RESEARCH ARTICLE

Strategic determinants of big data analytics in the AEC sector: a multi-perspective framework

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ABSTRACT

With constant flow of large data sets generated by different organisations, big data analytics promises to be a revolutionary game changer for Architecture, Engineering and Construction (AEC) industry. Despite the potential of Big Data, there has been little research conducted thus far to understand the Big Data phenomenon, specifically in the AEC industry. The objective of this research therefore is to understand the contributing factors for adopting big data in AEC firms. The investigation combined the perceived strategic value of BDA with the TOE framework (technology, organization, and environment), to develop and test a holistic model on big data adoption. A set of hypotheses derived from the extant literature was tested on data from structured surveys of about 365 firms, categorised as construction service firms (engineering and architecture) and construction firms (firms engaged in managing construction projects). The results indicated that the inhibitors and facilitators of BDA adoption are different in the construction services (architecture and engineering) and construction firms. For effective adoption of BDA solutions, the findings will guide the business managers to have realistic expectations of BDA integration challenges in AEC sector.

INTRODUCTION

As strategic emphasis on data-driven decision-making and innovation increases, firms today cannot afford to ignore the rewards of data science and advanced analytics for real-time insights of customers and machines by a big data application (BDA)-driven environment. Firms thereby are almost being compelled to increase IT investments on BDA (Wu, et al., 2017). Herein, it is interesting to note that both construction firms and construction service firms do play an essential role within a nation's economy. Construction firms (like manufacturing) include the 'hard' part, i.e. construction of non-residential (heavy industrial, institutional and commercial, engineering), and residential buildings; while, construction services consist of the 'soft' part, i.e. activities where people offer the time and knowledge to improve productivity, sustainability, performance, and potentiality through innovation (Huang, Lu and Chen, 2017; Sarnovsky, Bednar and Smatana, 2018). Today, BDA is equally important in the service industry, as the quality of service provided just tends to be the key differentiator, as opposed to the traditional construction industry, where it is the quality of product, which is more important (Math, 2018).

With major economic development and urbanisation in progress, India is estimated to annually build 700–900 million square meters of residential and commercial space, till about 2020 (McKinsey, 2010). With such anticipated volume of construction, the Indian Architecture, Engineering and Construction (AEC) sector is certainly going to play a significant role in contributing to the Indian economy (Ahmed, et al., 2017). The key antecedents that can help in achieving adoption success of BDA include big data quality (Verma, 2018), support of top management (Gunasekaran, et al., 2017), external pressure (Verma and Bhattacharyya, 2017), organisational data environment (Verma and Bhattacharyya, 2017) and perceived benefits (Verma, 2018; Verma and Chaurasia, 2019). BDA implementation requires major modifications in the existing business processes to enable willing organisations to adapt, while looking to match the capabilities of their current system (Wang, et al., 2016a; Chaurasia and Rosin, 2017; Wang, et al., 2018b).

However, despite the benefits of BDA, not all AEC firms are accelerating BDA solution adoption (Chen, Preston and Swink, 2015). Specifically, SMEs (Small and Medium Enterprise), which dominate the supply chain, have a fragmented data pool, which are collected by different organisations during an asset's life cycle (Ahmed, et al., 2017). Thus, collating them under one umbrella is a humongous task in itself. Moreover, organisations in specific sectors may work within a constrained budget for technology; for instance, the micro, small and medium enterprises (MSME) may have inadequate technical capabilities, whereby they depend on smaller groups of IT support staff or professionals for their IT needs (Verma, 2018). However, one must acknowledge the fact that although BDA is a disruptive technology, the reasons for reluctance to adopt BDA solutions are real and noteworthy (Wang, Kung and Byrd, 2018a). Review of existing literature also suggests that the BDA phenomenon is not a panacea for all firms (Verma, 2018).

So, the objective of this research is to understand the contributing factors for adopting BDA, vis a vis its strategic value to AEC firms. As preceding studies on BDA focused on operational and technical issues (Raguseo, 2018), the current investigation seeks to develop

and test a model by integrating the Technology-Organization-Environment (TOE) (Tornatzky and Fleischer, 1990) and strategic value of big data analytics perspectives (Grandon and Pearson, 2004) that underlie its adoption.

LITERATURE REVIEW

Adoption Models

Tornatzky and Fleischer (1990) investigated the TOE factors primarily through the TOE framework. The TOE framework considers three main features of a firm, which in turn impacts any innovation's adoption, i.e., technology, organisation, and environment (Tornatzky and Fleischer, 1990). Grandon and Pearson (2004) and Sutanonpaiboon and Pearson (2006) have earlier investigated the strategic value of IT through the Perceived Strategic Value based Adoption Model (PSVAM). However, studies using models like Theory of Planned Behaviour, Theory of Reasoned Action, Technology Acceptance Model and Unified Theory of Acceptance models, are significantly less, especially in an organisational context (Oliveira and Martins, 2011). On the other hand, Diffusion of Innovation (DOI), Technology-Organization-Environment (TOE) Framework and Perceived Strategic Valued based Adoption Model (PSVAM) have been widely used in studying technology adoption at an organisational level (Sutanonpaiboon and Pearson, 2006). Therefore, researchers in the IT domain have suggested integrating the TOE framework with PSVAM, which does not seem to have been done before.

The strategic value of technology and the business manager's perceptions of innovation constructs predominate PSVAM (Saffu, Walker and Mazurek, 2012). The elements prompting the adoption of an innovation within organisations include external characteristics (i.e. system openness), individuals (i.e. leadership's attitude toward change), and internal organisational structure (i.e. centralisation, complexity, interconnectedness, organisational slack and the size of employees) of a firm.

RELATED LITERATURE ON BIG DATA ANALYTICS ADOPTION

As mentioned earlier, several research in the past have discussed the operational and technical adoption concerns related to BDA (Table 1). Erstwhile researchers have also studied themes like BDA service selection, based on costs and associated risks (Kwon, Lee and Shin, 2014); big data audit protocol for computation and secure storage (Whyte, et al., 2016); financial readiness (Verma and Bhattacharyya, 2017) and economic performance (Dubey, Gunasekaran and Samar Ali, 2015); data management and computation software and technology (Shin, 2015); issues of privacy, information loss and security risks (Chen, Preston and Swink, 2015).

Table 1   Big data analytics research published

IT adoption as Dependent variable	Adoption theory	Methods	Author
Big data analytics	Resource-based view and Isomorphism	Structural equation modeling based on partial least squares analysis	Kwon et al., 2014

Table 1   continued

IT adoption as Dependent variable	Adoption theory	Methods	Author
Big data services	UTAUT model	Quantitative data based on a survey method, and quantitative data based on an interpretative method	Shin, 2015
Big data analytics	TOE Framework and dynamic capabilities theory	Partial least squares	Chen et al., 2015
Big data	Socio-technical systems theory	Qualitative and quantitative	Shin et al., 2014
Big data analysis	TOE framework and assimilation model	case-based study and survey-based study	Nam et al., 2018
Big data analytics	TOE framework and perceived strategic value	Qualitative study	Verma and Bhattacharyya, 2017
Big data analytics sytems	TAM	Quantitative study	Verma et al., 2018

Grounded on review of existing literature (Table 2), a BDA adoption model has been proposed (Figure 1). This model advocates that the BDA adoption is mostly governed by a perceived strategic value of top management. Importantly, in this model, TOE factors do influence the strategic value of BDA adoption.

Table 2   TOE framework and PSVAM framework Model constructs in peer-reviewed journals

Model/theory	Source	Perceived strategic value	Quality	Complexity	Compatibility	Technology Readiness	Top management support	Firm size	Competitive pressure	Regulatory support
PSVAM	Grandon and Pearson (2004)	X				X			X	
PSVAM	Sutanonpaiboon and Pearson (2006)	X				X			X	
PSVAM	Saffu et al. (2012)	X	X		X	X			X	
TOE	Oliveria et al. (2014)			X	X	X	X	X	X	X
PSVAM and TOE	Lin (2014)	X					X	X	X	
PSVAM and TOE	Verma & Bhattacharyya (2017)	X		X	X		X	X	X	
TOE	Wang et al. (2016)		X	X	X		X	X	X	
PSVAM and	Hsu et al.	X							X	

RESEARCH MODEL AND HYPOTHESES

By combining the perceived strategic value of BDA with the TOE framework (technology, organization and environment), this study aims to develop and test a holistic model on adoption of IT innovation.

HYPOTHESES OF PERCEIVED STRATEGIC VALUE CHARACTERISTICS

Urbany, et al. (1997) argued 'utility' to be an important predictor of purchase intention and behaviour. Additionally, perceived strategic value compares the benefits with challenges, and is therefore, an indicator of adoption intention. Innovations (e.g. BDA) with clear and explicit competitive advantage in creating operational and strategic effectiveness have a more significant incentive for adoption (Verma and Bhattacharyya, 2017). Furthermore, if the benefits of the technology (i.e., BDA) surpass prevailing processes and practices (Shin, 2015), the strategic value will positively steer its adoption. Therefore,

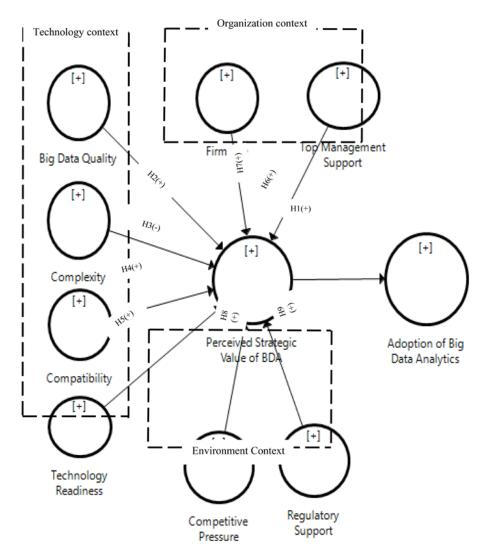> **H1.** The perceived strategic value will positively influence the adoption of BDA in AEC.

Figure 1   Proposed research model

HYPOTHESES DEVELOPMENT FOR TOE FRAMEWORK

The technology perspective

Technology perspective outlines the technological characteristics present in an organisation for technology adoption (Wang, Wang and Yang, 2010).

Big Data Quality

Big data quality includes adequate characterisation of data, real-time view of data, right interpretation of results and determining the relevance of results, while addressing the trustworthiness of input data. Van den Broek and Van Veenstra (2017) pointed out that inadequate level of big data quality can be distracting, as it tends to increase errors and wastes time and efforts. Erstwhile researchers identified big data quality as an important driver in building perception about the benefits and potential values of BDA (Wamba, et al., 2015). We thus posit…

> **H2. Big data quality in AEC will positively influence the perceived strategic value of BDA.**

Complexity

It is the degree to which an innovation is perceived to be comparatively challenging to use and understand (Low, Chen and Wu, 2011). Chance of BDA adoption is more when businesses incorporate innovation into its operations (Oliveira and Martins, 2014). Connectivity (i.e. straightforward and instant), system reliability (i.e., and consistently available and error-free), and efficiency (i.e. minimal response time) are used to measure the complexity of innovation. If precise protocol for data security, protecting the business process, and privacy within a shared environment are not completely developed, challenges could also mount in the usage of BDA-based solutions (Verma, 2018). Thus, we posit…

> **H3. Complexity will negatively influence the strategic value of BDA in AEC.**

Compatibility

It is the extent to which an innovation suits with the prospective adopter's current needs and existing values (Oliveira and Martins, 2014). It is a key determinant of innovation adoption (Wang, et al., 2016). It refers to an innovation congruence with the value systems and business practices of a firm (Verma and Bhattacharyya, 2017). The compatibility construct includes the fitment of innovation from an integration perspective (Wang, et al., 2016). Gangwar, Date and Ramaswamy (2015) reasoned that if an innovation integrates smoothly with an existing system, it has a positive impact on the perceived strategic value. Therefore, compatibility could also affect the strategic value of innovation. Thus, we posit…

> **H4. Compatibility will positively influence the strategic value of BDA in AEC.**

Technology Readiness

Technology readiness defines the technological preparedness and IT support resources (Zhu, et al., 2004). It defines the skills and knowledge required to leverage BDA associated IT applications (Wang, Wang and Yang, 2010). However, firms that do not have a robust technology and IT expertise may not understand the strategic benefits of an innovation per se (Yang, et al., 2015). On the other hand, firms with greater technology awareness and readiness

are in better position to understand the benefits of innovation and are thereby in a better position to adopt it (Chen, Preston and Swink, 2015). Thus, we posit…

H5. Technological readiness will positively influence the strategic value of BDA in AEC.

The Organisation Perspective

The organisational context represents the resources that are required for sustenance of technology adoption process (Wang, et al., 2016).

Top Management Support

Support of top management is an integral organisational factor, which does play an essential role in BDA adoption, as it guides the re-engineering of business processes, it helps in allocating appropriate resources, while integrating the services (Dutta and Bose, 2015; Kim, Jang and Yang, 2017). The management that recognises and understands the benefits or strategic values associated with BDA, would naturally be inclined to apportion the required resources. This apart, they also influence and motivate the entire chain below them to implement the change. Therefore, we posit…

H6. Top management support in AEC will positively influence the strategic value of BDA.

Firm Size

Big organisations have an added advantage over smaller ones due to the availability of more resources, based on which they are willing to take greater risks associated with innovation adoption (Wang, et al., 2016). Although several studies have found smaller organisations to be more versatile, as they have less understanding about the benefits associated with newer technologies and innovation (Alshamaila, Papagiannidis and Li, 2013). Therefore, firm size is certainly an important determinant of the strategic value of BDA (Martins, Oliveira and Popovič, 2014). Hence, we posit…

H7. Firm size will positively influence the strategic value of BDA.

The Environment Perspective

The environmental context describes the arrangement in which a company manages its business (Wang, et al., 2016). Among all factors, the determinants, which do tend to have an impact on BDA, include the regulatory environment along with a firm's competitiveness (Shin, 2015).

Competitive Pressure

It can be defined as the extent of pressure experienced by a firm from its competitors (Martins, Oliveira and Popovič, 2014). The strategic value associated with innovation is mostly a necessity to compete in the marketplace (Yang, et al., 2015). BDA can benefit firms by providing higher operational efficiency, real-time analytics, better insights, customer segmentation and better market visibility (Gangwar, Date and Ramaswamy, 2015). Hence, we posit…

H8. Competitive pressure does positively influence the strategic value of BDA.

Regulatory Support

It is the support given by a government authority for the adoption and assimilation of IT innovation (Zhu, et al., 2004). The effect of existing rules, policies, and regulations can be

acute, especially while creating a perception about values associated with innovations (White, 2012). For instance, a government prerequisite for organisations to comply with big data-specific protocols and standards, may lead to more awareness of the potential benefits for organisations, which subsequently leads to their willingness to adopt BDA (Verma and Bhattacharyya, 2017). Thus, we posit…

H9. Regulatory support does positively influence the strategic value of BDA.

METHODOLOGY

Preceding technology adoption investigations has been majorly steered in developed nations (Alshamaila, Papagiannidis and Li, 2013; Dubey, Gunasekaran and Samar Ali, 2015). So, the current study limits the scope of the current study to developing country (i.e. Indian AEC firms).

MEASUREMENT

Extant literature from relevant areas have been used to select the items of the questionnaire to evaluate the theoretical constructs (Table 3). The constructs (i.e. perceived strategic value, big data quality, compatibility, complexity, technology readiness, top management support, firm size, competitive pressure and regulatory support) were measured using a five-point Likert scale (extending from 'strongly disagree' to 'strongly agree'). Number of employees along with the organisation's turnover volume were used to measure the organisation size (Martins, Oliveira and Popovič, 2014; Wang, et al., 2016). Six academic and industry experts in big data, business analytics and business intelligence from the AEC sector pretested the questionnaire (i.e. two from each). 34 firms were chosen for a pilot test, and to test the instrument. The main survey did not include these firms. According to Hair, et al. (2012), Cronbach's alpha value greater than 0.7 are acceptable. Also, Hair, et al. (2012) recommended to remove items with inter-item correlations greater than 0.3 from the instrument. Three items were removed due to low correlations with the other items of constructs. This lead to improve the Cronbach's alpha values of constructs. The outcomes of the pilot test indicated that the scales had translation equivalence, along with confirming its validity and reliability (Brislin, 1970).

Table 3   Measurement items

Constructs	Source
Perceived Strategic Value of big data analytics	Sutanonpaiboon and Pearson (2006); Saffu et al. (2012)
Complexity	Low et al., (2011)
Compatibility	Wang et al., (2010)
Technology readiness	Oliveria et al., (2014)
Top management support	Low et al., (2011)
Firm size	Oliveria et al. (2014)
Competitive pressure	Alshamaila et al., (2013)
Regulatory support	Chen et al., (2015); Shin, (2015)
Big data quality	Gandomi and Haider, (2015); Chen and Zhang, (2014)
Adoption intention	Oliveria et al. (2014)

DATA

The structured survey questionnaire was emailed to the identified individuals (i.e. CTOs, CIOs, Directors, Senior business managers and IT managers) of 1800 Indian AEC firms. The sample firms were non-probabilistically selected from Bloomberg database, and a popular construction industry magazine. Respondents were categorised for construction service firms (i.e. engineering and architecture) and construction firms (i.e. firms engaged in managing construction projects). Construction firms were categorised as all operative builders and general contractors, primarily engaged in the construction of non-residential (i.e. heavy industrial, institutional and commercial, engineering), and residential buildings. Further, the study utilised key informants' data collection approach (Alam, Ali and Jani, 2011) to classify the respondents in the organisation who were knowledgeable and/or involved in BDA projects. Respondents self-qualified them self as adopter or non-adopter, along with categorising selves on big data characteristics (volume, velocity, variety, veracity and value) proposed by Gandomi and Haider (2015).

Follow-up communication were made with the respondents with the purpose of improving the response rate. Finally, a total of 386 responses were received, out of which 21 responses were unusable; thus, there were 365 valid responses. A response rate of 18.5% can be compared with other similar preceding research studies (Martins, Oliveira and Popovič, 2014). From construction service firms 57.3% (208 firms), while from construction firms 42.7% (157 firms) valid responses were received (Table 4). The sample distribution of the late and early respondent groups was compared using the K-S (Kolmogorov-Smirnov) test for testing the nonresponse bias. As the sample distribution of the respondents' groups differed statistically, it indicated the absence of response bias. Also, no significant common method bias (using Harman's one-factor test) was identified. Table 5 summarises the standard deviation and mean of all the constructs from the sub and full samples.

RESULTS

An analysis of the full sample was done to appreciate the critical factors of BDA adoption. Furthermore, in order to examine the determinants variation across different sectors, both construction and construction service firms were analysed using specific sub-sample data.

Table 4   Sample Characteristics (N= 365)

Variables	Frequency	Percentage (%)
Number of employees		
<=250	88	24.1%
400-800	98	26.8%
>800	179	49.1%
Role in organization		
CEO/COO/CIO/CFO	58	15.9 %
V.P., General Manager, etc.	94	25.7 %
Director, Controller, etc.	108	29.6 %
Manager, Senior Analyst, etc.	105	28.8 %
Industry		
Construction Services firms	209	57.3%
Construction firms	156	42.7%
Turnover (in millions INR)		
Turnover <=750	53	14.5%
750< Turnover <=3000	102	27.9%
Turnover > 3000	210	57.6%

Table 5   Standard deviation and mean of sub-samples and full samples

Constructs	Full sample (n=365)		Construction firms (n=156)		Construction Service Firms (n=209)	
	Mean	SD	Mean	SD	Mean	SD
Perceived strategic value of BDA	3.35	0.91	3.17	0.88	3.53	0.89
Big data quality	3.04	0.82	2.97	0.85	3.19	0.79
Complexity	2.47	0.80	2.52	0.83	2.19	0.78
Compatibility	2.86	0.79	2.71	0.79	2.89	0.79
Technology readiness	4.18	1.18	3.96	1.25	4.39	1.12
Top management support	2.92	0.97	2.86	0.96	2.98	0.99
Firm size	2.63	0.87	2.65	0.85	2.64	0.89
Competitive pressure	3.12	0.91	3.10	0.89	3.19	0.93
Regulatory support	2.91	0.87	2.89	0.89	2.94	0.87
BDA adoption	2.89	1.46	2.76	1.28	3.02	1.49

MEASUREMENT MODEL

This study utilized structural equation modelling method to empirically test the theoretical model. More specifically, Partial least square (PLS) was employed as a tool for measurement and structural analysis as it overcome the limitation of Exploratory factor analysis (EFA) analysis and several researchers in business, management and information systems field has recognized as an effective analytical method for measuring construct reliability and validity and model testing (Hair, et al., 2012). The reliability of the scales was examined using Cronbach's alpha and composite reliability (CR) (Table 6). The results suggested that scales were reliable (Henseler, Ringle and Sinkovics, 2009). The full sample measurement model of both sectors demonstrated convergent validity (loadings higher than 0.7) (Table 6). Moreover, the discriminant validity was measured using Fornell-Larcker criteria (Henseler, Ringle and Sinkovics, 2009) and cross-loadings (Lowry and Gaskin, 2014). Both measures indicated that constructs fulfilled the requirements for the full sample along with the sector-specific samples (Table 7).

Table 6   Reliability indicators for sub-samples and full samples

Constructs	Full sample			Construction sub-sample			Construction Service sub-sample		
	AVE	CR	Cronbach's alpha	AVE	CR	Cronbach's alpha	AVE	CR	Cronbach's alpha
Perceived strategic value of BDA	0.557	0.897	0.868	0.594	0.909	0.882	0.538	0.890	0.858
Big data quality	0.590	0.871	0.855	0.586	0.908	0.899	0.511	0.829	0.816
Compatibility	0.548	0.829	0.730	0.664	0.887	0.832	0.577	0.884	0.752
Complexity	0.651	0.882	0.826	0.603	0.851	0.793	0.583	0.841	0.837
Technology readiness	0.562	0.890	0.653	0.591	0.805	0.700	0.554	0.886	0.733
Top management support	0.563	0.837	0.760	0.638	0.876	0.819	0.527	0.817	0.728
Firm size	0.714	0.909	0.876	0.735	0.917	0.882	0.689	0.898	0.873
Competitive pressure	0.517	0.809	0.763	0.578	0.883	0.740	0.554	0.831	0.782
Regulatory support	0.588	0.850	0.785	0.663	0.887	0.838	0.576	0.873	0.756
BDA Adoption	0.762	0.906	0.847	0.771	0.910	0.856	0.750	0.900	0.835

Table 7   Correlations and AVEs.

	1	2	3	4	5	6	7	8	9	10
BDA Adoption	**0.873**									
Big data quality	0.336	**0.764**								
Compatibility	0.354	0.514	**0.740**							
Complexity	-0.165	0.035	0.035	**0.807**						
Competitive pressure	0.494	0.321	0.331	-0.022	**0.719**					
Firm size	0.061	0.192	0.241	0.165	0.092	**0.845**				
Regulatory support	0.119	0.202	0.191	0.192	0.098	0.242	**0.767**			
Perceived strategic value of BDA	0.536	0.524	0.436	-0.147	0.490	0.177	0.205	**0.747**		
Top management support	0.392	0.484	0.535	0.018	0.433	0.230	0.275	0.565	**0.750**	
Technology readiness	0.305	0.398	0.436	0.001	0.309	0.196	0.148	0.499	0.427	**0.749**

*Bold diagonal values are the square root of AVE

STRUCTURAL MODEL

Table 7 illustrates the correlation and average variance extracted (AVE). With the suggested VIF threshold value of 5 (Marcoulides and Chin, 2013); the outcome indicated no apprehensions of multicollinearity.

The hypotheses were analysed by examining some standardised paths (Table 8 and Figure 2). The path significance level between dependent and independent variables were assessed by bootstrapping method (500 re-samples). For the full sample, an inspection of R2 as a descriptive measure showed that technology, organisation and environment factors explained 62.8% of the perceived strategic value of BDA. Furthermore, the hypothesis of the perceived strategic value of BDA as a predictor for BDA adoption is confirmed (p<0.01). The hypotheses for big data quality (H2) (p<0.01), complexity (H3) (p < 0.01), top management support (H6) (p<0.01), technology readiness (H5) (p<0.01), firm size (H7) (p<0.10) and competitive pressure (H8) (p<0.01) were also confirmed. Regulatory support (H9) and Compatibility (H3) were not statistically significant. Holistically speaking, the research model explained 42.8% of BDA adoption. The results suggest that the proposed model is significant in explanation of BDA adoption by AEC organisations. Analysis of sector-specific sub-samples demonstrated that technology, organisation and environment factors, are able to explain 57.4% and 64.6% of the perceived strategic value of BDA for the construction and construction services sectors, respectively. Interestingly, for both (construction and construction services sectors), the hypothesis (H1) of the perceived strategic value of BDA as a predictor of BDA adoption is confirmed (p<0.01).

For construction firms', hypotheses strategic value of BDA (H1) (p<0.01), big data quality (H2) (p<0.05), complexity (H3) (p < 0.05), firm size (H7) (p<0.01) and competitive pressure (H8) (p<0.01) are confirmed. While, compatibility (H3), technology readiness (H5), top management support (H6) and regulatory support (H9) are not statistically significant. The research mode explains 39.7% of BDA adoption among construction firms. For the construction service firms' sub-sample, perceived strategic value of BDA (H1) (p<0.01), complexity (H3) (p<0.0.05), big data quality (H2) (p<0.01), top management support (H6) (p<0.01), technology readiness (H5) (p<0.01), and competitive pressure (H8) (p<0.01) are confirmed. Compatibility (H3), firm size (H7) and regulatory support (H9) are not statistically significant. The research model explains 46% of BDA adoption in construction service firms.

Table 8   Model results

Constructs	Full sample (n=365)		Construction firms sub-sample (n= 157)		Construction services firms sub-sample (n=208)	
	Path coeff.	T-Value	Path coeff.	T-Value	Path coeff.	T-Value
Perceived strategic value of big data analytics	0.540	8.523***	0.587	5.966***	0.505	6.377***
	R²=0.628		R²=0.574		R²=0.646	
	Technological factors					
Big data quality	0.226	5.014***	0.217	1.969**	0.204	4.265***
Complexity	-0.152	3.285***	-0.231	2.019**	-0.116	1.770**
Compatibility	0.003	0.002	0.128	0.888	-0.006	0.240
Technology readiness	0.174	4.565***	0.068	1.043	0.229	5.295***
	Organizational factors					
Top management support	0.242	4.367***	0.020	0.125	0.297	5.262***
Firm size	0.052	1.726*	0.086	2.297***	0.033	0.301
	Environmental factors					
Competitive pressure	0.219	5.115***	0.304	4.797***	0.202	3.218***
Regulatory support	0.036	0.731	0.063	1.129	0.030	0.246

*Significance at $p < 0.10$
**Significance at $p < 0.05$
**Significance at $p < 0.01$
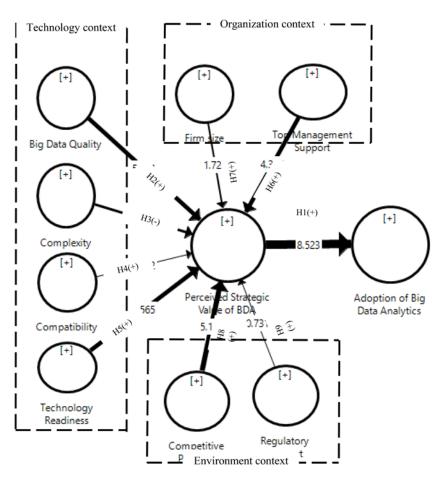Full Sample = Construction firms + Construction service firms

Figure 2   Model testing for Full sample

ALTERNATIVE MODEL

The proposed research model integrates PSVAM with the TOE framework. The core logic of the proposed framework has been based on the recommendation of Martins, Oliveira and Popovič (2014) who encouraged integrating the TOE framework with other theories/models to increase its predictive power. However, it is essential to investigate the appropriateness of the proposed model with alternative models, to assess the extent to which each contextual factor predicts and explains the intention to adopt BDA. Table 9 summarises the comparison of alternative models.

Table 9   Sub-samples and full samples explanatory power

Constructs	Full sample	Construction service firms sub-sample	Construction service firms sub-sample
Technology-organization-environment factors	$R^2 = 0.364$	$R^2 = 0.331$	$R^2 = 0.409$
Technology-organization-environment+ perceived strategic value factors	$R^2 = 0.378$	$R^2 = 0.347$	$R^2 = 0.424$
Integrated PSV-TOE framework	$R^2 = 0.428$	$R^2 = 0.397$	$R^2 = 0.460$

First, this study examined the TOE framework as a direct antecedent to the intention to adopt BDA (Table 9). Wang, et al. (2016) argued that these variables, when used as direct antecedents, could be weak predictors of adoption intention. Out of eight direct antecedents to BDA adoption intention, only three have been found to be significant, wherein even the path coefficients are low (6 of 8 are < 0.1). Moreover, the explanatory power for BDA adoption intention is only 36.4% for the full sample. Further, this study tested a model where perceived strategic value of BDA along with TOE actors are incorporated as BDA adoption intention's direct antecedents (Table 9). In aggregate, nine direct factors marginally increase the explanatory power for BDA adoption intention from 36.4% to 37.8%. As compared to the proposed research model, the alternative model provides less explanatory power. Additionally, it limits the understanding of the role of technology, organisation and environment variables in shaping perceived strategic value of BDA, and its adoption intention. Consistent with the underlying theory, this study shows empirical evidence of integrating TOE framework with PSVAM to increase its predictive power.

DISCUSSION AND CONCLUSION

The outcomes of our analysis also indicated that the inhibitors and facilitators of BDA adoption intention were different in construction service firm's vis a vis construction firms. For perceived strategic value of BDA, the results yielded a positive impact on BDA adoption. It is coherent with the preceding investigation of Sutanonpaiboon and Pearson (2006). Perceived strategic value of BDA is similarly important for firms, both in construction service and construction firms. Grandon and Pearson (2004) in similar lines, found a strategic value of BDA, which was significant among construction service firms. Out of the eight perceived strategic value variable of BDA, big data quality, top management support, technology readiness, competitive pressure and firm size are confirmed as being the significant drivers to describe the perceived strategic value of BDA. Ahmed, et al. (2017) found that data quality acts as a hindrance to BDA adoption in the construction industry. It is indeed a challenge to structure data, while attaining both uniformity & consistency. This observation inferred from

the results concurs with previous studies that have found big data quality (Verma, 2018), technology readiness (Dubey, et al., 2017), top management support (Martins, Oliveira and Popovič, 2014), firm size (Sun, et al., 2018) and competitive pressure (Alshamaila, Papagiannidis and Li, 2013).

Complexity was found to be an important inhibitor to explicate the perceived strategic value of BDA. This result concurred with the work of Low, Chen and Wu (2011) and Wang, et al. (2016). Interestingly, Ismail, Bandi and Maaz, (2018) in the construction context, argued that layered and complex data sources negatively impact data utilisation, which the industry needs to fathom in order establish newer frontlines for the construction sector. Project focused, active, uneven characteristic of the sector results into difficulty in data integration and analytics during the course of a project amongst varied stakeholders (Cerovsek, 2011). As there are counter arguments to this proposition (Low, Chen and Wu, 2011), a more definite conclusion does require additional research. In contrary, compatibility was not found to be significant for BDA perceived strategic value in construction firms as well as construction service firms. Integration of BDA does not seem to be an issue for firms, which are aware of the strategic benefits of BDA. The compatibility across sectors was found non-significant. It may be due to the characteristic of applications. For example, the distinct domination of flexible internal software architectures that can improve the integration and synchronisation of BDA (Zhang, et al., 2017). Nassar (2007) stated that lack of standardisation within the construction industry, does negatively impact the collection and storage of data, hindering the compatibility aspect thereby.

This study found empirical evidence that technology readiness is significant in describing the strategic value of BDA. In line with this, Ismail, Bandi and Maaz, (2018) proposed that one of the primary challenges that the construction companies face while adopting big data, is their readiness. Ahmed, et al., (2017) in their seminal work assessed the readiness of AEC firms for adopting big data; their findings revealed that only 33% of participants were supposedly ready for adopting BDA, whereas 67% responded that the industry at large was still not ready. Firms with a stable workforce, technical competence and necessary skills are the perfect fit for BDA adoption and integration (Ramdani, Kawalek and Lorenzo, 2009). However, the outcomes of this investigation indicate that technology readiness is not necessarily significant in construction firms. Plausible explanation could be, as compared to non-IT centric construction manufacturing businesses, BDA investment lead to substantial improvements in a firm's productivity of IT centric businesses (Lee and Kim, 2006; Müller, Fay and vom Brocke, 2018).

From the organisational context, top management support was found to be significant in explaining the perceived strategic value of BDA. Support from extant research reveals that top management can indeed be a stimulus to influence the perception of the strategic benefits of BDA, by demonstrating support in developing appropriate policies, engaging in the process and committing to other organisational and financial resources (Ramdani, Kawalek and Lorenzo, 2009). Construction firms could view BDA services as sustained risk and high costs (Dutta and Bose, 2015). Additionally, one needs to consider the operational challenges too, like inability to source the right talent to work on new technology that can interpret AEC, vis a vis the cost of the technology itself, which act as an inhibitor of BDA usage in AEC (Ahmed, et al., 2017).

Firm size was found to be a facilitator for the strategic value of BDA in construction firms; but they were not found to be significant in construction service firms. Larger construction firms may explain BDA's importance in the construction industry, as they can

bear the investment risks of innovation, and have more resources to support the cost incurred (Wang, Wang and Yang, 2010). On the other hand, for construction service firms, the non-significance of firm size may be supported by the IT-based operations and its work-style preference that predominate among organisations in such sector (Wang, Wang and Yang, 2010).

The results indicated that, out of two variables in the environmental context (i.e., regulatory pressure and competitive pressure), only competitive pressure was found as a significant determinant of BDA adoption. For competitive pressure to be a predictor of BDA adoption, the finding of this study concurs with extant literature, suggesting thereby that it tends to push firms across industries to adopt BDA more quickly (Sun, et al., 2018). Labrinidis and Jagadish, (2012) argued that competitive pressure acts as an enabler to big data adoption in the construction industry. BDA aids construction companies to understand the reasons for decline in performance; it facilitates managing construction projects by identifying diverse characteristics of customers, markets, costs, partners, and operations (Huang, Lu and Chen, 2017; Edirisinghe, 2018). Regulatory support was found to be non-significant to perceived strategic value of BDA. However, the insignificant relation between regulatory support and perceived strategic value of BDA does not necessarily indicate that organisations disregard prevailing regulations and standards (Sun, et al., 2018). The possible reason could be that existing policies have not been intently embraced in order to protect and encourage the use of BDA, so that it subsequently encourages organisation level decision–makers to make and stick to their decisions (Zhu, et al., 2004).

MANAGERIAL IMPLICATIONS

For effective adoption of BDA solutions, business managers are required to have realistic expectations of the quality of big data along with its integration challenges. Managers steering BDA adoption projects are required to organise a team of experts, whose skillsets encompass the traditional analytics platforms and environment. In terms of the organisational context, it is important to note that top management support is a necessary support and a facilitator of the perceived strategic value of BDA. Firm size is also a facilitator of the perceived strategic value of BDA, but only to construction firms. Larger firms are inclined to invest more enthusiastically in BDA-based solutions, and therefore are more aware of both the benefits and risks associated with the innovation. From environmental perspective, the study recommends that competitive pressure is a significant driver of perceived strategic value of BDA; however, regulatory support is not a significant driver of BDA's strategic value. Thus, fluctuations in government regulations are not significant in adoption of BDA in both construction and construction services firms.

LIMITATIONS AND FUTURE DIRECTIONS

This study has been restricted to India, which implies that the findings reflect the situation only within similar economies. Industry-specific models may be formulated in future research, rather than a comprehensive model, which could possibly look to combine the strategic value and characteristics of innovation. Moreover, this study extends opportunities for further investigation and alteration of the variables/constructs to explain further BDA adoption, and adoption intention in firms. Finally, for extended viability, the proposed research model can be applied to other economies in order to explore an exciting path forward.

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