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Beyond Technological Capabilities: The Mediating Effects of Analytics Culture and Absorptive Capacity on Big Data Analytics Value Creation in Small- and Medium-Sized Enterprises

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***Abstract*—Research on the ability of small- and medium-sized enterprises (SMEs) to harness value from their big data analytics (BDA) investment is a major challenge facing executives but research on this issue involving SMEs is scant. Drawing on the BDA capabilities literature, this article tests the mediating roles of two factors—analytics culture and BDA-specific absorptive capacity—on the ability of SMEs to generate strategic business value from their BDA investments. This article is based on a sample of 447 Canadian SMEs using structural equation modeling with partial least squares. The results confirm that both analytics culture and BDA-specific absorptive capacity amplify the impact of technological and human capabilities on strategic business value. The findings contribute theoretically and empirically to the emerging BDA literature on SMEs. The findings can help executives develop BDA strategies to harness their investments.**

***Index Terms*—Absorptive capacity, analytics culture, big data analytics (BDA) capabilities, Canada, management capabilities, small- and medium-sized enterprises (SMEs), value creation.**

I. Introduction

BIG data analytics (BDA) describes the ability of firms *to assemble, integrate, and deploy Big-Data-specific resources* [1] to gain *insights for managerial decision-making* [2]. Big Data refers to large, complex, dynamic datasets generated from multiple sources including mobile devices, sensors, software logs, click streams, social media, Internet of Things, and business and customer interactions and transactions [3]. In the digital economy, BDA has become a central theme in scholarly research due to its far-reaching impact on organizations. BDA can fundamentally alter organizational structures, strategies, processes, performance, and competitiveness [4].

In spite of these potential benefits, the evidence indicates that BDA does not always result in value for adopters because of knowledge gaps concerning how to transform data into actionable insights that generate real value [5], [6]. Also, the implementation of BDA poses significant technical, managerial, and organizational challenges [7], [8], [9]. Additionally, as the breadth of BDA adoption increases, there seems to be a leveling-out of competitive advantage from BDA insights and firms must become more creative to move from competitive parity to competitive advantage [10]. Therefore, the gap between potential and realized value creation from BDA investments requires further investigation [11]. Günther et al. [5] observed that despite notable theoretical and empirical contributions, the existing literature is still evolving and can be characterized by its many speculations and opinions. Thus, more empirical studies are needed to provide clearer explanations on how organizations capture value from BDA. Further, the bulk of current knowledge is based on studies of large firms since most small- and medium-sized enterprises (SMEs) are behind in adopting BDA technologies [5], [12]. It is unclear whether insights from large firms are generalizable to SMEs. Thus, there is a knowledge gap regarding BDA in SMEs.

The precise reasons for the challenges SMEs face in harnessing the benefits from BDA remain unclear even though some have argued, based on the experiences of large firms, that lack of understanding and the unique resource capabilities of BDA may account for this [1], [7]. The lack of human BDA capabilities (BDAC) [1], [9] and technological BDAC are also cited as possible explanations [13], [14]. Moreover, Wamba et al. [7] argue that other factors beyond BDAC should be examined. For example, they argue that without a data-driven culture, organizations cannot fully exploit BDA since BDA decision-making *requires a culture of deciding on the bases of "what we know" instead of "what we think"* [15]. Similarly, it has been argued that absorptive capacity [16] is an important mechanism for enhancing business analytics capabilities for competitive advantage [17], [18] since the bulk of BDA technologies, infrastructure, and capabilities are distributed and external to most firms [10],

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[19] and must be effectively assimilated and transformed for value creation.

Despite these very useful insights, there is limited research focusing on BDA implementation challenges in SMEs [5], [12], [20]. Most studies on SMEs rely on small samples or case studies [21]. We have not found any empirical study, which focuses exclusively on SMEs based on large-scale samples, particularly with respect to Canadian SMEs. Essentially, we still lack a good understanding of what factors enable SMEs to derive strategic business value from their BDA initiatives. Therefore, the research question examined is *how do analytics culture and organizational absorptive capacity mediate the impact of BDAC on strategic business value?* A conceptual model showing the mediating effects of analytics culture and absorptive capacity is developed and validated through structural equation modeling (SEM) with SmartPLS [22], [23], [24] on a sample of 447 Canadian SMEs. The model was developed drawing from various works of literature that link BDAC and value creation including the resource-based view (RBV) of the firm [25], [26], BDAC [7], [27], analytics culture [28], [29], and absorptive capacity [16], [17].

An important novelty of this article is that it is the first large sample quantitative study of Canadian SMEs, which complements evidence from other countries. This article enriches the BDA literature on SMEs by validating the impact of analytics culture and absorptive capacity as mediators of BDA value creation. Given that a substantial amount of BDA data, infrastructures, technologies, and capabilities are leveraged from external partners [10], [30], absorptive capacity is crucially important but has so far received scant attention in the BDA literature, particularly in the context of SMEs. The model also sheds light on how human (management and staff) and technological BDAC contribute to value creation in SMEs. From a managerial perspective, the findings could help SMEs better understand the nature of capabilities they need to harness greater value from their BDA investments.

The rest of this article is organized as follows. Section II discusses the theoretical foundations, Section III describes the methodology, Section IV describes the results, and Section V discusses the implications of the findings. Finally, Section VI concludes this article.

II. Theory Background

BDA involves collecting, curating, and analyzing very large volumes of data from disparate sources to generate unique, actionable insights that drive managerial decision-making, which can influence firm performance [31], [32]. Current BDA research has emphasized four interrelated pillars—data, technology, people, and organizational culture—when appropriately configured, could generate competitive advantage [19], [33], [34], [35]. Additionally, the most widely used theoretical lenses employed to analyze BDA are the RBV of the firm [26], [36], dynamic capabilities [37], [38], [39], IT capability [40], and organizational culture since they establish a strong link between resources, capabilities, and competitive advantage [41]. Data, which is a key asset [19], [42] and an intangible resource [1],

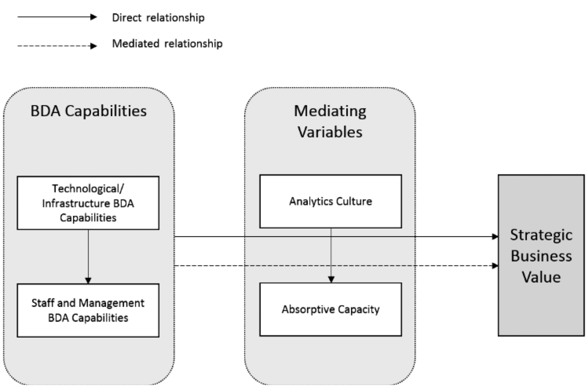

Fig. 1. Conceptual model.

require technology infrastructure (hardware, software, tools, and platforms) and an array of technical and analytical skills to prepare it for analysis and sharing [30]. Both managerial and staff capabilities are needed to obtain unique insights that can be used to enact strategies for competitive advantage [4], [9], [31]. Further, a data-driven culture is key to extracting and using insights from Big Data [10], [31].

Considering the above theoretical arguments, we propose and test a model (see Fig. 1) based on data on SMEs. The model explicitly considers the mediating effects of both analytics culture and absorptive capacity, two dimensions that have received limited attention but are extremely important to SMEs given their general lack of BDA resources, capabilities, and skills [12], [21]. Each component of the model is described next, beginning with strategic business value, the outcome variable.

A. Strategic Business Value

Value is often viewed in terms of economic and financial performance but also includes nonfinancial benefits [43]. Nonfinancial value is derived from technological investments to generate innovations, efficiencies, and lock-in of customers and partners [6], [43]. These nonfinancial benefits are often more important than financial ones since their impacts are more persistent, which in turn provides sustainable competitive advantage through enhanced product and service innovation, operational efficiencies, customer loyalty, and value [44]. Some indicators of value include customer satisfaction, customer loyalty, improved marketing performance, innovation, and new product-service development capability [45], [46]. Indeed, BDA can be a value generator for firms given the focus on gathering, analyzing, and deploying large and rapidly changing data for decision-making and strategy formulation [44]. BDA enables firms to improve business processes through better coordination and deeper understanding of customers and the business environment, thereby leading to improved value creation [46].

B. BDA Capabilities

According to the extant literature, firms need BDAC to exploit Big Data for competitive advantage. BDAC is defined as the ability to assemble, integrate, and deploy Big-Data-specific

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resources to obtain competitive advantage [1]. BDAC is a multidimensional construct comprising of BDA human, technological and organizational capabilities [13], [14], [47]. BDA management and talent capabilities consist of BDA technical, managerial, and relational competencies possessed by managers and specialized employees such as data scientists, data analysts, and Big Data architects [48]. These capabilities consist of both hard and soft skills including technical, analytical, and business, critical thinking, problem-solving, communication, and collaboration skills [49], [50]. Technological capabilities focus on the ability of firms to mobilize and synergistically deploy IT and other resources and capabilities (e.g., data, hardware, software, technology, BDA implementation experience, and technical expertise) [40], [51]. IT enables the optimization of operational and strategic business processes [46] leading to competitive advantage [13].

Moreover, these BDAC dimensions are inextricably intertwined and mutually supportive [7] and when combined effectively is a rare and imperfectly imitable resource [14]. For example, building BDA technological capabilities requires managers and staff to update their technical and analytical skills or hire new talent with the requisite skills [52]. This was a huge challenge for many firms [35], [50], [53]. BDAC generates a competitive advantage since it entails exploiting existing and newly-acquired firm-specific capabilities [14]. BDAC is embedded within the organization; they are developed over time, and cannot be easily bought from external factor markets [54]. Thus, we propose the following hypotheses.

Hypothesis 1a: BDA technological capabilities will enhance strategic business value.

Hypothesis 1b: BDA-specific human capabilities will enhance strategic business value.

Hypothesis 1c: BDA-specific technological capabilities will positively impact BDA-specific human capabilities.

C. Mediating Role of Analytics Culture

Analytics culture is viewed as an important mediator in transforming IT investments into business value [45]. Analytics culture encompasses an organization's norms, values, and behavior that foster systematic ways of curating, analyzing, and sharing data to enhance decision-making [29]. Strong analytics culture is observed through management's commitment to using data in decision-making and their support for analytics throughout the organization [10]. Analytics culture can differentiate an organization from its competitors and provides a competitive advantage [29], [45].

Further, a culture of data-driven decision-making stands to achieve better performance [14]. Thus, decision-makers are urged to make evidence-based decisions and rely less on prior experience, cognition, and intuition [10]. Essentially, analytics culture leads to reduced dependence on instincts and hunches [55]. Building a strong analytics culture requires leadership and commitment from top-level decision-makers and the engagement of all employees and organizational units [29]. BDA needs to be seen as more than data or a technology; it must be central to the fabric of organizations to be effective [19]. Based on these arguments, we propose the following hypotheses.

Hypothesis 2a: Analytics culture mediates the relationship between BDA-specific technological capabilities and strategic business value.

Hypothesis 2b: Analytics culture mediates the relationship between BDA-specific human capabilities and strategic business value.

D. Mediating Role of Absorptive Capacity

Absorptive capacity is the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends [16, p. 128]. External knowledge sources are critical for innovation [56], but the ability of firms to absorb external knowledge is shaped by their prior related knowledge since prior knowledge facilitates the learning of new scientific knowledge or technological developments in a given field [16]. From this perspective, it is expected that firms with strong IT capabilities are well-positioned to exploit BDA, given the close connection to the IT field. Braganza et al. [19] contend that BDA initiatives test the absorptive capacity of firms to use external resources and knowledge and to act using the results from Big Data. BDA involves close integration of business and IT knowledge, which requires considerable collaboration, information sharing, effective communication [4], [35] as well as shared language and symbols within the firm and across subunits - all basic elements of BDA absorptive capacity [16].

Absorptive capacity is both outward-looking (acquiring and exploiting external knowledge) and inward-looking (knowledge sharing within the firm and across subunits) [16]. BDA requires curating internally and externally generated data and responding quickly to changes in the marketplace [14]. BDA-enhanced absorptive capacity promotes continuous learning and new routines, which are needed to gain strategic insights from rapidly changing Big Data [41]. Further, BDA-enhanced organizational absorptive capacity can help firms renew their BDA applications and organizational routines to harness new opportunities [17]. To achieve this, staff members and organizational units must actively seek out new ways to create new insights and must embrace ongoing organizational changes [17]. Thus, firms with strong BDA absorptive capacity may be better equipped to create value through new product innovation, reconfiguring existing innovative capabilities, assimilating new technologies, and enhancing creativity [17], [57]. Thus, the following hypotheses are proposed.

Hypothesis 3a: Absorptive capacity mediates the impact of BDA-specific technological capabilities on strategic business value.

Hypothesis 3b: Absorptive capacity mediates the impact of BDA-specific human capabilities on strategic business value.

Hypothesis 3c: Analytics culture will positively impact BDA absorptive capacity.

III. Methodology

A. Data

This article evaluates the impact of BDA on strategic business value in SMEs, which is defined as enterprises with less than 500 employees. The data collection for this article was guided by a two-step process involving case studies and an online survey. The case studies were designed to gain practical insights about BDA in SMEs. These insights were used to guide the second step of the article—the online survey. In step one, 10 in-depth case study interviews were conducted with managers of SMEs that have implemented BDA initiatives in their companies to better understand their experiences. The interviews were conducted following an extensive review of the BDA literature. The interviews lasted approximately one hour each and covered a wide range of BDA topics. These interviews provided practical insights into several important aspects including the nature of BDA in SMEs, factors affecting BDA adoption and implementation, and organizational, managerial, and value creation challenges. Interviewees provided practical viewpoints on the constructs developed from our literature review [58]. The interviews led us to consider the inclusion of BDA-specific absorptive capacity as a construct in our model. Using insights obtained from the case studies, we developed a questionnaire for step two of the article. The questionnaire was assessed by five BDA academic researchers for content validity, a process that is commonly used in questionnaire design [27], [58]. Additionally, we sought the input of our interview respondents who were asked to provide feedback regarding the content, completeness, accuracy, flow, and wording of the questionnaire. A few wording edits resulted from this process and respondents provided suggestions as to who should be targeted for our online survey.

In step two, the questionnaire was pretested with managers of 12 different SMEs to get their feedback on several aspects such as whether the questions are clearly articulated, the response options are appropriate, the response burden to complete the questions, and whether they have the required knowledge to answer the questions accurately [59]. Only a few minor edits were made to the wording of the questions. The pretest responses are not used in the analysis. Following the pretest, data were gathered through an online survey of midlevel executives, analytics professionals, managers, vice presidents, presidents, CEOs, and founders since they are considered to be the most knowledgeable of their organizations' BDA efforts [13], [60], [61] and have been used in prior influential BDA research (e.g., [1], [7], [9], [13], [27], [45]). A leading national Canadian market research firm with a very large panel of business entities and executives was contracted to collect the data. The market research firm was given the screening criteria for participant selection. The screening criteria require that respondents must be only mid- to senior-level executives who are knowledgeable about their firms' BDA efforts. The firms must have adopted some level of BDA into their operations and only firms with between 20 and 499 employees were included in the sample. Firms with less than 20 employees may be less likely to have adequate BDA operations to provide the depth of insights required for the article. The inclusion criteria and the scope of questions in the questionnaire were developed following the two-step process outlined above. Considering the high cost of data collection and the funding available to the researchers, the sample size was restricted to 447 fully completed and usable questionnaires. For confidentiality reasons, the market research company does not provide nonresponse rates. We assessed sampling adequacy using the Kaiser–Meyer–Olkin (KMO) test. The KMO value is 0.97, which lies between 0.8 and 1, thereby satisfying the condition for sample adequacy [62]. Further, our sample size satisfies the "10-times rule" [63], a used criterion to determine sample adequacy with partial least squares (PLS). The rule states that sample sizes should be greater than 10 times the maximum number of links in the model. Our model has 36 links, which requires a sample 360 but our sample is 447, which is much larger. Table I highlights the background of the respondents.

TABLE I
Respondents' Profile (N=447)

Demographic characteristics	Frequency	Percentage
Gender		
Male	317	70.9%
Female	130	29.1%
Age		
18-24	37	8.3%
25-34	182	40.7%
35-44	118	26.4%
45-54	60	13.4%
Over 55	50	11.2%
Position level		
Specialist	148	33.1%
Manager/Head	194	43.4%
Director	54	12.1%
President, CEO, Founder, VP	51	11.4%
BDA Knowledge Level		
Quite knowledgeable	280	62.6%
Extremely Knowledgeable	167	37.4%
Experience in their current position		
5 years or less	210	47.0%
More than 5 years	237	53.0%
Years of BDA experience		
5 years or less	240	53.7%
More than 5 years	207	46.3%
Years of management experience over career		
5 years or less	184	41.2%
More than 5 years	263	58.8%
Firm Size – Number of Employees		
20-99	180	40.3%
100-499	267	59.7%

The split between male and female respondents is roughly 70% to 30%, respectively. Two-thirds of respondents (67%) are between the ages of 25 and 44 years. In terms of position level, most of the respondents (43.4%) were managers/department

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heads, followed by specialists (33.1%). About 22% are in the senior executive category, i.e., directors, vice presidents, presidents, CEOs, and founders. Additionally, more than 50% of respondents have more than five years' experience working for their current firm (53%), just under half of the respondents (46.3%) have more than five years of BDA experience, and 58.8% had more than five years of combined managerial experience over their careers. Thus, most respondents are quite experienced and knowledgeable about BDA and their firms' BDA initiatives. Furthermore, approximately 40% of the sample are small-sized enterprises having 99 or fewer employees and 60% are medium-sized enterprises having between 100 to 499 employees. Cross-tabulations of years of BDA experience and years of management experience show a good distribution of respondents with solid BDA and management experience. Also, *t*-tests for variables such as gender, age, and experience on key variables show no differences, thus we conclude that there are no discernable biases in the responses.

B. Measures

The measures used for the constructs were adapted from established scales used in prior research. The constructs are multi-items Likert scales ranging from 1 = strongly disagree to 7 = strongly agree (7). The *technology/infrastructure capabilities* construct was adopted from [1] and [54]. The construct captures access to Big Data and the availability of technology infrastructures and tools to collect, process, integrate, analyze, and visualize data quickly. The *management and staff capabilities* construct was adopted from [1] and focuses on the extent to which managers understand the data needs of various functional units, coordinate BDA activities across functional units, and understand and apply the insights from BDA. The *staff* component focuses on the education, skills, experience, and training of BDA staff to undertake analytics tasks. The items for *analytics culture* were adopted from [54] and [10]. The items comprising this construct capture the behaviors, values, decision-making norms, and outcomes around BDA [10]. The scale items for *absorptive capacity* were adapted from [64] and emphasize knowledge acquisition and exploitation capabilities. The items for *strategic business value* were adopted from [65] and [6] and focus on strategic, operational, efficiency, and innovation impacts of BDA.

Table II presents the means and standard deviations of the indicators comprising the model constructs.

TABLE II
SUMMARY STATISTICS OF THE INDICATORS

Variable/item	Avg. [a]	Std.Dev.
Technological/Infrastructure BDA Capabilities (6)		
Access to big data (e1)	5.521	1.296
Technology infrastructure (e2)	5.443	1.335
Data visualization tools (e3)	5.459	1.285
Cloud-based services (e4)	5.604	1.308
Open-source software (e5)	5.098	1.566
Technological analytics capabilities (e6)	5.224	1.473
Staff and Management BDA Capabilities (7)		
Understanding the business needs (e7)	5.456	1.343
Coordinating big data-related activities (e8)	5.409	1.402
Understanding and evaluating the outputs (e9)	5.553	1.343
Understanding where to apply (e10)	5.501	1.322
Having suitable education (e11)	5.537	1.372
Having the right skills and experiences (e12)	5.477	1.370
Having right mix of soft skills (e13)	5.389	1.470
Analytics Culture (3)		
Data use to justify decisions (e14)	5.383	1.349
Data is first when making decisions (e15)	5.085	1.396
Dependence on data is encouraged (e16)	5.477	1.303
Absorptive Capacity (3)		
Absorbing new knowledge (e17)	5.425	1.279
Linking existing knowledge with new insights (e18)	5.586	1.198
Applying new knowledge (e19)	5.624	1.197
Strategic Business Value (7)		
Transforming business processes & models (e20)	5.579	1.246
Improving customer experience (e21)	5.698	1.292
Improving innovation (e22)	5.810	1.159
Improving business decision-making (e23)	5.772	1.131
Increasing efficiency (e24)	5.875	1.139
Creating competitive advantage (e25)	5.740	1.235
Being responsive to change (e26)	5.770	1.069

[a] All items measure on 1 (strongly disagree) to 7 (strongly agree) scale, N=447.

C. Common Method Bias (CMB)

Since this article is based on cross-sectional data and self-reported data collection approaches, CMB is a potential concern [66], [67]. CMB could influence the validity and reliability of the results and the covariation between latent constructs [68]. To address CMB concerns, several approaches were employed as suggested by Podsakoff et al. [69]. These include protecting the confidentiality and privacy of participants, avoiding vagueness of questions by using well-established scales, clustering items from different construct together, dividing the questionnaire into sections corresponding to the constructs, pretesting the questionnaire, and selecting respondents who are most knowledgeable about their firms' BDA initiatives [68], [69], [70]. Harman's one-factor test was performed [71]. The result indicated that a multifactor solution rather than a single-factor solution explained more variance and there is no single factor in the unrotated factor structure [71]. This is consistent with established guidelines, thus, CMB does not appear to be problematic [71]. Additionally, a marker variable was used to assess CMB [67]. We use marker variables that meet two criteria—be theoretically unrelated to the dependent variable [67] and have similar social desirability bias as the dependent variable [72]. One example of social desirability is if respondents are inclined to rate the dependent variable more positively, then the marker variable must also be rated more positively [73]. The marker variable used

TABLE III
CRONBACH'S ALPHA, COMPOSITE RELIABILITY, AND AVE

Variable	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Technological/Infrastructure Capabilities	0.877	0.907	0.62
Staff and Management BDA Capabilities	0.943	0.952	0.739
Analytics Culture	0.834	0.9	0.751
Absorptive Capacity	0.849	0.909	0.768
Strategic Business Value	0.905	0.925	0.637

TABLE IV
CROSS LOADING

Item	Technological/ Infrastructure Capabilities	Staff and Managem-ent BDA	Analytics Culture	Absorptive Capacity	Strategic Business Value
e1	**0.746**	0.519	0.571	0.447	0.489
e2	**0.83**	0.625	0.548	0.503	0.574
e3	**0.796**	0.561	0.582	0.513	0.548
e4	**0.74**	0.54	0.55	0.414	0.485
e5	**0.776**	0.615	0.614	0.49	0.496
e6	**0.83**	0.691	0.625	0.554	0.545
e7	0.665	**0.879**	0.672	0.637	0.637
e8	0.685	**0.912**	0.682	0.661	0.681
e9	0.616	**0.859**	0.639	0.648	0.648
e10	0.636	**0.876**	0.638	0.663	0.665
e11	0.66	**0.829**	0.629	0.568	0.603
e12	0.651	**0.85**	0.617	0.603	0.652
e13	0.635	**0.809**	0.587	0.592	0.586
e14	0.659	0.712	**0.88**	0.621	0.631
e15	0.611	0.571	**0.846**	0.54	0.542
e16	0.651	0.643	**0.873**	0.569	0.604
e17	0.567	0.645	0.578	**0.858**	0.592
e18	0.552	0.652	0.608	**0.89**	0.628
e19	0.515	0.614	0.568	**0.881**	0.653
e20	0.567	0.617	0.597	0.529	**0.75**
e21	0.463	0.574	0.481	0.602	**0.77**
e22	0.548	0.593	0.524	0.595	**0.811**
e23	0.604	0.599	0.631	0.603	**0.819**
e24	0.474	0.569	0.48	0.51	**0.795**
e25	0.516	0.591	0.549	0.56	**0.829**
e26	0.531	0.602	0.553	0.573	**0.811**

TABLE V
FORNELL–LARCKER CRITERION

	Technological/Infrastructure Capabilities	Staff and Management BDA Capabilities	Analytics Culture	Absorptive Capacity	Strategic Business Value
Technological/Infrastructure Capabilities	**0.787**				
Staff and Management BDA Capabilities	0.755	**0.86**			
Analytics Culture	0.74	0.744	**0.867**		
Absorptive Capacity	0.621	0.726	0.667	**0.876**	
Strategic Business Value	0.665	0.743	0.685	0.712	**0.798**

focus on whether the effort and attention spent filling the survey warrant using their responses since this fulfills both conditions of marker variables. The results show that the marker variable did not render any significant correlations insignificant [74]; thus, we conclude that there are no serious CMB concerns.

D. Data Analysis Technique

PLS-SEM was used since it is recommended [24] and widely used in BDA studies [7], [13], [48], [54], [60]. PLS-SEM is a statistical approach suitable for modeling complex multivariable relationships among observed and latent variables [23]. PLS-SEM allows for the simultaneous estimation of one or more exogenous construct(s) and one or more endogenous construct(s) in a single model. It can also estimate moderating and mediating effects even with relatively small sample sizes [23]. Additionally, PLS-SEM can handle complex models efficiently, it is well-suited for exploratory and confirmatory research, requires less rigorous assumptions regarding multivariate normality, and is favored to remove the uncertainty of inadmissible solutions in complex models [23], [24], [75], [76], [77]. We used SmartPLS Version 3.3.7 [22]. The analysis follows a two-step approach recommended by Hair et al. [23], where the reliability and validity of the measurement model are established first and then followed by an assessment of the structural model.

IV. RESULTS

A. Measurement Model

Table III displays Cronbach's alpha, composite reliability, and average variance extracted (AVE). Cronbach's alpha and composite reliability values for all the variables are above 0.80, which exceeds the 0.70 threshold [23]. Moreover, the calculated values of the AVE, which assesses convergent validity, are well above the 0.50 cutoff [78], thereby indicating adequate convergent validity.

Discriminant validity was evaluated through the cross loading and the Fornell–Larcker criterion, which compares the square root of the AVE with their interconstruct correlations [79]. Since the square root of the AVE of each construct (bolded diagonal items) is greater than their corresponding interconstruct correlations, we conclude that there is adequate discriminant validity. Hair Jr. et al. [77] suggest that the cross-loadings for each item should be greater than 0.7 with its own construct and less with other constructs. Table IV presents that the cross-loadings meet this threshold, thereby indicating adequate discriminant validity. Additionally, Fornell–Larcker values should be above 0.6, and each diagonal value should be larger than nondiagonal values to confirm discriminant validity [80]. The results displayed in Table V indicate that the values exceed the 0.6 threshold.

B. Structural Model

We begin by examining the overall model before evaluating the path coefficients and hypotheses. PLS produces various measures that can be used to infer model fitness [77]. These measures include the normed fit index (NFI), standardized root mean square residual index (SRMR), and rms-theta index [81], [82]. For good model fit, the value for the NFI index must be

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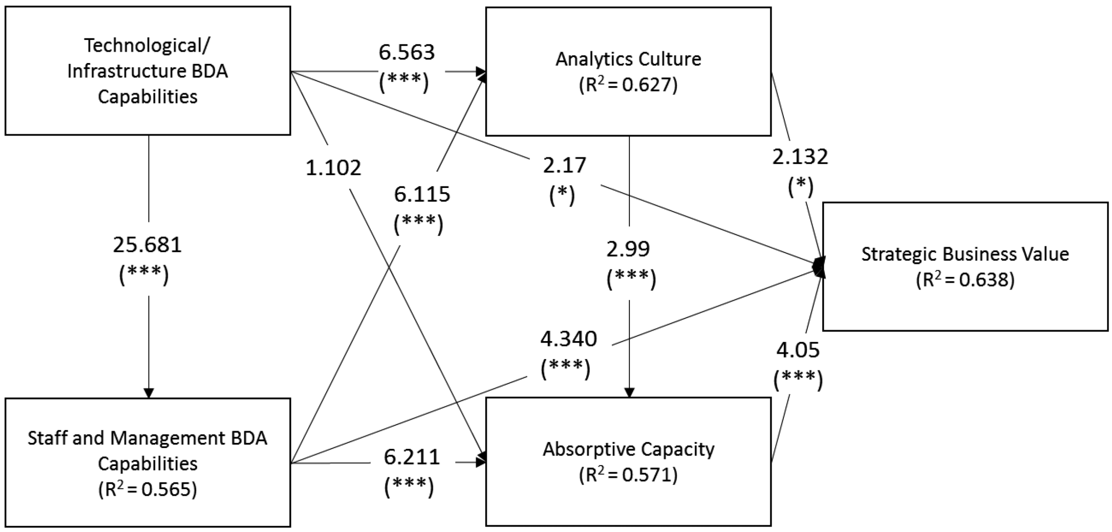

Fig. 2. Results of the path coefficient analysis. Note: p-value $\leq 0.05 = *$, p-value $\leq 0.01 = **$, and p-value $\leq 0.001 = ***$.

TABLE VI
Q^2 AND R^2 VALUES

Endogenous latent variable	Q^2	R^2
Staff and Management BDA Capabilities	0.390	0.565
Analytics Culture	0.444	0.627
Absorptive Capacity	0.409	0.571
Strategic Business Value	0.377	0.638

at least 0.8 [82], and the value for the SRMR index must not exceed 0.08 [83]. In our article, the NFI is 0.88, the SRMR is 0.047, and rms-theta of 0.11 does not exceed the 0.12 threshold suggested by Henseler et al. [84]. Since all model fit measures are within their thresholds, we reckon that there is a good model fit.

The model's predictive relevance is assessed by Stone–Geisser's Q^2 test [85], [86]. Table VI presents the Q^2 and R^2 values for our model. As a guideline, values above 0.25 indicate relatively good predictive power [23]. In our model, the Q^2 values of all endogenous constructs are well above 0.25, indicating good predictive power. Moreover, the R^2 of the different paths highlight the explanatory power of the model [77], [80] and our results exceed the 0.33 threshold value [79]. These results indicate that our model not only has good predictive power but also provides substantial explanatory power since the R^2 values range from a low of 0.565 to 0.638.

Now, we analyze the path coefficients to determine if they support the research hypotheses. Variance inflation factors (VIFs) are examined first to assess if there are collinearity problems among the constructs. Hair Jr. et al. [80] suggest that VIFs should be less than 5. The VIFs in our model range from 1.7 to 3.7, which are well below the threshold of 5. Thus, we do not detect any collinearity problems. Fig. 2 displays the path coefficients results, which are also summarized in Table VII. SmartPLS performs path coefficients analysis using standardized estimate, T-statistics, and p-value. Relationships with p-values ≤ 0.05 are

TABLE VII
TESTS OF HYPOTHESES FOR DIRECT EFFECTS BETWEEN THE VARIABLES

Model	Path coefficient value	Standard Deviation (STDEV)	T Statistics	P-Value[a]	Result
Technological/ Infrastructure Capabilities → Strategic Business Value	0.124	0.061	2.031	0.042 (*)	H1a - Supported
Staff and Management BDA Capabilities → Strategic Business Value	0.308	0.074	4.142	0 (***)	H1b - Supported
Technological/ Infrastructure Capabilities → Staff and Management BDA Capabilities	0.755	0.03	25.454	0 (***)	H1c - Supported
Analytics Culture → Absorptive Capacity	0.259	0.076	3.399	0.001 (***)	H3c - Supported
Technological/ Infrastructure Capabilities → Analytics Culture	0.413	0.065	6.358	0 (***)	Sig.[b]
Technological/ Infrastructure Capabilities → Absorptive Capacity	0.061	0.07	0.877	0.381	Not Sig[c].
Staff and Management BDA Capabilities → Analytics Culture	0.432	0.069	6.233	0 (***)	Sig.[b]
Staff and Management BDA Capabilities → Absorptive Capacity	0.487	0.08	6.084	0 (***)	Sig.[b]
Analytics Culture → Strategic Business Value	0.162	0.072	2.253	0.02 (*)	Sig.[b]
Absorptive Capacity → Strategic Business Value	0.303	0.078	3.91	0 (***)	Sig.[b]

[a]P-value ≤ 0.05 = *, p-value ≤ 0.01 = **, and p-value ≤ 0.001 = ***.
[b], [c]Sig = significant, Not Sig= not significant; No hypotheses were developed for these paths given our exclusive focus on mediation.

statistically significant. We have indicated the level of support for all hypotheses that were explicitly tested in the article. The significance of all other paths is presented for completeness even though they were not developed and tested given our focus on mediation of two key constructs, *analytics culture* and *BDA absorptive capacity*.

C. Mediation Analysis

The method proposed by Preacher and Hayes [87] was employed to test for mediation effects. To support the mediation hypotheses, three conditions need to be satisfied [80]. First, the direct relationship in the model in which the mediator variables are excluded must be significant. For this, we developed the model without the mediator variables, *analytics culture* and *absorptive capacity*, and did path analysis to assess the direct relationships. Second, the mediated relationship in the model in which the mediator variables are included must be statistically significant. For this condition, we examined the indirect path effects of the model in which all the mediator variables are included. Lastly, the variance accounted for must be greater than 20% to confirm partial mediation and greater than 60% to confirm full mediation [87]. In our model, as presented in Table VIII, hypotheses 2a, 2b, and 3b are supported since they met all the conditions of the mediation test. However, hypothesis 3a is not supported since the two last conditions are not satisfied. In addition, we performed Sobel's test [88] to provide extra support for the mediation hypotheses. Sobel's test values greater than 1.96 indicate statistically significant mediation paths. In our model, the Sobel test values are greater than 1.96 except for hypothesis 2b.

Summarizing, our analysis supports the mediation effects of analytics culture and BDA absorptive capacity on strategic business value. The model shows a very good fit and strong predictive and explanatory power given that established thresholds were exceeded. The many tests conducted indicate that there are no discernable problems with sample adequacy, CMB, and multicollinearity. Thus, the results can be accepted with a high level of confidence as being statistically significant.

TABLE VIII
TESTS OF HYPOTHESES FOR MEDIATION EFFECTS

Path	Path coefficient - direct relationship[a, c]	Path coefficient - mediated relationship[b, c]	Standard Deviation (P-value)	Mediation Tests	Result
Technological/ Infrastructure Capabilities → Strategic Business Value	0.242 (***)	0.124 (*)	0.061 (0.042)	Sobel test: 2.121 VAF: 0.240	Partial Mediation - H2a is supported
Technological/ Infrastructure Capabilities → Analytics Culture → Strategic Business Value		0.067 (*)	0.033 (0.042)		
Technological/ Infrastructure Capabilities → Strategic Business Value	0.242 (***)	0.124 (*)	0.061 (0.042)	Sobel test: 0.850 VAF: 0.024	No Mediation - H3a is not supported
Technological/ Infrastructure Capabilities → Absorptive Capacity → Strategic Business Value		0.019	0.023 (0.409)		
Staff and Management BDA Capabilities → Strategic Business Value	0.559 (***)	0.308 (***)	0.074 (0.000)	Sobel test: 2.170 VAF: 0.451	Partial Mediation - H2b is supported
Staff and Management BDA Capabilities → Analytics Culture → Strategic Business Value		0.07 (*)	0.032 (0.028)		
Staff and Management BDA Capabilities → Strategic Business Value	0.559 (***)	0.308 (***)	0.074 (0.000)	Sobel test: 3.275 VAF: 0.331	Partial Mediation - H3b is supported
Staff and Management BDA Capabilities → Absorptive Capacity → Strategic Business Value		0.148 (***)	0.043 (0.001)		

[a]In this model the mediator variables are excluded.
[b]In this model the mediator v ariables are included.
[c]P-value ≤ 0.05 = *, p-value ≤ 0.01 = **, and p-value ≤ 0.001 = ***.

V. DISCUSSION

Our work contributes to filling the need for more empirical research on the ways SMEs can realize value from BDA investments [5], [6], [33], [89]. We examined the impact of BDAC, principally in terms of BDA-specific technological and human (management and staff) capabilities that enable firms to harness value from BDA investments. Additionally, we examine the mediating effects of analytics culture and BDA-enhanced absorptive capacity on the ability of SMEs to create and enhance strategic business value from their BDA initiatives. Our results confirm the importance of both BDAC and the mediating roles of analytics culture and BDA-enhanced absorptive capacity. This article complements emerging BDA research in the following ways.

A. Theoretical Contributions

This article makes three theoretical contributions to BDA research, particularly regarding SMEs, where scholarly research is scarce. First, the article complements existing BDA research that shows both BDA technological and BDA human capabilities contribute directly and positively to the enhancement of strategic business value. This article also shows that the impact of BDAC on value creation is enhanced through the influence of both analytics culture and absorptive capacity. This finding suggests that BDA-specific technological and human capabilities must be backed by strong commitments to analytics culture and organizational learning to amplify the value to be derived from BDA investments.

The implication is that converting BDA investments to strategic business value requires more than BDA-specific technological and human capabilities; cultural shifts in decision-making,

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that is, greater use of data in decision-making throughout all levels of the organization can have a significant positive impact. Similarly, absorptive capacity enhances value creation through internal and external knowledge acquisition, sharing, and exploitation. This suggests that analytics culture and absorptive capacity must become integral to the organization's BDA strategy [10]. A culture of analytics-driven decision-making combined with continuous knowledge acquisition, assimilation, exploitation, sharing, and learning are essential elements for the effective conversion of BDA investments into strategic business value [17], [28]. This finding aligns with prior research indicating that greater conversion effectiveness will result in better performance from BDA investments [29].

The results provide theoretical insights into the black box facing SMEs—how to convert BDA investments into strategic business value [5], [12]. This suggests that senior managers must ensure ongoing technology, business, and organizational strategies alignment [27], [90]. Top management support and commitment to building a strong analytics culture and promoting continuous organizational-wide learning are necessary for effective conversion [91]. The firm-specific combination of these BDA-specific tangible and intangible assets and resources [54] can make them rare and inimitable [26], [38], [92], resulting in a competitive advantage for firms [93].

Second, this article underscores the importance of absorptive capacity as an important mediator and contributor to strategic business value creation. Absorptive capacity has been given little consideration in BDAC research, especially in studies of SMEs. The implementation of BDA initiatives requires extensive use of external data, sourcing of external technologies, tools, and infrastructures as well as employees with cross-disciplinary competencies (technical, analytical, and business) and soft skills [30], [50], [94]. Additionally, the dynamic nature of BDA data, technologies, and infrastructures means firms must continually update their BDAC to keep abreast of the latest development. Thus, firms must establish structures, processes, routines, and rewards to not only promote the timely sharing of information internally but also to acquire and exploit external information. Internal absorptive capacity promotes collaboration, effective communication, and sharing of resources among organizational units that can lead to greater operational efficiencies, productivity, and innovation. In this regard, [95] showed how the coupling of BDA and innovative leadership create resilient supply chains in the context of a major external shock (Covid-19 pandemic) through information sharing, information processing, and responsiveness. Similarly, Rahman et al. [52] and Konanahalli et al. [91] argue that providing employee training can improve the technical competencies of BDA staff, which is crucial for enhancing individual and organizational absorptive capacity [17], especially in a constantly-evolving BDA world [7], [10].

Third, this article contributes to the emerging literature that argues for the centrality of analytics culture in optimizing BDA investments [55], [96]. The finding of a positive relationship within the context of SMEs demonstrates that a strong analytics culture is not a large-firm-only phenomenon but is equally to all firm sizes. It also supports the view that analytics culture is the glue that binds together diverse roles and functions (e.g., IT, business, manufacturing, human resources, and finance) across organizational units to shape business strategies [90]. Indeed, a digital culture that is enthusiastically embraced by employees and organizational units can promote data-driven insights that can result in value generation. A strong analytics culture demonstrates to employees the extent of top management support and commitment to BDA in shaping the firm's strategy, structure, processes, routines, and rewards system, which in turn should influence its performance [4], [29], [97].

Although our findings show that a strong analytics culture enhances value creation from BDA investments, we also recognize the arguments of Nell et al. [98, p. 164] and others that overreliance on quantitative data over holistic judgment and intuition could result in costly mistakes since many strategic problems are ill-structured and messy, and only partially lend themselves to purely quantitative analysis. Further, easy access to Big Data and useful insights combined with a push to build an analytics culture can encourage managers to oversimplify complex problems and disregard experience [98]. Thus, building an analytics culture and fostering BDA-specific absorptive capacity must be carefully thought out and articulated by senior managers. As one of our interviewees remarked, "*building an analytics or data-driven culture is not straight forward but very complicated and many firms struggle with this – a clearly articulated vision can bring everyone on board, even your detractors.*" We note that the process and challenges involved in building an effective BDA culture have not received much attention to date.

B. Managerial Implications

From a managerial perspective, the results provide evidence that firms trying to gain strategic advantage solely through BDA-specific technological and talent capabilities are likely to fail in their quest. Executives need to also focus on intervening processes [29], such as committing to developing and supporting a strong analytics culture and encouraging organizational absorptive capacity to maximize the value from their BDA investments. BDA can produce operational efficiencies, enhanced decision-making, innovation in products and services, better customer engagement, enhanced service delivery, and more productive relationships with suppliers, distributors, and other members of its supply chain [46]. However, to reap these benefits, managers must envision and implement practical strategies to build a strong analytics culture and promote individual and organizational-wide absorptive capacity where both external and internal knowledge are harnessed, assimilated, shared, and exploited [17]. In the first instance, it is important for managers in the executive suite to adopt an analytics mindset, enhance their BDA skills, and be champions of the move toward an analytics culture. They need to demonstrate their commitment and articulate a vision that employees can follow. This requires investments in technology, people, and processes. Given the dynamic and ever-expanding nature of BDA, organizations must invest in the right technology, people, talent, and capabilities to be able to continuously extract value from BDA investments. For example, Duan et al. [51] argue that strong synergies can be derived from

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combining Big Data and artificial intelligence (AI) since it will become increasingly inefficient to rely on human computing. While this may be challenging for SMEs, given their resource constraints, managers must be ready for this eventuality given the proliferation of AI in decision-making and organizational processes. Overall, a deeper understanding of emerging BDA technologies, business operations, and customers can result in better strategies to boost competitive advantage in dynamic markets. The takeaway for executives is to develop, configure, and orchestrate their resources in a firm-specific and inimitable manner to reap sustained competitive advantage. This must be done in a dynamic way recognizing that the BDA environment is constantly evolving, and they must keep abreast with the changes.

In terms of people and talent, organizations must recruit employees with the right skills, talents, and mindsets who are willing to learn and become change agents within the organization [49], [50]. This requires people with strong soft skills such as effective communication, ability to collaborate and work in teams, and willingness to learn from others [49], [50]. Additionally, training of employees at all levels, and reward schemes to promote knowledge sharing, creativity, and learning have had positive impacts on BDAC and value creation [52], [91], [95]. Further, to promote BDA-specific absorptive capacity in a rapidly changing BDA landscape, managers must encourage and reward employees to innovate via experimentation and failures must not be punished but managed and valued for the potential learning [98]. Employees must be given the opportunity to monitor the technology and business environments to quickly identify changes that may impact the organization's strategies, business model, and technological and talent capabilities [13]. This could reveal potential threats or opportunities for the firm. Strong internally focused absorptive capacity can strengthen interunit communication, collaboration, and resource sharing that can lead to greater operational efficiencies, productivity, and innovation. Similarly, externally focused absorptive capacity can enable the firm to uncover new opportunities to grow their businesses in new markets, new technological fields, and even improve or launch completely new products. These can enhance the competitive advantage of the firm and ultimately its financial performance [99].

VI. Conclusion

The BDA literature has shown that despite progress in implementing BDA initiatives, many businesses still struggle to convert their BDA investments into strategic business value. Prior research has identified a firm's technological and management capabilities as key drivers for creating business value from BDA investments. More recently, scholars suggest that analytics culture is a key consideration in generating business value from BDA investments. Absorptive capacity as an important factor has received far less attention. Additionally, the existing literature is built largely around big businesses and it is still an open question as to the extent to which the reported findings apply to SMEs. Against this backdrop, this article examined how analytics culture and BDA-specific absorptive capacity enhance value creation in SMEs. The research draws extensively from the BDAC literature.

The relationships between BDAC, analytics culture, absorptive capacity, and business value creation were tested using a sample of 447 Canadian SMEs employing PLS-SEM with SmartPLS. The data were collected through an online survey by a large, national Canadian market research company. Respondents were midlevel managers, analytics professionals, vice presidents, presidents, CEOs, and founders. The data analysis indicates that respondents are highly knowledgeable about BDA initiatives at their companies and have substantial managerial experience. Tests for sample adequacy and CMB reveal that the sample was adequate and CMB is not a concern.

The results confirm that analytics culture and BDA-specific absorptive capacity significantly enhance the impact of BDA-specific technological and human capabilities on value creation. This implies that for firms to harness the full potential of their BDA investments, firms must look beyond technological and talent capabilities. They must commit to building a strong analytics culture and promote absorptive capacity at both the individual and organizational level. The findings make several theoretical and managerial contributions to emerging BDA research on SMEs. Theoretically, the article provides evidence that strong analytics culture is a significant contributor to the ability of SMEs to harness the full potential of BDA. This finding contributes empirically to the literature since the bulk of current evidence is based on large firms with adequate resources and capabilities compared to resource-constrained SMEs. A second theoretical contribution concerns the significance of BDA-specific absorptive capacity as a key mediating variable enhancing value capture from BDA. There is a paucity of studies that have considered the role of BDA-specific absorptive capacity in harnessing value from BDA. This article is among the earliest attempts to examine BDA absorptive capacity on value creation in SMEs and the finding that it is positive and significant is noteworthy. Third, this article provides theoretical insights into the black box of how to convert BDA investments into strategic business value—a vexing challenge facing SMEs. The insights from this article indicate that SMEs must not only focus on building technological and human capabilities but must also focus on organizational dimensions since better alignment of BDAC with organizational processes and culture enhances the ability to harness value from BDA. In a nutshell, better alignment of technical capabilities, business strategies, and organizational processes leads to greater conversion effectiveness. The firm-specific configuration of technological, talent, and organizational capabilities can generate sustained competitive advantage for firms.

From a practical perspective, the results can guide strategic actions aimed at harnessing the full potential of BDA. First, the results indicate that executives of SMEs should take a holistic approach to leverage their BDA efforts. Managers must recognize that while building technological capabilities and talent is important, these must be integrally coupled with organizational processes aimed at fostering a strong analytics culture and promoting learning, knowledge acquisition, sharing, and exploitation. These organizational processes are crucially important to building an agile and responsive organization in the face of a rapidly changing and evolving BDA environment. Without an agile and responsive organization, managers may be stymied in their efforts to grasp opportunities or address competitive threats. Managers must be proactive in understanding the market environment they are operating in to develop and implement winning strategies.

Second, since BDA initiatives generally require extensive use of external data, external technologies, tools, and infrastructures as well as employees with a wide range of cross-disciplinary competencies, these intervening organizational processes are needed to strengthen both internal and external collaboration, foster teamwork, and enable firms to continually update their BDAC to keep abreast of the latest developments. Third, to enable analytics culture and BDA-specific absorptive capacity to flourish, executives must demonstrate their commitment to analytics-driven decision-making by developing an analytics mindset, articulating a vision for a culture shift, committing resources to BDA initiatives, and becoming champions of change by recruiting, retaining, and rewarding the right talent. In this regard, managers must not only recruit and retain employees with the right technical talent or business acumen but also ensure they are willing to learn, share their knowledge, work in teams, collaborate, and become agents of change. This can be accomplished through training, providing opportunities for employees to improve their knowledge of BDA developments through conferences, workshops, seminars, and offering reward schemes that reward knowledge sharing, experimentation, and innovation.

Finally, despite the article's contribution to emerging BDA research, there are certain limitations that dictate caution in interpreting and generalizing the findings, but which could also be used as starting points for future studies. A limitation of this article is the cross-sectional approach employed since this only allows for insights within a specific time and longitudinal approaches are needed to establish the validity of the insights over time. Another limitation pertains to data. Since the article looks at only one country (Canada), the findings may not be generalizable to other countries due to country-specific characteristics that may be different than Canada. Even if the variables are significant in other country contexts, the magnitude of the impacts or their relative importance may be different. More country-specific studies should be undertaken. Further, this article paves the way for future studies to examine other theoretical constructs that are particularly relevant to SMEs such as market orientation, entrepreneurial orientation, industry effects, and AI as either moderators or mediators of value creation. Another limitation of our work relates to the fact that our strategic business value variable focuses on nonfinancial outcomes generated from BDA to the exclusion of financial indicators. Finally, even though we took several steps to reduce CMB and have conducted various analyses, which seem to indicate that CMB is not a serious concern, we can never rule out the possibility of CMB.

References

[1] M. Gupta and J. F. George, "Toward the development of a big data analytics capability," *Inf. Manage.*, vol. 53, pp. 1049–1064, Dec. 2016.

[2] S. Akter and S. F. Wamba, "Big data analytics in E-commerce: A systematic review and agenda for future research," *Electron. Markets*, vol. 26, pp. 173–194, 2016.

[3] A. Bhimani, "Exploring big data's strategic consequences," *J. Inf. Technol.*, vol. 30, pp. 66–69, 2015.

[4] R. Sharma, S. Mithas, and A. Kankanhalli, "Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations," *Eur. J. Inf. Syst.*, vol. 23, pp. 433–441, 2014.

[5] W. A. Günther, M. H. R. Mehrizi, M. Huysman, and F. Feldberg, "Debating big data: A literature review on realizing value from big data," *J. Strategic Inf. Syst.*, vol. 26, pp. 191–209, 2017.

[6] G. Elia, G. Polimeno, G. Solazzo, and G. Passiante, "A multi-dimension framework for value creation through big data," *Ind. Marketing Manage.*, vol. 90, pp. 617–632, 2020.

[7] S. F. Wamba, S. Akter, and C. Guthrie, "Making big data analytics perform: The mediating effect of big data analytics dependent organizational agility," *Systemes d'Information Manage.*, vol. 25, pp. 7–31, 2020.

[8] G. George, M. R. Haas, and A. Pentland, "Big data and management," *Acad. Manage. J.*, vol. 57, pp. 321–326, 2014.

[9] R. Vidgen, S. Shaw, and D. B. Grant, "Management challenges in creating value from business analytics," *Eur. J. Oper. Res.*, vol. 261, pp. 626–639, 2017.

[10] D. Kiron, P. K. Prentice, and R. B. Ferguson, "The analytics mandate," *MIT Sloan Manage. Rev.*, vol. 55, pp. 1–25, 2014.

[11] H. Hallikainen, E. Savimäki, and T. Laukkanen, "Fostering B2B sales with customer big data analytics," *Ind. Marketing Manage.*, vol. 86, pp. 90–98, 2020.

[12] R. Eller, P. Alford, A. Kallmünzer, and M. Peters, "Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization," *J. Bus. Res.*, vol. 112, pp. 119–127, 2020.

[13] S. F. Wamba, M. M. Queiroz, L. Wu, and U. Sivarajah, "Big data analytics-enabled sensing capability and organizational outcomes: Assessing the mediating effects of business analytics culture," *Ann. Oper. Res.*, pp. 1–20, 2020. [Online]. Available: https://link-springer-com.proxy.bib.uottawa.ca/article/10.1007/s10479-020-03812-4#citeas

[14] M. Yasmin, E. Tatoglu, H. S. Kilic, S. Zaim, and D. Delen, "Big data analytics capabilities and firm performance: An integrated MCDM approach," *J. Bus. Res.*, vol. 114, pp. 1–15, 2020.

[15] A. McAfee, E. Brynjolfsson, T. H. Davenport, D. Patil, and D. Barton, "Big data," *Harv. Bus. Rev.*, vol. 90, pp. 61–67, 2012.

[16] W. M. Cohen and D. A. Levinthal, "Absorptive capacity: A new perspective on learning and innovation," *Administ. Sci. Quart.*, vol. 35, pp. 128–152, 1990.

[17] S. Wang, W. Yeoh, G. Richards, S. F. Wong, and Y. Chang, "Harnessing business analytics value through organizational absorptive capacity," *Inf. Manage.*, vol. 56, 2019, Art. no. 103152.

[18] P. Upadhyay and A. Kumar, "The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance," *Int. J. Inf. Manage.*, vol. 52, 2020, Art. no. 102100.

[19] A. Braganza, L. Brooks, D. Nepelski, M. Ali, and R. Moro, "Resource management in big data initiatives: Processes and dynamic capabilities," *J. Bus. Res.*, vol. 70, pp. 328–337, Jan. 2017.

[20] P. Maroufkhani, M.-L. Tseng, M. Iranmanesh, W. K. W. Ismail, and H. Khalid, "Big data analytics adoption: Determinants and performances among small to medium-sized enterprises," *Int. J. Inf. Manage.*, vol. 54, 2020, Art. no. 102190.

[21] C. Gurău and A. Ranchhod, "Implementing big data analytics in small firms: A situated human practice approach," *Can. J. Administ. Sci./Revue Canadienne des Sci. de l'Admin.*, vol. 37, pp. 111–121, 2020.

[22] C. M. Ringle, S. Wende, and J.-M. Becker, "SmartPLS 3. SmartPLS GmbH, Bönningstedt," *J. Serv. Sci. Manage.*, vol. 10, pp. 32–49, 2015.

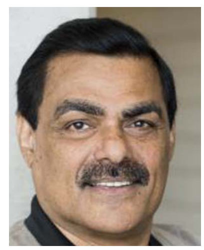
[23] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *Eur. Bus. Rev.*, vol. 31, no. 1, pp. 2–24, 2019.

[24] S. Akter, S. F. Wamba, and S. Dewan, "Why PLS-SEM is suitable for complex modelling? An empirical illustration in big data analytics quality," *Prod. Plan. Control*, vol. 28, pp. 1011–1021, 2017.

[25] B. Wernerfelt, "The resource-based view of the firm: Ten years after," *Strategic Manage. J.*, vol. 16, pp. 171–174, 1995.

[26] J. Barney, "Firm resources and sustained competitive advantage," *J. Manage.*, vol. 17, pp. 99–120, 1991.
[27] S. Akter, S. F. Wamba, A. Gunasekaran, R. Dubey, and S. J. Childe, "How to improve firm performance using big data analytics capability and business strategy alignment?," *Int. J. Prod. Econ.*, vol. 182, pp. 113–131, 2016.
[28] C. Lin and A. Kunnathur, "Strategic orientations, developmental culture, and big data capability," *J. Bus. Res.*, vol. 105, pp. 49–60, 2019.
[29] S. Krishnamoorthi and S. K. Mathew, "Business analytics and business value: A comparative case study," *Inf. Manage.*, vol. 55, pp. 643–666, 2018.
[30] A. Gandomi and M. Haider, "Beyond the hype: Big data concepts, methods, and analytics," *Int. J. Inf. Manage.*, vol. 35, pp. 137–144, 2015.
[31] S. F. Wamba, A. Gunasekaran, S. Akter, S. J. F. Ren, R. Dubey, and S. J. Childe, "Big data analytics and firm performance: Effects of dynamic capabilities," *J. Bus. Res.*, vol. 70, pp. 356–365, 2017.
[32] S. Mithas, N. Ramasubbu, and V. Sambamurthy, "How information management capability influences firm performance," *MIS Quart.*, vol. 35, pp. 237–256, 2011.
[33] G. George and Y. Lin, "Analytics, innovation, and organizational adaptation," *Innov., Org. Manage.*, vol. 19, pp. 16–22, 2017.
[34] A. Gunasekaran et al., "Big data and predictive analytics for supply chain and organizational performance," *J. Bus. Res.*, vol. 70, pp. 308–317, 2017.
[35] S. Ransbotham, D. Kiron, and P. K. Prentice, "Beyond the hype: The hard work behind analytics success," *MIT Sloan Manage. Rev.*, vol. 57, pp. 3–16, 2016.
[36] B. Wernerfelt, "A resource-based view of the firm," *Strategic Manage. J.*, vol. 5, pp. 171–180, 1984.
[37] D. J. Teece, "Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance," *Strategic Manage. J.*, vol. 28, pp. 1319–1350, 2007.
[38] D. J. Teece, G. Pisano, and A. Shuen, "Dynamic capabilities and strategic management," *Strategic Manage. J.*, vol. 18, pp. 509–533, 1997.
[39] C. E. Helfat et al., *Dynamic Capabilities: Understanding Strategic Change in Organizations*. Hoboken, NJ, USA: Wiley, 2009.
[40] A. S. Bharadwaj, "A resource-based perspective on information technology capability and firm performance: An empirical investigation," *MIS Quart.*, vol. 24, pp. 169–196, 2000.
[41] P. Mikalef, M. Boura, G. Lekakos, and J. Krogstie, "Big data analytics and firm performance: Findings from a mixed-method approach," *J. Bus. Res.*, vol. 98, pp. 261–276, 2019.
[42] S. Nambisan, M. Wright, and M. Feldman, "The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes," *Res. Policy*, vol. 48, 2019, Art. no. 103773.
[43] R. Amit and C. Zott, "Value creation in e-business," *Strategic Manage. J.*, vol. 22, pp. 493–520, 2001.
[44] N. Côrte-Real, T. Oliveira, and P. Ruivo, "Assessing business value of big data analytics in European firms," *J. Bus. Res.*, vol. 70, pp. 379–390, 2017.
[45] G. Cao, Y. Duan, and G. Li, "Linking business analytics to decision making effectiveness: A path model analysis," *IEEE Trans. Eng. Manage.*, vol. 62, no. 3, pp. 384–395, Aug. 2015.
[46] M. Pagani and C. Pardo, "The impact of digital technology on relationships in a business network," *Ind. Marketing Manage.*, vol. 67, pp. 185–192, 2017.
[47] T. H. Davenport and J. Harris, *Competing on Analytics: Updated, With a New Introduction: The New Science of Winning*. Boston, MA, USA: Harvard Bus. Press, 2017.
[48] F. Ciampi, S. Demi, A. Magrini, G. Marzi, and A. Papa, "Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation," *J. Bus. Res.*, vol. 123, pp. 1–13, 2021.
[49] M. J. Sousa and Á. Rocha, "Skills for disruptive digital business," *J. Bus. Res.*, vol. 94, pp. 257–263, 2019.
[50] A. Persaud, "Key competencies for big data analytics professions: A multimethod study," *Inf. Technol. People*, vol. 34, pp. 178–203, 2020.
[51] Y. Duan, J. S. Edwards, and Y. K. Dwivedi, "Artificial intelligence for decision making in the era of big data—Evolution, challenges and research agenda," *Int. J. Inf. Manage.*, vol. 48, pp. 63–71, 2019.
[52] N. Rahman, T. Daim, and N. Basoglu, "Exploring the factors influencing big data technology acceptance," *IEEE Trans. Eng. Manage.*, Apr. 2021, pp. 1–16.
[53] R. Dubey and A. Gunasekaran, "Education and training for successful career in big data and business analytics," *Ind. Commercial Training*, vol. 47, pp. 174–181, 2015.
[54] P. Mikalef, M. Boura, G. Lekakos, and J. Krogstie, "Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment," *Brit. J. Manage.*, vol. 30, pp. 272–298, 2019.
[55] A. McAfee, E. Brynjolfsson, and T. H. Davenport, "Big data: The management revolution," *Harvard Bus. Rev.*, vol. 90, pp. 60–68, 2012.
[56] M. F. Manesh, M. M. Pellegrini, G. Marzi, and M. Dabic, "Knowledge management in the fourth industrial revolution: Mapping the literature and scoping future avenues," *IEEE Trans. Eng. Manage.*, vol. 68, no. 1, pp. 289–300, Feb. 2021.
[57] K. Božič and V. Dimovski, "Business intelligence and analytics for value creation: The role of absorptive capacity," *Int. J. Inf. Manage.*, vol. 46, pp. 93–103, 2019.
[58] A. Behl, J. Gaur, V. Pereira, R. Yadav, and B. Laker, "Role of big data analytics capabilities to improve sustainable competitive advantage of MSME service firms during COVID-19—A multi-theoretical approach," *J. Bus. Res.*, vol. 148, pp. 378–389, 2022.
[59] J. M. Converse and S. Presser, *Survey Questions: Handcrafting the Standardized Questionnaire*, vol. 63. Newbury Park, CA, USA: Sage, 1986.
[60] A. Lutfi et al., "Factors influencing the adoption of big data analytics in the digital transformation era: Case study of Jordanian SMEs," *Sustainability*, vol. 14, 2022, Art. no. 1802.
[61] J. Song et al., "The source of SMEs' competitive performance in COVID-19: Matching big data analytics capability to business models," *Inf. Syst. Front.*, vol. 24, pp. 1167–1187, 2022.
[62] B. Williams, A. Onsman, and T. Brown, "Exploratory factor analysis: A five-step guide for novices," *Australas. J. Paramedicine*, vol. 8, pp. 1–13, 2010.
[63] D. X. Peng and F. Lai, "Using partial least squares in operations management research: A practical guideline and summary of past research," *J. Oper. Manage.*, vol. 30, pp. 467–480, 2012.
[64] T. C. Flatten, A. Engelen, S. A. Zahra, and M. Brettel, "A measure of absorptive capacity: Scale development and validation," *Eur. Manage. J.*, vol. 29, pp. 98–116, 2011.
[65] S. Gregor, M. Martin, W. Fernandez, S. Stern, and M. Vitale, "The transformational dimension in the realization of business value from information technology," *J. Strategic Inf. Syst.*, vol. 15, pp. 249–270, 2006.
[66] W. A. Harrison, "Is it finally time to kill self-report outcome measures in road safety? An investigation of common method variance in three surveys of a cohort of young drivers that included the driver behaviour questionnaire," in *Proc. Australas. Road Saf. Res., Policing Educ. Conf.*, 2010, pp. 1–8.
[67] M. K. Lindell and D. J. Whitney, "Accounting for common method variance in cross-sectional research designs," *J. Appl. Psychol.*, vol. 86, pp. 114–121, 2001.
[68] S. B. MacKenzie and P. M. Podsakoff, "Common method bias in marketing: Causes, mechanisms, and procedural remedies," *J. Retailing*, vol. 88, pp. 542–555, 2012.
[69] P. M. Podsakoff, S. B. MacKenzie, and N. P. Podsakoff, "Sources of method bias in social science research and recommendations on how to control it," *Annu. Rev. Psychol.*, vol. 63, pp. 539–569, 2012.
[70] C. W. Craighead, D. J. Ketchen, K. S. Dunn, and G. T. M. Hult, "Addressing common method variance: Guidelines for survey research on information technology, operations, and supply chain management," *IEEE Trans. Eng. Manage.*, vol. 58, no. 3, pp. 578–588, Aug. 2011.
[71] C. M. Fuller, M. J. Simmering, G. Atinc, Y. Atinc, and B. J. Babin, "Common methods variance detection in business research," *J. Bus. Res.*, vol. 69, pp. 3192–3198, 2016.
[72] M. J. Simmering, C. M. Fuller, H. A. Richardson, Y. Ocal, and G. M. Atinc, "Marker variable choice, reporting, and interpretation in the detection of common method variance: A review and demonstration," *Org. Res. Methods*, vol. 18, pp. 473–511, 2015.
[73] M. Rönkkö and J. Ylitalo, "PLS marker variable approach to diagnosing and controlling for method variance," in *Proc. Int. Conf. Inf. Syst.*, 2011, pp. 1–16.
[74] R. Sharma, P. Yetton, and J. Crawford, "Estimating the effect of common method variance: The method–method pair technique with an illustration from TAM research," *MIS Quart.*, vol. 33, pp. 473–490, 2009.
[75] J. Hulland, M. J. Ryan, and R. K. Rayner, "Modeling customer satisfaction: A comparative performance evaluation of covariance structure analysis versus partial least squares," in *Handbook of Partial Least Squares*. Berlin, Germany: Springer, 2010, pp. 307–325.

[76] W. W. Chin, "Bootstrap cross-validation indices for PLS path model assessment," in *Handbook of Partial Least Squares*. Berlin, Germany: Springer, 2010, pp. 83–97.
[77] J. F. Hair Jr., M. Sarstedt, C. M. Ringle, and S. P. Gudergan, *Advanced Issues in Partial Least Squares Structural Equation Modeling*. Newbury Park, CA, USA: Sage, 2017.
[78] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *J. Marketing Res.*, vol. 18, pp. 39–50, 1981.
[79] W. W. Chin, "The partial least squares approach to structural equation modeling," *Modern Methods Bus. Res.*, vol. 295, pp. 295–336, 1998.
[80] J. F. Hair Jr., G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Newbury Park, CA, USA: Sage, 2021.
[81] J. Henseler et al., "Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013)," *Org. Res. Methods*, vol. 17, pp. 182–209, 2014.
[82] J.-B. Lohmöller, "Predictive vs. structural modeling: PLS vs. ML," in *Latent Variable Path Modeling With Partial Least Squares*. Berlin, Germany: Springer, 1989, pp. 199–226.
[83] L. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Struct. Equ. Model., Multidisciplinary J.*, vol. 6, pp. 1–55, 1999.
[84] J. Henseler, C. M. Ringle, and R. R. Sinkovics, "The use of partial least squares path modeling in international marketing," in *New Challenges to International Marketing*. Bingley, U.K.: Emerald Group Publ. Ltd., 2009.
[85] M. Stone, "Cross-validatory choice and assessment of statistical predictions," *J. Roy. Statist. Soc., Ser. B (Methodol.)*, vol. 36, pp. 111–133, 1974.
[86] S. Geisser, "The predictive sample reuse method with applications," *J. Amer. Statist. Assoc.*, vol. 70, pp. 320–328, 1975.
[87] K. J. Preacher and A. F. Hayes, "Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models," *Behav. Res. Methods*, vol. 40, pp. 879–891, 2008.
[88] M. E. Sobel, "Asymptotic confidence intervals for indirect effects in structural equation models," *Sociol. Methodol.*, vol. 13, pp. 290–312, 1982.
[89] S. Erevelles, N. Fukawa, and L. Swayne, "Big data consumer analytics and the transformation of marketing," *J. Bus. Res.*, vol. 69, pp. 897–904, 2016.
[90] R. Bean and D. Kiron, "Organizational alignment is key to big data success," *MIT Sloan Manage. Rev.*, vol. 54, p. 1, 2013.
[91] A. Konanahalli, M. Marinelli, and L. Oyedele, "Drivers and challenges associated with the implementation of big data within UK facilities management sector: An exploratory factor analysis approach," *IEEE Trans. Eng. Manage.*, vol. 69, no. 4, pp. 916–929, Aug. 2022.
[92] D. G. Sirmon, M. A. Hitt, and R. D. Ireland, "Managing firm resources in dynamic environments to create value: Looking inside the black box," *Acad. Manage. Rev.*, vol. 32, pp. 273–292, 2007.
[93] D. C. Hambrick, "The top management team: Key to strategic success," *Calif. Manage. Rev.*, vol. 30, pp. 88–108, 1987.
[94] C. Ashurst, P. Cragg, and P. Herring, "The role of IT competences in gaining value from e-business: An SME case study," *Int. Small Bus. J.*, vol. 30, pp. 640–658, 2012.
[95] S. Bag, S. Gupta, T.-M. Choi, and A. Kumar, "Roles of innovation leadership on using big data analytics to establish resilient healthcare supply chains to combat the COVID-19 pandemic: A multimethodological study," *IEEE Trans. Eng. Manage.*, 2021, pp. 1–14.
[96] R. B. Ferguson, "The big deal about a big data culture (and innovation)," *MIT Sloan Manage. Rev.*, vol. 54, pp. 1–5, Winter 2013.
[97] T. H. Davenport, C. Kim, and B. Lev, "Enterprise analytics: Optimize performance, process, and decisions through big data," *Interfaces*, vol. 43, pp. 495–497, Sep. 2013.
[98] P. C. Nell, N. J. Foss, P. G. Klein, and J. Schmitt, "Avoiding digitalization traps: Tools for top managers," *Bus. Horiz.*, vol. 64, pp. 163–169, 2021.
[99] P. Akhtar, J. G. Frynas, K. Mellahi, and S. Ullah, "Big data-savvy teams' skills, big data-driven actions and business performance," *Brit. J. Manage.*, vol. 30, pp. 252–271, 2019.



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