Email: thongchad@hookarchitects.com

by committing to diverse industries, including real estate, energy, and transportation. Various factors influence the performance of contractor companies in Thailand's construction industry, Foreign Investments, Technological Advancements and Skilled Workforce.

The Technology Evolution in Thailand Construction Industry has evolved over the years, with technology playing a central role in transforming the way projects are planned, executed, and managed (Pacharawanit, Pongpeng,& Chinda, 2019). This evolution has been marked by the adoption of various building construction simulation technologies, such as Building Information Modeling (BIM) (Pacharawanit et al., 2019), Geographic Information Systems (GIS) (Rajabifard et al., 2017) The Big Data Analytics and drone technology (Dowgiallo, 2020).These advancements have allowed the industry to enhance productivity, improve safety, and reduce environmental impacts (Sutrisna et al., 2018).

Dowgiallo (2020) predicts that the utilization of innovative technologies Future Trends like AI, virtual reality (VR), IoT, and further advancements in Big Data analytics will continue to influence the advancement of technology used in the construction of Thailand. These technologies could revolutionize the industry by automating processes, improving decision-making, and enhancing stakeholder collaboration (Sutrisna et al., 2018).

The field of Big Data analytics has expanded considerably in recent years due to the rapid advancements with computing power, storage capacity, and data generation capabilities. As a result, Big data has established a software platform for various industries including finance, marketing, and services, as it enables organizations to optimize their strategies, enhance customer experiences, and uncover hidden opportunities (Katal et al., 2013).

The primary goal of Big data analytics is to extract valuable insights from large data sets that can drive better decisions and create competitive advantages. Identifying and extracting this value requires skilled data scientists and appropriate tools (Sivarajah et al., 2017).

Nowadays, Big Data has the potential to enhance an organization's problem-solving strategies. Studies have shown that "More data usually beats better algorithms," implying that investing in processing larger data sets could be more valuable for organizations than costly algorithms. The abundance of data can lead to the identification of correlations that would be difficult to discover when analyzing separate or smaller data sets.

However, processing large datasets may also present challenges due to limitations in processing capabilities. Big data technology significantly affects the constructionindustry by transforming various aspects of construction projects. For example, enhanced decision-making, resource optimization, improved project planning and scheduling, analyzes past project performance, allowing to create more accurate project plans and schedules (Chen, & Zhang, 2017). support cost management, cost overruns and potential budget risks management and hazards in construction projects by analyzing patterns in collected data set. (El-Gohary & Aziz, 2014)

Big Data Analytics Implementation in Thailand's Construction Sector

Big Data Analytics has brought about considerable transformations in numerous industries worldwide including Thailand's construction sector. By utilizing large volumes of data, construction firms can streamline their projects, make better decisions, and boost overall effectiveness. This introduction offers an insight into the role of the Big Data Analytics construction industry of Thailand and its ramifications.

Thailand's construction industry has experienced significant growth in recent years, primarily due to rapid urbanization and government initiatives to improve infrastructure. As projects become larger and more complex, the need for effective data management has become increasingly important. Big Data Analytics allows construction professionals to gain valuable insights from various sources, such as project management systems, BIM, and IoT (Boonmee et al., 2021).

By analyzing Big Data, construction companies can identify patterns and trends to help them make informed decisions, optimize project performance, and minimize risks.For instance, they can predict cost overruns, improve scheduling, and enhance stakeholder collaboration (Limsakul & Saithanu, 2019). Additionally, Big Data can be used for predictive maintenance, leading to significant cost savings and increased asset reliability (Phruksaphanrat et al., 2020). Furthermore, Big Data Analytics can be instrumental in promoting sustainable construction practices in Thailand. By analyzing energy consumption, waste generation, and resource usage data, construction companies can develop more environmentally friendly solutions, which can contribute to achieving the country's sustainability goals (Sornchuer & Charoenngam, 2021).

Regarding opportunities, integrating Big Data Analytics with other emerging technologies, such as AI and ML, can significantly accelerate the construction process. These technologies can be used to create more accurate predictive models, automate routine tasks, and develop intelligent systems for managing construction projects (Kaur & Singh, 2020).

1.2 Research Objective

This research seeks to thoroughly understand the factors impacting the perceived strategic value, evaluation, and adoption of Big Data Analytics by clarifying the causal correlation among environment to arrange an alternative extensively and potentially ensures that the study's findings are valid and reliable, offering valuable insight, decision-makers and to explore the factors that impact the intention to use perceived strategic for more effective value of Big Data adoption within the contractor company located in Bangkok throughout Thailand's top ten revenue share contractor companies using 8 variables specifically complexity (CPX), compatibility (CMP), organizational readiness (OR), external support (ES), top management support (TS), evaluation (EV), perceived strategic value of Big Data Analytics (PSV) and Big Data analytics Adoption (BDA) examined and analyzed to clarify the causal relationship by integrating several research theories and previous literature from different perspectives to test

In-depth details for adopting variables were address as follows:

1. To determine the significance of the causal correlation between Complexity and perceived strategic value of Big Data Analytics implementation.
2. To determine the factor significance of the causal correlation between Compatibility and perceived strategic value of Big Data Analytics implementation.
3. To determine the significance of the causal correlation between Organization Readiness and Evaluation of Big Data Analytics implementation.
4. To determine the significance of the causal correlation between outermost company (External) Support and Evaluation of Big data analytics implementation.
5. To determine the significance of the causal correlation between Top management support and Big data analytics Adoption in the top ten revenue share contractor companies in Bangkok, Thailand.
6. To identify the significance of the causal correlation between Evaluation and Big Data Analytics Adoption in Bangkok, Thailand's top ten revenue share contractor companies.
7. To identify the significance of the causal correlation between the perceived strategic value of Big Data Analytics and Big Data Analytics Adoption in Bangkok, Thailand's top ten revenue share contractor companies.

1.3 Research Question

The hypothesis serves as a statement that aims to validate researchers' predictions through the insights or findings from a research study. Seven hypotheses were proposed to be tested and verified referring to the conceptual research schema.

1. Does Complexity (CPX) significantly impact the perceived strategic value (PSV) of Big Data Analytics (BDA)?
2. Does Compatibility (CMP) significantly impact the perceived strategic value (PSV) of Big Data Analytics (BDA)?
3. Does Organization Readiness (OR) significantly impact the Evaluation (EV) of Big Data Analytics adoption?
4. Does External Support (ES) significantly impact the Evaluation (EV) of Big Data Analytics Adoption (BDA)?
5. Does Top management (executive level in contractor company) (TS) support significantly impact Big Data Analytics Adoption?
6. Does Evaluation (EV) significantly impact Big Data Analytics Adoption?
7. Does the perceived strategic value (PSV) of Big Data Analytics significantly impact Big Data Analytics implementation (BDA)?

2. Literature Review

2.1 Theories Related to the Variables

The theories of each variable for the study of Big data Analytic adoption were reviewed, containing the definition and literature related to the variables. The variables studied comprise Complexity, Compatibility, Organizational readiness, External Support, Top management support, Perceived Strategic Value of Big Data Adoption, and Evaluation.

2.2 Complexity (CPX)

Complexity refers to new solution is considered challenging to Understand and apply Rogers (2003) a more complex innovation would be less likely to be adopted. The intricacy of technology adds to the uncertainty surrounding its successful implementation, consequently increasing the risk associated with the technology adoption decision (Premkumar & Roberts, 1999). To foster higher adoption rates, novel technologies must be user-friendly and straightforward (Sahin, 2006). While complexity has been found to negatively correlate with IT adoption in organizations (Grover, 1993), it remains a critical determinant of organizational IT adoption (Thong, 1999).

2.3 Compatibility (CMP)

Compatibility refers to a new technology integrated fits to beliefs, past backgrounds, and needs of potential implementors and assessors. Rogers (2003). In the context of organizational systems. Compatibility denotes the way a new technology integrates into the current framework. Maroufkhani et al. (2019)

2.4 Organization Readiness (OR)

Organization Readiness refers to the extent to which an organization can access financial, technological, and requirement of personal skills that are necessary for technology implementation. Maroufkhani et al. (2019). Current circumstance of SME organizations, organizational readiness pertains to their availability of funding, trainedstaff, expertise, analytical skills, and necessary infrastructure necessary for the full utilization of Big Data Analytics. Inadequate resources and capabilities can render investing in technology futile, despite its potential benefits, as noted by Alsetoohy et al. (2019).

2.5 External Support (ES)

External support refers to key element in a company's choice to implement technology, referring to extended assistance from a service provider or third party (Gangwar, 2018) For the organization, third parties and vendors can be the support of technological context and assist in pushing the company to embrace essential innovation as the external support parties. (Al-Qirim, 2006).

2.6 Top Management Support (TS)

Top Management Support refers to company's finite resources and technical know-how are directed toward fulfilling the vital requirements of emerging technologies. By creating a supportive environment, Top management is vital for driving technology adoption and fostering innovation within an organization. This factor pertains to the degree of assurance and capital backing the upper-level stakeholders that provide for next-generation technology adoption. Premkumar (2003)

2.7 Evaluation (EV)

Evaluations refers to the early adoption stages; nevertheless, there is a need for additional research on evaluating organizational perspective on Big Data strategies. Rogers (2003). The Conceptual Framework to pinpoint the drivers behind organizations' implementation of Big Data. However, their model is not comprehensive, as it was created from a principled standpoint derived from an examination of existing literature on IT implementation.

2.8 Perceived Strategic Value of Big Data Analytic (PSV)

Perceived Strategic Value of Big Data Analytic refers to valuable insights, unravel critical data, and ultimately improve the caliber and performance of their company problem-solving processes. Chen and Zhang (2014) An organization's business strategy perceives Big Data Analytics with an in-depth awareness of the constituent components, encompassing Big data analytics and commercial operation strategy. Mikalef et al. (2019)

2.9 Big Data Analytics Adoption (BDA)

Big Data Analytics Adoption refers to insights that analyzing from vast amount of data to uncover strategic information and emerging to organization particularly leads to an enhancement in the quality. Organizations can refine their market surveillance and improve the acceptance of their products and services by leveraging Big Data Analytics. This technology also enables organizations to comprehend their business environment better (Chen & Zhang, 2014).

3. Research Methods and Material

3.1 Research Framework

The research path created the basic theories and constructed the variables are descriptions of the theoretical and conceptual frameworks (Adom et al., 2018). The framework can illustrate the correlations of factors, better comprehend the research field's theoretical construction, and facilitate generalization. This research aimed to explore factors impacting the perceived strategic value (PSV), evaluation, and adoption of Big Data Analytics for the case study of the top ten revenue share contractor companies in Bangkok, Thailand. The researcher has applied by using three major theoretical frameworks to develop and support the conceptual framework.

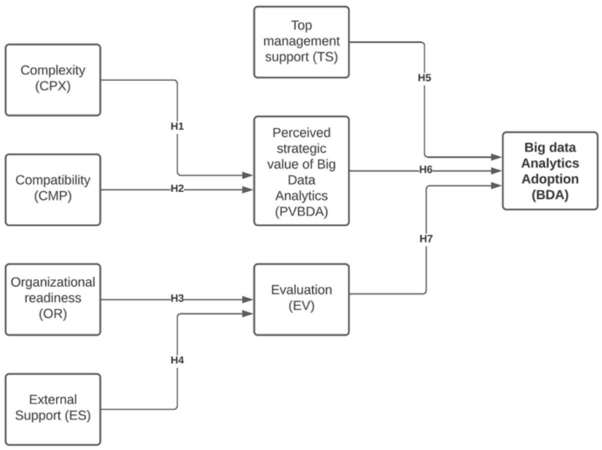

Figure 1: The Conceptual Framework of "Factor Impacting the Perceived strategic value, evaluation, and Adoption of Big Data adoption - the case study of the Top Ten Revenue Share Contractor Companies in Bangkok, Thailand"
Source: Author

H1: Complexity has a significant impact on the Perceived strategic value of Big Data Analytics
H2: Compatibility has a significant impact on the Perceived strategic value of Big Data Analytics
H3: Organization readiness has a significant impact on Evaluation.
H4: External Support has a significant impact on evaluation.
H5: Top management support has a significant impact on Big data Analytics Adoption
H6: Evaluation has a significant impact on Big data Analytics Adoption.
H7: The perceived strategic value of Big Data Analytics significantly impacts Big Data Analytics adoption.

3.2 Research Methodology

This study uses the questionnaire survey and quantitative method to collect data from target groups. Using a quantitative study design, the researcher distributed questionnaires to workers who worked in the Top 10 revenue construction company. The questionnaire was made up of four main parts. It contained screening questions and the measurement of all variables. The questions were close-ended questions with a limited choice of a five-point Likert scale. The last part was a demographic question of the respondents in the questionnaire.

Since the questionnaires were distributed in Thailand, the questions were translated into Thai for respondents to read and understand. The first part of the questionnaire were designed to be a screening questions to determine whether they would be qualified because this study required workers who work with data analytics and digital implementation in the top ten share revenue contractors company. The second part is demographic question to collect information about the respondents' background characteristics. And the third part investigated the factors impacting the adoption of big data analytics. In this study, questionnaires were designed using a five-point Likert scale determine whether workers who work with data and Big Data are analytic factors to impact the company to adopt Big Data analytics and to obtain numerical results for the statistical analysis.

The questionnaire was created and distributed through an online survey of 'Questionnaire Star'. Collecting data through the online channel has many advantages compared to other methods. In order to reach the number of respondents defined for each selected university, online distribution was an effective and fastest way to complete the data collection. Sills and Song (2002) mentioned that internet surveys significantly reduced time and lowered costs. Another advantage of online surveys is that there is no need to input or encode data manually, which reduces human error because the participant enters all the data and automatically keeps it in an electronic format.

3.3 Population and Sample

3.3.1 Population characteristic

The population considered for the research are workers with at least five years of experience, exclusively employed in the top 10 revenue construction companies and specializing in data analytics and digital implementation.

3.3.2 Sample Size

In this paper, parameter values were calculated to discover the sample size Calculator for Structural Equation Models via Soper (n.d.). The basic sample size for the analysis are 444 samples (Per Table 1). For this study, the questionnaire was targeted to distribute to 500 respondents.

Table 1: Sample Size Calculator for Structural Equation Modeling

Items	No.
Anticipate effect size	0.2
Desired statistical power level	0.8
Number of latent variables	8
Number of observed variables	26
Probability level	0.05
Minimum sample size to detect effect	444
Minimum sample size for model structure	166
Recommended minimum sample size	444

3.3.3 Sampling Technique

The population for this research calculated using multi-stage sampling to systematically narrow down from purposive sampling scope in top 10 market shares of the construction company in Bangkok. Then using quota sampling method as second stage in each company population proportional. Finally, using convenience sampling method to targeted respondents based on their work in data analytics, digital information implementation with at least five years of experience.

Table 2: Number of Questionnaires Distributed to Each Company

Company Name		%REV	PPL
Italian-Thai Development PCL	(ITD)	35.7	178.5
Sino-Thai Engineering & Construction PCL	(STECON)	19	95
Ch. Karnchang PCL	(CK)	15.1	75.5
Unique Engineering Company Limited	(UNIQ)	6.9	34.5
Power Line Engineering PCL	(PLE)	5.5	27.5
Syntec Construction PCL	(SYNTEC)	4.9	24.5
Nawarat Patanakarn PCL	(NWR)	4.5	22.5
Christiani & Nielsen (Thai) PCL	(CNT)	4.2	21
Pre-Built PCL	(PREB)	2.5	12.5
Seafco PCL	(SEAFCO)	1.7	8.5
Total		**100**	**500**

Note: REV - Revenue, PPL - Population

4. Results

4.1 Demographic Information

Demographic information collected from 500 respondents were on gender and year of study, the top ten revenue Thailand contractor companies. The respondents consist of 339 females and 161 males which represents 67.8%, and 32.2%, respectively. For worked experience with the Data in company, there were 54 persons with 1-3 years experienced workers (10.80%), 95 persons with 4-6 years experienced workers (19%), 108 persons with 7-9 years experienced workers (21.60%) and 243 persons with over 10 years experienced workers (48.60%). For the demographic characteristics of the participants based on year of work. Among the total 500 participants, 243 persons (48.60%) with over 10 year's experience, 108 persons (21.60%) with 7-9 year's experience, 95 persons (19%) with 4-6 year's experience and 54 persons (10.80%) with 1-3 year's experience.

Table 3 Demographic Characteristics of participants clarify by gender and year of work

		Counts	% of total
Gender	Male	161	32.2%
	Female	339	67.8%
Year of work	Over 10	243	48.60%
	7-9	108	21.60%
	4-6	95	19.00%
	1-3	54	10.80%

Note: n = 500

4.2 Confirmatory Factor Analysis (CFA)

Table 4: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Complexity (CPX)	Zhu et al. (2006), Lai et al. (2018)	**3**	0.889	0.735-0.807	0.819	0.602
Compatibility (CMP)	Chen and Preston (2015), Ghobakhloo et al. (2011),	**3**	0.927	0.848-0.903	0.900	0.751
Organizational readiness (ORR)	Chen and Preston (2015)	**4**	0.942	0.826-0.891	0.911	0.720
External Support (ES)	Ghobakhloo et al. (2011)	**3**	0.848	0.850-0.919	0.919	0.791
Top management support (TS)	Chen and Preston (2015), Lai et al. (2018), Priyadarshinee et al. (2017)	**4**	0.963	0.812-0.865	0.900	0.693
Evaluation (EV)	Chan and Chong (2013)	**3**	0.895	0.883-0.925	0.928	0.812
Perceived strategic value of Big Data Analytics (PSV)	Priyadarshinee et al. (2017)	**3**	0.926	0.859-0.875	0.902	0.755
Big data Analytics Adoption (BDA)	Raguseo and Vitari (2018)	**3**	0.955	0.770-0.826	0.843	0.642

The measurement model was evaluated by using confirmatory factor analysis to confirm model fitness. There are 7 latent variables illustrated in the Table 5 of measurement model, Complexity, Compatibility, Organizational readiness, External Support, Top management support, Evaluation, Perceived strategic value of Big Data Analytics. Modification to the measurement model was not necessary for this study as the original measurement model has already presented a model fit.

The model fit was presented by the acceptable values of goodness-of-fit indices in table 5.5. The statistical values of indices were compared to the acceptable criteria. In which, the values were CMIN/DF = 1.597, GFI = 0.939, AGFI = 0.921, NFI=0.955, CFI = 0.982, TLI = 0.979, and RMSEA = 0.035.

Table 5: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	≤ 5.00 (Marsh et al., 2004)	432.685/271 = 1.597
GFI	≥ 0.80 (Nayir, 2013)	0.939
AGFI	≥ 0.80 (Nayir, 2013)	0.921
NFI	≥ 0.80 (Wu & Wang, 2006)	0.955
CFI	≥ 0.80 (Nayir, 2013)	0.982
TLI	≥ 0.80 (Sharma et al., 2005)	0.979
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.035
Model summary		In harmony with empirical data

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI, normalized fit index, TLI = TuckerLewis index, CFI = comparative fit indeand RMSEA = root mean square error of approximation

Discriminant validity is confirmed when the square root of the AVE was larger than the coefficient of any intercorrelated construct (Fornell & Larcker, 1981). As illustrated in table 6,the square root of AVE for all constructs at diagonal line were greater than the inter-scale correlations. Hence, the discriminant validity was guaranteed.

Table 6: Discriminant Validity

	ES	CPX	CMP	ORR	PSV	TS	BDA	EV
ES	**0.889**							
CPX	0.528	**0.776**						
CMP	0.575	0.612	**0.867**					
ORR	0.542	0.593	0.485	**0.848**				
PSV	0.550	0.431	0.446	0.428	**0.869**			
TS	0.592	0.485	0.384	0.481	0.436	**0.832**		
BDA	0.399	0.444	0.372	0.391	0.453	0.345	**0.801**	
EV	0.287	0.350	0.383	0.460	0.232	0.271	0.295	**0.901**

Note: The diagonally listed value is the AVE square roots of the variables According to Fornell and Larcker (1981).

Structural Equation Model (SEM)

The model fit was evaluated compare the statistic value from indices against the acceptable values of goodness-of-fit in table 7. The statistical values of indices were CMIN/DF = 3.564, GFI = 0.867, AGFI = 0.840, NFI=0.892, CFI = 0.919, TLI = 0.910, and RMSEA = 0.072. From the values, indices of GFI, AGFI, NFI, and TLI were not acceptable. Therefore, the structural model was modified and recalculated good-of-fit.

Table 7 : Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values
CMIN/DF	≤ 5.00 (Marsh et al., 2004)	1033.556/290 = 3.564
GFI	≥ 0.80 (Nayir, 2013)	0.867
AGFI	≥ 0.80 (Nayir, 2013)	0.840
NFI	≥ 0.80 (Wu & Wang, 2006)	0.892
CFI	≥ 0.80 (Nayir, 2013)	0.919
TLI	≥ 0.80 (Sharma et al., 2005)	0.910
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.072
Model summary		In harmony with empirical data

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation

4.4 Research Hypothesis Testing Result

The magnitude of correlation among the independent and dependent variables proposed in the hypothesis is measured by regression coefficients or standardized path coefficients. As presented in Table 8, Complexity and Compatibility have a significant impact on the Perceived strategic value of Big

Data Analytics, Organization readiness has a significant impact on Evaluation, and Top management support, Evaluation, and The perceived strategic value of Big Data Analytics have a significant impact on Big data Analytics Adoption.

Table 8: Hypotheses Result of the Structural Model

Hypothesis	(β)	t-value	Test result
H1:CPX→PSV→BDA	0.260	4.057*	Supported
H2:CMP→PSV→BDA	0.292	4.755*	Supported
H3:ORR→EV	0.432	7.730*	Supported
H4:ES→EV	0.054	1.017	Not Supported
H5:TS→BDA	0.156	3.239*	Supported
H6:EV→BDA	0.189	3.977*	Supported
H7:PSV→BDA	0.377	7.496*	Supported

Note: *=p-value<0.05

The result in Table 8 can be refined that H1 complexity has a significant impact on the perceived strategic value of Big Data Analytics adoption, with a standardized path coefficient of 0.260 and a t-value of 4.057. Highlighting the importance of managing data complexity to enhance decision-making and competitive advantage.

H2 compatibility significantly impacts the perceived strategic value of Big Data Analytics adoption, with a standardized path coefficient of 0.292 and a t-value of 4.755. ensuring Big Data Analytics adoption compatibility with existing organizational processes and IT infrastructure is crucial for maximizing its perceived value.

H3 organizational readiness is the strongest impact on evaluation with a standardized path coefficient of 0.432 and a t-value of 7.730 indicating that organizations with a stable workforce and technical competence are more prepared for Big Data Analytics Adoption.

H4 external support does not significantly impact the evaluation process, with a standardized path coefficient of 0.054 and a t-value of 1.017. This finding suggests that internal factors such as organizational readiness and capabilities may play a more crucial role than external support in the evaluation process.

H5 Top management support significantly impacts Big Data Analytics adoption, with a standardized path coefficient of 0.156 and a t-value of 3.239. This underscores the importance of executive commitment in providing strategic direction, allocating resources, and fostering a supportive organizational culture.

H6 evaluation significantly impacts Big Data Analytics adoption, with a standardized path coefficient of 0.189 and a t-value of 3.977. emphasizing the importance of proper evaluation methods in assessing the potential benefits and risks associated with Big Data Analytics adoption, influencing organizational adoption decisions.

H7 the Perceived Strategic Value of Big Data Analytics is the second strongest impact on Big Data Analytics adoption with a standardized path coefficient of 0.377 and a t-value of 7.496. emphasizing that organizations recognizing the strategic benefits of Big Data Analytics adoption are more likely to invest in its implementation and integration into their business processes.

4.5 The Result of Structural Model

The relationship among the variables can be affected directly and indirectly, which AMOS software helps calculate and determine these effects. Direct effect (DE) of relationship implies that two variables are correlated with no effect from moderating variables. Whereas indirect effect (IE) relationship is the correlation of variables that exist only through at least one moderating variable. Total effect (TE) is the summation of direct and indirect effects of a relationship path. R square (R2) value indicates the proportion of variation in the dependent variable (Fornell & Larcker, 1981). In other words, the R square value determines the variance in the variable that can be explained by the other variable. The acceptable level of R2 is at least 0.1 and the results present the R2 values of 0.215, 0.202 and 0.246, which were all greater than the minimum level. Table 5.10 illustrates the direct, indirect, and total effects of the relationship based on the hypotheses proposed.

Two factors had a direct impact on Evaluation, which were external support (0.054), and Organizational readiness (0.432), The variation impact on evaluation can be explained by independent variables at 48%.

Two factors had a direct impact on Perceived strategic value of Big Data Analytics, which were compatibility (0.292), and Complexity (0.260), The variation impact on evaluation can be explained by independent variables at 55%.

Three factors had a direct impact on Big Data Analytics adoption, which were Top management support (0.156), Evaluation (0.189), Perceived strategic value of Big Data Analytics (0.377). Indirect effects independent variables were External Support (0.010), Organizational readiness (0.081), Compatibility (0.110), and Complexity (0.098),

The variation impact on Big Data Analytics adoption can be explained by independent variables at 72%.

5. Discussion and Conclusions

5.1 Answer to the Research Questions

This research aims to examine the factors impacting the Perceived Strategic Value Of Big Data Analytics, evaluation, and adoption of Big Data Analytics within organizations. The study developed a conceptual framework based on a comprehensive review of relevant literature and theories.Potential determinants of Big Data Analytics adoption were identified from previous research studies.

The research objectives and problem statements were clearly defined to shape the conceptual framework. This study employed quantitative methods to gather data from organizations experienced with Big Data Analytics. Data collection involved factor analysis and correlation regression analysis through Confirmatory Factor Analysis and Structural Equation Modelling. The research outcomes confirmed the theories and relationships between the factors impacting Big Data Analytics adoption.

The findings indicate that complexity significantly impacts the perceived strategic value of Big Data Analytics adoption. This aligns with the research by Davenport et al. (2012), emphasizing the importance of managing data complexity for enhancing decision-making and gaining a competitive advantage. The intricate nature of Big Data Analytics requires sophisticated handling of data variety, velocity, and volume, highlighting the critical role of robust data management practices.

Compatibility with existing organizational processes and IT infrastructure significantly influences the perceived strategic value of Big Data Analytics adoption. This finding underscores the necessity for organizations to ensure that new technologies align with their current systems and processes to maximize the benefits of Big Data Analytics Adoption, as supported by Gupta & Sarker (2021) and Singh and Rathi (2018).

Organizational readiness emerged as the strongest factor impacting the evaluation of Big Data Analytics Adoption. Organizations with a stable workforce, technical competence, and essential skills are better positioned to adopt new technologies successfully. This result supports the findings of Ismail et al. (2018) and Holt et al. (2007), highlighting the importance of preparing the organization for technological advancements.

Contrary to expectations, external support does not significantly impact the evaluation process of Big Data

Analytics Adoption. This suggests that internal factors such as organizational readiness and inherent capabilities are more critical than external assistance from technology vendors and consultants. This finding aligns with Premkumar and Roberts (1999) and Rogers (2003), emphasizing the need for a strong internal foundation for successful Big Data Analytics Adoption.Top management support significantly impacts the adoption of Big Data Analytics Adoption. Executive commitment in providing strategic direction, allocating resources, and fostering a supportive organizational culture is paramount for driving Big Data Analytics Adoption initiatives. This conclusion is consistent with the research conducted by Yeoh and Popovič (2016), and Sharma (2020), underscoring the importance of leadership in technological adoption.

The evaluation process significantly influences Big Data Analytics Adoption. Proper evaluation methods are essential for assessing the potential benefits and risks associated with Big Data Analytics Adoption, thereby guiding informed adoption decisions. This finding is in line with Babar and Stamelos (2022) and LaValle et al. (2020), who emphasize the necessity of thorough evaluations to ensure alignment with organizational goals and capabilities.

The perceived strategic value of Big Data Analytics Adoption is a significant driver of its adoption. Organizations recognizing the strategic benefits of Big Data Analytics Adoption are more likely to invest in its implementation and integration into their business processes. This supports the conclusions of Akter and Wamba (2016), and Davenport et al. (2012), highlighting the motivational role of perceived value in technology adoption.

The findings of this study provide valuable insights into the factors that influence the adoption of Big Data Analytics Adoption, highlighting the importance of managing complexity, ensuring compatibility, fostering organizational readiness, securing top management support, and conducting thorough evaluations to realize the strategic value of Big

Data Analytics Adoption. These insights can guide organizations in developing strategies to effectively adopt and utilize Big Data Analytics Adoption for improved performance and competitive

advantage.

5.2 Implications for Practice

Organizations should prioritize strategies to manage the complexity of Big Data Analytics. This includes investing in advanced data management technologies and developing robust data governance frameworks. By effectively handling the variety, velocity, and volume of data, organizations can enhance decision-making processes and gain a competitive edge. Training and development programs focused on data analytics skills can also help employees better manage and utilize complex data.To maximize the perceived strategic value of Big Data Analytics, organizations need to ensure that new analytics technologies are compatible with existing IT infrastructure and business processes. This involves conducting thorough compatibility assessments before adoption and making necessary adjustments to current systems to facilitate seamless integration.

Compatibility ensures that Big data Analytics tools can be effectively utilized without disrupting existing operations.

5.3 Future Research

One limitation of this research is the scope and sample size. The study was conducted within a specific context and limited sample, which may not fully represent all types of organizations or industries. This limitation could affect the generalizability of the findings across different contexts.

Future research should consider longitudinal designs to track changes in Big Data Analytics adoption over time. This approach can provide a deeper understanding of organizational readiness, top management support, market dynamics, regulatory environments, technological trends, financial performance, operational efficiency, a competitive advantage, considered the perspective of different stakeholder can provide tangible evidence to Big Data Analytics adoption in the long term.

Overall, continued research in this area is crucial as organizations increasingly rely on data-driven decision-making. By addressing the current limitations and pursuing further studies, researchers can contribute valuable knowledge that supports organizations in successfully implementation and benefiting from Big Data Analytics adoption.

5.4 Conclusion

The study provides practical implications for organizations aiming to adopt Big Data Analytics .

Recommendations include investing in advanced data management technologies, ensuring compatibility with existing systems, enhancing organizational readiness, focusing on internal capabilities, securing top management support, developing comprehensive evaluation criteria, and clearly communicating the strategic value.

Addressing the limitations of this research and exploring further studies in areas such as longitudinal designs, broader industry contexts, external environmental factors, mixed-methods approaches, the direct impact on organizational performance, technological comparisons, and stakeholder perspectives can significantly advance the understanding an adoption.

In conclusion, this research offers a comprehensive framework for understanding the critical factors influencing the adoption of Big Data Analytics. By considering these factors, organizations can enhance their readiness, ensure a smooth adoption process, and leverage analytics for improved performance and competitive advantage. Continued research in this area is essential to support organizations in successfully adopting and benefiting from Big Data Analytics.

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