

# **The Mediating Role of Entrepreneurial Orientation in Big Data Analytics Capability-Value Creation**

## **Abstract**

Many studies on big data analytics provide empirical evidence showing that Big Data Analytics Capabilities (BDAC) do not always result in value creation or competitive advantage. This study posits that entrepreneurial orientation (EO) plays a key role in generating value creation and competitive advantage from big data analytics capabilities. Thus, this study explores the mediating role of EO on the relationship between BDAC and value creation in small and medium-sized enterprises (SMEs). To test this relationship, data was collected from a sample of 447 senior executives of Canadian SMEs. Partial least squares structural equation modelling (PLS-SEM) was used to analyse the data. The results confirm that EO mediates the relationship between BDAC and value creation suggesting that SMEs with strong EO are better positioned to proactively leverage their internal BDAC for high-risk innovation activities. The results suggest that SMEs need to focus not only on building BDA capabilities but also on developing an entrepreneurial orientation to harness the full potential of BDAC for value creation. A practical implication for senior executives is that creating an entrepreneurially oriented organisation can lead to better mobilisation of BDAC for value creation. A theoretical implication is that EO can complement other organizational capabilities such as analytics culture to extract greater value from BDA investments. This is the first study to quantitatively examine the mediating role of EO in BDAC value creation based on a large-scale study of SMEs. The empirical evidence provided in this study complements previous studies that have examined other mediators such as analytics culture and absorptive capacity. It provides fresh insights into how SMEs can create value from their BDA investments by being more innovative, proactive and encouraging risk-taking across the organization.

**Keywords:** Big Data, Analytics Capabilities, Value Creation, SMEs, Entrepreneurial Orientation, Analytics Culture, Competitive Advantage

## **Managerial Relevance Statement**

Most small and medium enterprises struggle to harness the full potential of their BDAC investments. Therefore, a clearer understanding of how managers can organize for superior

performance is needed. This study demonstrates that managers of SMES must extend their focus beyond big data technological capabilities and devote attention to the complementary effects of human capabilities. Moreover, the results show that the direct effects of BDAC on value creation is mediated by a strategic entrepreneurial orientation defined in terms of the firm's proactiveness, risk-taking, and innovativeness. This finding shows that firms can achieve above-average value and performance from their BDAC investments by enacting policies, processes, routines, practices, and decision-making activities that are entrepreneurial.

## **1. Introduction**

Small and medium-sized enterprises (SMEs) across many industries have made significant investments in big data analytics (BDA) technologies [1]. However, most SMEs face formidable challenges trying to harness value from their BDA investments [1-4]. Thus, there is a need for a deeper understanding of how firms can derive greater value from their investments. In the search for possible explanations, scholars argue that firms need to go beyond developing BDA technological and human capabilities and focus on other organisational dynamics since BDA is not strictly a technical project [5, 6]. Recent studies have examined various mediating and moderating factors including analytics culture [7], agility [8], dynamic capability [9], knowledge management [10], and analytics culture [4].

Despite the progress made in studying different organisational routines on BDAC, one important dimension that has thus far received very little attention is entrepreneurial orientation (EO) [3, 11]. EO portrays the entrepreneurial behaviour and attitudes of firms [12] expressed by a firm's proactiveness, risk-taking, and innovativeness relative to their rivals [13]. EO can also be enhanced by the availability of relevant capabilities and resources (e.g., BDAC), which in turn can affect performance [14]. While the application of EO in BDAC studies is scarce; it has been studied in other contexts such as resource orchestration [15] and firm performance [16-18] in the context of SMEs [19, 20]. Moreover, EO has been studied as a mediator in various context including between environmental factors and entrepreneurial intention [21], resource orchestration and cultural contingencies [20] and innovativeness [22]. Despite these contributions, there is a paucity of research on the influence of EO on BDAC value creation [23]. Thus, this study investigates the

relationships between BDAC and EO and whether EO mediates the relationship between BDAC and value creation:

To investigate these relationships, a model in which EO mediates the relationship between BDAC and value creation is developed and tested on a sample of 447 Canadian SMEs, i.e., firms with fewer than 500 employees using partial least squares structural equation modelling (PLS-SEM) with Smart PLS. The model allows for deeper insights into how firms' strategic entrepreneurial orientation enables them to leverage BDA resources and capabilities to create value. The findings add richness to the BDA literature by demonstrating the extent to which EO, characterized by proactiveness, risk-taking, and innovativeness lead to greater value creation from BDAC investments. Similarly, the findings provide practical insights that managers can use to better orchestrate their BDA resources and capabilities for greater value creation. SMEs are chosen as the context of this study for a few reasons. First, there is a dearth of BDA research on SMEs and most of what is known about the relationship between BDAC and value creation comes from studies of large firms [24]. The validity of these findings to SMEs remains speculative [2]. Second, SMEs are resource-constrained businesses looking to build BDA capabilities, which is a resource-intensive endeavour. Achieving this has proven challenging, therefore, understanding how SMEs mobilise and orchestrate resources [25] can yield practical insights. Third, although SMEs are late adopters of BDA [23] and they still find it difficult to capture value from their BDA investments. It appears that being later adopters did not benefit them.

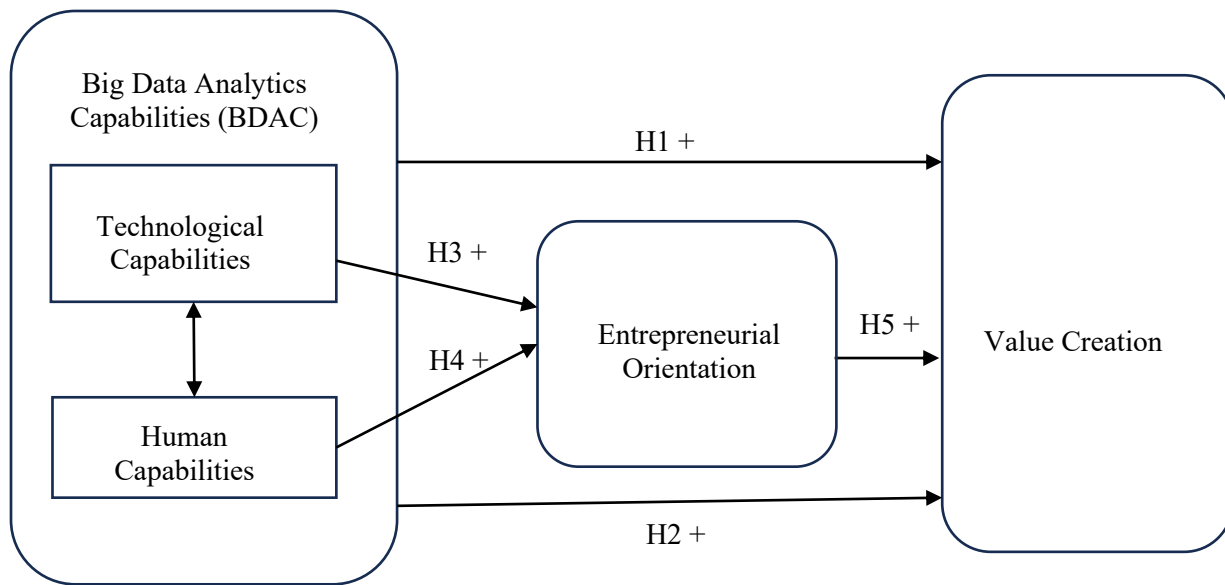
To the best of the researchers' knowledge, this study is the first to quantitatively validate EO as a capability that enhances BDAC value creation using a large sample of SMEs. This study makes several important contributions to the emerging literature on BDAC-driven value creation. First, it fills the knowledge gap on BDAC-driven value creation in SMEs, complementing evidence based on large firms and anecdotal cases. Second, it provides empirical evidence on how EO enhances BDAC value creation in SMEs. Third, it complements previous studies that have examined other organizational constructs such as agility, ambidexterity, and analytics culture. Fourth, from a practical perspective, the findings can inform managerial actions to improve BDAC value creation.

The remainder of this article is organised as follows: Section two presents the theoretical background and hypotheses. Section three describes the methodology and analytical techniques. Section four presents the results, and section five discusses the theoretical and practical implications of the findings, the limitations of the study and future research directions.

## 2. Theory and Hypotheses

The conceptual model guiding the study is depicted in Figure 1, which is described in greater detail below.

Figure 1 Conceptual Model



### 2.1 Big Data Analytics Capability and Value Creation

BDA scholars have developed the concept of *big data analytics capabilities (BDAC)*, which establishes a link between BDA-specific resources and capabilities and competitive advantage [7, 26]. Specifically, BDAC “is a firm’s ability to assemble, integrate, and deploy its big data resources” [27, p. 1049]. BDA-specific resources include relevant human resources, big data skills, advanced technologies, mathematical and statistical techniques, and machine learning tools that produce and process large data sets to generate analytical reports and actionable insights [28]. BDAC is a multidimensional construct consisting of both BDA technological and human talent (management and staff) capabilities [29].

In terms of technological capabilities, the emphasis is on the ability of firms to mobilise and synergistically use IT resources and capabilities (e.g., data, hardware, software, technology, experience) [30]. The ability to assemble and configure technologies to address current and ongoing organizational challenges and opportunities is a key technological capability since technical staff (e.g. engineers, data scientists, etc) must constantly be aware of and able to use an array of new and evolving big data technologies – software, hardware, infrastructure, etc [5, 31]. Agility in assembling and orchestrating BDA-specific IT capability is key to success [32].

Regarding the human resources and capabilities, the focus is on management and workers' knowledge, experience, and skills, which include business acumen, problem-solving, leadership qualities, relationships with others and so on [27]. In the context of big data, the ability to weave seamlessly technical, data and managerial skills is key to effectively leverage its BDA investments to develop new products, services, markets, innovations, business models, and revenue streams [6, 27, 33]. Human capabilities include big data skills, specialised competencies of management and staff, and a range of hard and soft skills (e.g., critical thinking, problem solving, communication, and collaboration skills) [34, 35]. For instance, Vidgen, et al. [5] found that data scientists must be curious, able to problem-solve, work independently, and be creative in addition to possessing strong statistical, mathematical and IT skills. The ability of IT staff and business staff to communicate effectively is crucial for the exchange of information and insights with the agility required in the big data environment [6, 35]. This is key to minimizing miscommunications and bottlenecks in translating data into insights to decisions. In line with the idea that big data analytics extends well beyond IT [5]. Management capabilities focus on the ability of management to establish organisational routines such as a data-driven culture, organisational learning, and absorptive capacity [4, 32]. Managers must appreciate the value of big data insights and be willing to use them to better understand current and nascent needs of customers, markets, partners and functional areas with their organization [27]. BDAC creates a competitive advantage for firms that can leverage existing and newly acquired BDA firm-specific capabilities [36]. Moreover, the knowledge, skills, and interpersonal relationships developed by employees and managers over time can enhance firm-specific BDAC, which may not be easily imitated or purchased from external factor markets [37]. In sum, human capital, which includes the education, experience, intelligence, judgment, knowledge, and skills of management and workers may be a source of

competitive advantage if they are sufficiently different from competitors' [20, 38]. Thus, we propose the following hypotheses:

Value creation is a primary goal of BDAC since the focus is on applying advanced technologies and analytic techniques to big data to generate unique insights that enhance managerial decision making at both strategic and operational levels [39]. Value is created when firms adopt new ways of doing things employing new methods, new technologies, and/or new forms of raw materials [40]. Lepak, et al. [41] argue that from an organizational perspective, value creation is influenced by issues of innovation, knowledge creation, invention, and management. According to Amit and Zott [42], value can be realized in the form of financial and strategic benefits. Strategic benefits include improved productivity, efficiency, innovation, and better customer service and supply chain relationships [39, 43]. Other value creation goals sought through BDA include increased market share [44], improved firm performance [36], and competitive advantage [45].

Based on the preceding arguments, the following hypotheses are proposed:

Hypothesis 1: BDA technological capabilities is positively related to value creation

Hypothesis 2: BDA human capabilities is positively related to value creation

### *2.2 Mediating Role of Entrepreneurial Orientation (EO) in BDAC-Value Creation*

The theoretical foundation of BDAC research is shaped by resource-based views (RBV) of the firm, dynamic capabilities, and resource orchestration theories [e.g., 9, 27, 36, 39, 46]. While RBV focuses on the resources and capabilities that a firm possesses [47, 48], dynamic capabilities and resource orchestration theories focus on the mechanisms by which firms learn, acquire new resources, and assemble and deploy existing resources and capabilities for competitive advantage [18, 25, 49, 50]. According to RBV, a firm's sustainable competitive advantage is derived from possessing resources that are valuable, rare, inimitable, and non-substitutable (VRIN) [47, 48] and variations in resources and capabilities account for heterogeneity in firm performance [51]. Extending this argument, dynamic capabilities and resource orchestration theories argue that while having VRIN resources is necessary, it is not sufficient to create competitive advantage; managers must know how to orchestrate resources to achieve superior performance [25, 52]. Essentially, it is not necessarily what resources you have but what you do with the resources you have [20, 53,

54]. Along this line, we contend that entrepreneurial orientation as a strategic orientation [12] and higher-order capability [43] can help companies better utilize their BDA resources and capabilities for greater value creation.

EO plays an essential role since it provides the mobilising vision to deploy firm resources [18] that can lead to value-creating activities through exploitation of existing innovations and exploration of new innovations [55]. In other words, EO activates the attitudes, behaviours, and practices needed [20] to effectively deploy BDA resources and capabilities toward value-creating activities [43]. EO contributes to firm performance when firms strategically acquire, develop and exploit resources that enhance both opportunity-seeking and advantage-seeking activities [55, 56]. As a strategic orientation, EO is concerned primarily not with the resources and capabilities the firm has but with what they do with those resource and capabilities [12, 20, 53]. Thus, to gain competitive advantage, the firm must implement processes, routines, practices, decisions-making activities [20] that will allow them to make full use of its resources and capabilities to explore and exploit opportunities [57]. EO firms exhibit a willingness to take risks, act proactively, and innovate to a greater degree than rivals [12, 58]. It is an entrepreneurial process by which firms implement creative ideas and proactively adapt to environmental changes through risk-taking and innovation leading to improved firm performance [55]. EO firms are inclined to tap into knowledge sources inside and outside the firm to leverage new and existing opportunities and invest ahead of rivals [4, 55].

As reported extensively in the firm performance studies [18, 20], resources and capabilities can have both 'direct' and 'indirect' effects on firm performance [20, 51]. In the context of big data analytics, the direct effects of BDAC on firm performance have been extensively investigated, however, there is a dearth of evidence on its indirect effects [39, 59]. This study explores the indirect mediating effects of EO on BDAC and the firm's value creation. We contend that a firm's endowment of BDA resources and capabilities can be used by managers to shape the firm's value creation potential [43] through its risk-taking, innovativeness, and proactiveness attitudes, behaviors, practices, and decision-making activities [12, 20]. Risk-taking is concerned with the willingness of managers to make large and risky resource commitments, even to projects that have a reasonable chance of costly failure [60]. Risk-taking behaviour is reflected in resource allocation

decisions, product and market choices [61], the willingness to depart from proven strategies, and to incur potential losses by venturing into the unknown [56]. Essentially, firms that exhibit risk-taking behaviour are more likely to seek out new opportunities and advantages [58]. Further, firms that are more prone to risk-taking may be more inclined to act on data-driven insights that go against their intuition, even at personal risk to their careers [62, 63]. EO firms are also more likely to encourage managers and employees to leverage BDA insights to develop new products, new markets, and new supply chains, and to strengthen existing products, markets, and customer relationships [43, 64].

Innovativeness reflects “a firm's tendency to engage in and support new ideas, novelty, experimentation, and creative processes that may result in new products, services, or technological processes” [58, p. 142]. Innovativeness occurs along a continuum from a simple willingness to either try a new product line or experiment with a new advertising venue to a serious commitment to mastering the latest advances in new products or technologies [58]. In this regard, EO can provide the mobilising behaviours for firms to exploit existing BDA innovations and to explore new BDA innovations. The proactiveness dimension enables a firm to be both proactive and reactive to environmental changes in technology markets, innovation, competition and customers [58]. Big data analytics has created many new possibilities for firms to be agile in exploiting existing products, markets, partners as well as to explore new and emerging opportunities. These arguments apply to both the technological resources and capabilities component of BDAC as well as the human resources and capabilities component of BDAC. Based on the preceding arguments, the following hypotheses are proposed:

*Hypothesis 3:* EO will mediate the relationship between BDA technological capabilities and value creation

*Hypothesis 4:* EO will mediate the relationship between BDA human capabilities and value creation

*Hypothesis 5:* EO is positively related to value creation

### **3. Methodology**

#### *3.1 Data*

This study focuses on SMEs i.e. companies with fewer than 500 employees. To reach a large sample of respondents with the requisite knowledge and experience, the researchers engaged the services of a leading national Canadian market research firm with an extensive panel of businesses executives. The researchers developed a questionnaire that was administered online by the market research firm. The questionnaire contained screening questions to ensure that only participants who met predetermined criteria were included. The inclusion criteria were: (1) participants must be mid- to senior-level executives; (2) they must be knowledgeable about their firms' BDA efforts; (3) the enterprises must have implemented BDA into their operations; (4) and firms with less than 20 employees were excluded since they were less likely to have sufficient BDA operations to provide the depth of insights needed for the study. Respondents were presidents, CEOs and founders, mid-level executives, analytics professionals, managers, and vice presidents.

Prior to developing the questionnaire, a thorough review of the BDA literature was undertaken, which led to the identification of several dimensions and measures. The researchers then conducted ten in-depth interviews with SME managers who had implemented BDA initiatives in their organisations. The interviews were designed to gain practical insights into BDA in SMEs and to validate the relevance of some of the measures reported in the literature. Each interview lasted approximately one hour. The findings from the interviews were used to develop the questionnaire. Before launching the questionnaire, some interviewees were asked to evaluate the content, completeness, accuracy, flow and wording of the questionnaire. Five academic researchers reviewed the questionnaire for content validity, a process commonly used in questionnaire design [45]. In addition, as suggested by Converse and Presser [65], the questionnaire was pretested with managers from a dozen different SMEs to obtain their feedback on key aspects, including whether the questions were clearly formulated, the response options were appropriate, the response burden to complete the questions was appropriate, and they had the necessary knowledge to answer the questions accurately. The feedback from these efforts led to minor wording changes. The pre-test responses were not used in the analysis.

Due budgetary limitations, the sample size was constrained to 447 fully completed questionnaires. For confidentiality reasons, the market research company does not provide non-response rates. Sampling adequacy was assessed using the Kaiser-Meyer-Olkin (KMO) test. The KMO value is 0.97, which lies between 0.8 and 1, and thus meets the condition of sampling adequacy [66]. The ‘10-times rule’, which is often used to determine sample adequacy with PLS [67] was used. This rule requires that the sample size be greater than 10 times the maximum number of links in the model. With 33 links in the model, the sample of 447 is adequate. Table 1 shows the demographics of the participants.

Table 1 Participant Demographics (n=447)

<b>Demographic characteristics</b>	<b>Frequency</b>	<b>Percentage</b>
<i>Gender</i>		
Male	317	70.9%
Female	130	29.1%
<i>Age</i>		
18-34	219	49%
35-44	118	26.4%
Over 45-54	110	24.6%
<i>Position level</i>		
Specialist	148	33.1%
Manager/Head	194	43.4%
Director, Vice President, President, CEO, Founder	105	23.5%
<i>BDA knowledge level</i>		
Quite knowledgeable	280	62.6%
Extremely knowledgeable	167	37.4%
<i>Experience in their current position</i>		
5 years or less	210	47.0%
More than 5 years	237	53.0%
<i>BDA experience</i>		
5 years or less	240	53.7%
More than 5 years	207	46.3%
<i>Management experience over career</i>		
5 years or less	184	41.2%
More than 5 years	263	58.8%
<i>Firm Size – Number of Employees</i>		
20-99	180	40.3%

Table 1 shows a 70-30% split between male and female respondents and a 49-51% split between respondents under the age of thirty-five and those over thirty-five. Two-thirds of respondents were managers/department heads, directors, vice presidents, presidents, CEOs and founders, and one-third was specialists (e.g., data scientists, senior data architects and senior analysts). In addition, 53% of respondents have more than 5 years of experience at their current company, 46.3% have more than 5 years of BDA experience, and 58.8% have more than 5 years of combined leadership experience over their careers. Thus, respondents are quite experienced and knowledgeable about BDA and their organisations' initiatives. Also, around 40% of the sample are small businesses (99 or fewer employees) and 60% are medium-sized businesses (between 100 and 499 employees). Furthermore, cross-tabulations and various t-tests of the variables show a good distribution of respondents in terms of years of BDA and management experience, which is consistent with the inclusion criteria of having knowledgeable and experienced participants. In addition, t-tests for gender, age and experience on several variables in the model (e.g. technological capability, management capability) show no differences, hence there is no discernible response bias.

### 3.2 Measurement

The items used to measure the constructs were taken from established scales that have been validated in previous studies (Table 2). Respondents responded to multi-item constructs measured on a 7-point Likert scale (1= strongly disagree, 7= strongly agree). Table 2 shows the constructs and measurement items. The *technological capabilities* construct captures access to big data and the nature of the technological infrastructure. The *human capabilities* construct focuses on the extent to which managers understand the data needs of the organisation, coordinate BDA activities, and apply BDA insights. It also captures the readiness of BDA personnel in terms of education, skills, experience, and training. The *business value* construct captures the strategic, operational, efficiency and innovation impacts of BDA. The *entrepreneurial orientation* construct focus on the innovativeness, risk-taking, and proactiveness characteristics of EO.

Table 2 Summary statistics of the indicators (n=447)

Constructs/items*	Avg.	Std.Dev
<b>Technological Capabilities</b> [9, 27]		
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
<b>Human Capabilities</b> [27]		
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 the right mix of soft skills (e13)	5.389	1.470
<b>Entrepreneurial Orientation</b> [18, 56]		
Having strong risk appetite (e14)	5.353	1.447
Believing bold and wide-ranging acts (e15)	5.528	1.327
Adopting a bold posture facing uncertainty (e16)	5.456	1.270
Tending to be ahead of competitors (e17)	5.434	1.339
Initiating actions before competitors (e18)	5.38	1.391
Being first in introducing new products/services (e19)	5.374	1.412
Having plan to launch new lines of products/services (e20)	5.501	1.408
Stressing R&D and technological leadership (e21)	5.434	1.436
Taking measures to achieve competitive advantage (e22)	5.425	1.390
<b>Strategic Business Value</b> [43, 68]		
Transforming business processes & models (e23)	5.579	1.246
Improving customer experience (e24)	5.698	1.292
Improving innovation (e25)	5.810	1.159
Increasing efficiency (e26)	5.875	1.139
Creating competitive advantage (e27)	5.740	1.235

\*Items are measured on 1 (strongly disagree) to 7 (strongly agree) scale.

### *3.4 Common method bias (CMB)*

Cross-sectional and self-reported data raise concerns about common method bias [69]. CMB could affect the validity and reliability of the results [70]. CMB was assessed using several approaches suggested in the literature. Some of the strategies used include protecting the confidentiality and privacy of participants, using established scales, dividing the questionnaire into sections, pre-testing the questionnaire, and selecting respondents who are most knowledgeable about their companies' BDA initiatives [70, 71]. Additionally, Harman's one-factor test showed that a multi-factor solution explains more variance than a single-factor solution, and there is no single factor in the unrotated factor structure [72]. This is in line with established guidelines and therefore CMB does not appear to be problematic. Further, a marker variable was used to analyse CMB [69]. The marker variable met two important criteria: it was theoretically unrelated to the dependent variable [69] and it had a similar social desirability bias as the dependent variable [73]. Social desirability requires that if respondents are inclined to rate the dependent variable more positively, they should also rate the marker variable more positively [74]. The marker variable used focuses on whether the effort and attention put into completing the survey justifies the use of their responses, as this fulfils both conditions of the marker variables. The results show that the marker variable did not render any significant correlations insignificant [75], so there are no serious CMB concerns.

### *3.5 Data analysis technique*

The data were analysed using PLS-SEM, which is widely used in BDA research [76]. PLS-SEM can efficiently model complex relationships between observed and latent variables, simultaneously estimate multiple exogenous and endogenous constructs in a single model, estimate moderating and mediating relationships, and perform well with small sample sizes [77]. Further, PLS-SEM requires less restrictive assumptions regarding multivariate normality and removes the uncertainty of inadmissible solutions [78, 79]. SmartPLS Version 3.3.7 was used to run the model [80]. Following the recommendations of Hair, et al. [77], the reliability and validity of the measurement model was first established, and then the structural model was evaluated.

## 4. Results

### 4.1 Evaluation of the measurement model

Table 3 shows the composite reliability (CR), Cronbach's alpha, and average variance extracted (AVE) values for each variable. CR and Cronbach's alpha assess the unidimensionality and internal consistency of the model. Both of these indicators are above their threshold of 0.7, supporting the internal consistency of the measurement model [77]. The AVE values are also significantly higher than the cut-off value of 0.50, indicating good convergent validity [81].

Table 3 The Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE)

Variable	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Technological Capabilities	0.877	0.907	0.620
Human Capabilities	0.943	0.952	0.738
Entrepreneurial Orientation	0.944	0.952	0.690
Strategic business value	0.867	0.904	0.652

Cross-loading values with a threshold of 0.7 are used to establish the discriminant validity of the measurement model [79]. Table 4 shows that the cross-loading values are higher than 0.7, thereby indicating adequate discriminant validity. Additionally, the Fornell-Larcker criterion was used to test for model discrimination [81]. Table 5 shows that the square root of each variable's AVE value (diagonal values) is above the 0.6 cut-off and greater than the variable's inter-construct correlations (off-diagonal values), indicating good discriminant validity of the model [82].

Table 4 Cross-loading values

Item	Technological Capabilities	Human Capabilities	Entrepreneurial Orientation	Strategic business value
e1	0.744	0.517	0.495	0.468
e2	0.833	0.627	0.525	0.557
e3	0.793	0.565	0.493	0.518
e4	0.739	0.543	0.458	0.452
e5	0.778	0.62	0.553	0.486
e6	<b>0.831</b>	0.694	0.582	0.529

e7	0.665	<b>0.87</b>	0.687	0.63
e8	0.686	<b>0.898</b>	0.688	0.674
e9	0.616	<b>0.832</b>	0.658	0.624
e10	0.636	<b>0.865</b>	0.677	0.661
e11	0.66	<b>0.834</b>	0.651	0.588
e12	0.652	<b>0.866</b>	0.683	0.639
e13	0.635	<b>0.847</b>	0.714	0.578
e14	0.569	0.636	<b>0.807</b>	0.509
e15	0.501	0.605	<b>0.821</b>	0.626
e16	0.537	0.641	<b>0.852</b>	0.569
e17	0.53	0.673	<b>0.866</b>	0.573
e18	0.553	0.686	<b>0.856</b>	0.589
e19	0.552	0.668	<b>0.846</b>	0.548
e20	0.51	0.573	<b>0.766</b>	0.62
e21	0.585	0.703	<b>0.824</b>	0.563
e22	0.59	0.729	<b>0.83</b>	0.604
e23	0.566	0.616	0.6	<b>0.778</b>
e24	0.464	0.564	0.518	<b>0.787</b>
e25	0.548	0.595	0.587	<b>0.813</b>
e27	0.474	0.565	0.54	<b>0.815</b>

Table 5 Fornell-Larcker Criterion

	Technological Capabilities	Human Capabilities	Entrepreneurial Orientation	Strategic business value
Technological Capabilities	<b>0.787</b>			
Human Capabilities	0.759	<b>0.859</b>		
Entrepreneurial Orientation	0.66	0.793	<b>0.83</b>	
Strategic Business Value	0.639	0.727	0.696	<b>0.808</b>

#### 4.2 Structural model

There are several indicators to assess the fitness of structural models, including the normed fit index (NFI), RMS-theta, and standardised root mean square residual (SRMR) indices [83-85]. NFI values above 0.8 [84], SRMR values below 0.8 [86], and RMS-theta below 0.12 [85] indicate good model fit. The results show an NFI of 0.88, an SRMR of 0.048 and an RMS-theta of 0.11, which indicate good model fit. The explanatory power and predictive relevance of the model were assessed using the coefficients of determination (R2) and Stone-Geisser (Q2) values, respectively. As Table 6 shows, the Q2 and R2 values for all endogenous variables are well above the thresholds

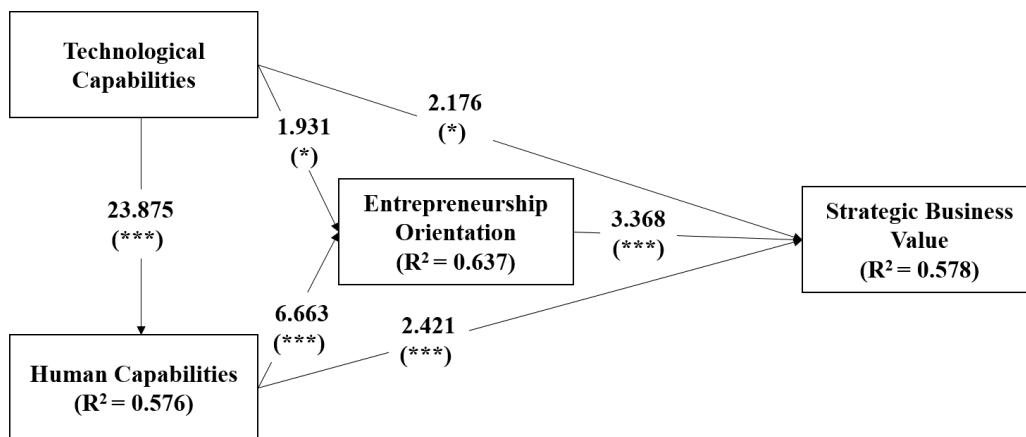
of 0.25 for  $Q^2$  [77] and 0.33 for  $R^2$  [87] indicating good predictive and explanatory power of the model.

Table 6 The coefficients of determination ( $R^2$ ) and Stone-Geisser's ( $Q^2$ ) values

Endogenous latent variable	$R^2$	$Q^2$
Human Capabilities	0.576	0.393
Entrepreneurial Orientation	0.637	0.407
Strategic Business Value	0.578	0.350

In general, variance inflation factor (VIF) values less than 5 indicate that multicollinearity is not a serious concern [88]. The VIF values in the study range from 1.7 to 3.7, indicating that multicollinearity is not a problem. Having ensured good model fit, adequate explanatory and predictive and power, and no multicollinearity problem, hypotheses was tested using path analysis. Figure 2 shows the unstandardised path coefficients and Table 7 shows the standardised path coefficient estimates, T-statistics and P-values. A one-tailed test was used with P-values below 0.05 to represent statistical significance - the hypotheses indicate positive associations [89]. The results of the path analysis show positive directions between all four variables.

Figure 2 The results of the path coefficient analysis



p-value  $\leq 0.05 = *$ , p-value  $\leq 0.01 = **$ , and p-value  $\leq 0.001 = ***$ .

Table 7 The path analysis results for direct effects between variables.

Model	Path coefficient value	Standard Deviation (STDEV)	T Statistics	P-Value <sup>a</sup>	Result
Technological Capabilities → Strategic Business Value	0.229	0.104	2.203	0.014 (*)	H1a-Supported
Human Capabilities → Strategic Business Value	0.300	0.127	2.367	0.009 (***)	H1b-Supported
Technological Capabilities → Human Capabilities	0.804	0.035	22.801	0.000 (***)	Sig. <sup>b</sup>
Technological Capabilities → Entrepreneurial Orientation	0.204	0.102	1.993	0.023 (*)	Sig. <sup>b</sup>
Human Capabilities → Entrepreneurial Orientation	0.647	0.097	6.704	0.000 (***)	Sig. <sup>b</sup>
Entrepreneurial Orientation → Strategic Business Value	0.36	0.105	3.447	0.000 (***)	Sig. <sup>b</sup>

<sup>a</sup>p-value ≤ 0.05 = \*, p-value ≤ 0.01 = \*\*, and p-value ≤ 0.001 = \*\*\*.

<sup>b</sup>Sig. = Significant. Given our specific focus on the mediation effect, no hypotheses were formed for these paths.

#### 4.3 Mediation Analysis

According to Hair Jr et al. (2021), three conditions must be met when testing for mediation effects. First, the indirect path of the relationship must be statistically significant. Two, the direct relationship must be significant given the exclusion of the mediator variable from the model. Third, the variance accounted for (VAF) values must be greater than 20%. Specifically, the VAF value should be above 20% for partial mediation and above 60% for full mediation. As shown in Table 8, these conditions were met in the model, demonstrating a partial mediation between technological/human capabilities and strategic firm value through EO. Further, the Sobel test for mediation effects was performed using a one-tailed test because the hypotheses suggest positive associations. The relevant p-values of the Sobel test are below 0.05, supporting significant mediation effects [90]. In addition, the p-values of the indirect paths are less than 0.05, indicating statistical significance. The mediated path coefficients of 0.074 and 0.239 between BDA technological capabilities and strategic business value and between BDA human capabilities and strategic business value, respectively, support the mediation hypotheses.

Table 8 Tests of hypotheses for mediation effects between the variables

Path	Path coefficient - direct relationship <sup>a</sup>	Path coefficient - mediated relationship <sup>b</sup>	Standard Deviation	P-value	Sobel test (P value = )	VAF	Result
Technological Capabilities → Strategic Business Value	0.355 (***)	0.229 (*)	0.104	0.014	1.728 (P value = 0.042)	0.243	Partial Mediation -
Technological Capabilities → Entrepreneurial Orientation → Strategic Business Value		0.074 (*)	0.044	0.046			H2a-Supported
Human Capabilities → Strategic Business Value	0.481 (***)	0.300 (***)	0.127	0.009	3.093 (P value = 0.001)	0.437	Partial Mediation
Human Capabilities → Entrepreneurial Orientation → Strategic Business Value		0.233 (***)	0.071	0.001			H2b-Supported

a: In this model the mediator variables are excluded

b: In this model the mediator variables are included

## 5. Discussion

This study is motivated by growing evidence that small and medium enterprises (SMEs) often struggle to gain full value from their investments in Big Data Analytics (BDA). Prior research calls for the investigation of how organizational routines may serve as mechanisms to achieve greater value from BDAC investments [91]. In response, this study aims to provide a deeper understanding of how organizational mechanisms impact BDAC value creation by investigating how entrepreneurial orientation (EO) as a firm-level strategic orientation [12] and a higher order capability [43] impact BDAC. Specifically, the role of EO as a mediator of the BDAC-value creation relationship is examined. As a firm-level strategic orientation, the focus is on three key characteristics of EO, namely, proactiveness, risk-taking, and innovativeness [12]. These three characteristics of EO provide the mobilizing vision [18] managers employ to enact routines, processes, practices, investments, and decision-making activities to leverage organizational resources to create value and attain above-average performance [15, 20].

Using Partial Least Squares Structural Equation Modelling (PLS-SEM) with data from 447 SMEs, the results support our hypotheses that EO plays a significant mediating role between BDAC and

value creation. Specifically, the results confirm all hypotheses, namely, the direct effects of BDAC technological and human capabilities on value creation (hypotheses 1 and 2), and the indirect effects of BDAC technological and human capabilities on value creation through EO (hypotheses 5). The hypothesized positive relationship between BDAC technological and human capabilities on EO are also supported (hypotheses 3 and 4). The results confirms that EO mediates the BDAC-value creation relationship. The results supports the viewpoint that it is not only the resources and capabilities that the firm is endowed with but rather with what they do with the resources [20, 25, 53, 54]. Further, our results support the role of EO as a mechanism to mobilize resources and capabilities [15, 18] that mediates the relationships between technological capabilities, human capital, and value creation. The results also suggest that managers should encourage EO since it leads to the enactment of processes, activities, practices, and decision-making that can ultimately generate competitive advantage [20].

These findings have important implications for both scholarly research and business managers. Notably, this study is the first to quantitatively test EO as a mediator in the BDAC–value creation link using a large sample of SMEs. The findings extend knowledge of how BDAC contribute to value creation by empirically demonstrating the significance of both its direct and indirect effects through EO. The results indicate that firms can achieve above-average value from their BDAC investments by enacting a strategic entrepreneurial orientation through proactiveness, risk-taking and innovativeness. The results also complement earlier works that explored related factors such as agility [32], analytics culture [7], and internal knowledge [92].

### *5.1 Theoretical implications*

This study extends the BDAC literature by providing evidence that EO is a higher-order capability that enhances BDAC value creation based on a large sample of SMEs. The combination of a large sample with rigorous data collection and systematic analyses validates the findings that SMEs can leverage BDAC for value creation through EO. This validation adds to previous research examining other dimensions such as analytics culture, ambidexterity, agility and absorptive capacity. The evidence presented also complements case study findings reported by Zeng and Khan [93] in the context of emerging markets. In addition, this study provides clear research evidence on SMEs, which has been lacking as most previous research has focused on large firms,

who were the early adopters [2]. The findings confirm that EO-oriented SMEs are better positioned to derive greater value from their BDA investments.

This perspective is consistent with evidence from Kiron, et al. [62], which shows that analytically innovative organisations outperform analytically challenged organisations in their ability to create competitive advantage. EO-oriented organisations are also more likely to discover and exploit market opportunities [55, 94] since managers are more willing to commit resources to high-risk, innovative projects, pursue opportunities that may be unrelated to their current business, introduce new products ahead of competitors, eliminate less profitable activities, and incentivise employees to engage in experimentation [61]. Additionally, EO firms tend to be not only reactive to their environment but also proactive by exploring new innovations [55] such as new business models, products and markets [95]. EO firms use their BDA capabilities to identify and exploit new opportunities earlier than competitors. Further, EO firms are better able to exploit BDAC knowledge through more effective decision making [76], which improves their ability to respond to both internal and external cues, enabling them to more proactively exploit market opportunities [95]. Moreover, EO firms are more likely to share BDAC knowledge across organisational units [92] and absorb external knowledge to enhance their BDA capabilities [96]. Such knowledge sharing can have positive impacts on value creation and competitive advantage.

### *5.2 Practical Implications*

The findings of this study provide evidence-based practical guidance for business and engineering managers, practitioners, and policy makers aimed at developing and implementing BDAC to maximise value creation. The results confirm that the relationship between BDAC and value creation is significantly mediated by EO, particularly through dimensions such as risk management, knowledge management, innovativeness, and the management of entrepreneurial behaviours. For instance, managers can enthusiastically foster and cultivate entrepreneurial behaviours among managers (i.e., middle managers) and employees [97] by providing them with the necessary tools, processes, data, insights, and incentives to facilitate data-driven decision making [36]. Middle managers and employees should be encouraged and rewarded for taking calculated risks, introducing innovations, being aggressive towards competitors and new opportunities, and experimenting with new ways of doing things. They should not be punished for

failing, as failure can reveal new knowledge that can subsequently contribute to success [57]. In addition, managers need to show an openness to act on BDAC insights by allocating adequate resources to projects where the outcome may be uncertain and the cost of failure is high [57]. Managers must also ensure that internal organisational processes are designed to promote value creation through collaboration, knowledge sharing, risk-taking, innovation and the proactive pursuit of new opportunities. Managers can demonstrate and encourage entrepreneurial behaviours through their preferences for bold versus cautious actions to achieve organisational goals [56].

Managers must recognise that BDAC insights can reveal numerous opportunities for incremental innovations that can improve various organisational processes and lead to significant value creation. For example, BDAC insights can identify opportunities to improve operational efficiency, build stronger customer relationships, increase supply chain efficiency, improve distribution channels, and promote more effective advertising, branding, pricing, and other business model innovations [43]. These incremental innovations and improvements can cumulatively create significant value and competitive advantage for the firm. The key is for managers to pursue these opportunities ahead of competitors [61] proactively. This may involve prioritising the full range of innovation choices generated by BDAC insights according to the firm's strategies, objectives, resources and capabilities. In essence, managers must ultimately recognise that the dynamic capabilities derived from their technological and human resources can be significantly enhanced by an entrepreneurial orientation, which can have a significant impact on value creation.

Similarly, for engineering managers, the results of this study indicate that technical and data-based competencies alone are insufficient to create value through BDAC analysis. BDAC must be applied within an entrepreneurial-oriented context, in which engineers and technical staff are encouraged to interpret and act upon data-driven insights by engaging in organisational innovation behaviours. Through such practices, they can allocate resources more effectively and mitigate risks while developing new or innovative operational processes. Furthermore, this study suggests that policymakers should design supportive operational frameworks that integrate advanced technological capabilities with entrepreneurial competencies to enhance evidence-based and innovation-driven policymaking.

This study also aligns with some UN Sustainable Development Goals (SDGs), especially SDG 8 (*Decent Work and Economic Growth*), because it promotes productivity and innovation among SMEs through data-driven entrepreneurial practices. SDG 9 (*Industry, Innovation, and Infrastructure*) through evolving innovative ecosystems with the integration of organisational capabilities and data analytics. And SDG 12 (*Responsible Consumption and Production*), as this study enables data-driven efficiencies in operations processes and managing resources of the firms.

## **Conclusion**

This research contributes valuable theoretical and practical insights into small and medium-sized enterprises (SMEs) ability to create value from their BDAC investments. A key finding is that a strategic entrepreneurial orientation (EO) enables firms to maximise the value potential of BDAC. By positioning EO as a higher-order capability, the study adds to the existing literature by showing how EO facilitates to management of both technological and human analytical resources into value-driven outcomes. This perspective is particularly relevant within the resource-based practice of SMEs. This study employs an appropriate methodological approach (PLS-SEM) to a substantial dataset comprising 447 Canadian SMEs, thereby enhancing the reliability of the findings. It also discusses important gaps in existing research related to EO and explains how BDAC create value for SMEs through BDAC. It highlights the need to encourage an entrepreneurial mindset across the organisation to make the most of BDAC's strategic and operational benefits. From a managerial perspective, the study results encourage SME leaders to adopt supportive policies that nurture entrepreneurial behaviour.

### *6.1 Limitations and Future Research*

Despite the unique findings of this study, there are some limitations, but these can serve as the basis for further research. The study is based on a single cross-sectional survey, which limits its ability to explain how EO affects BDAC value creation over time. Future research based on longitudinal data can shed light on how the relationship between BDAC, EO and value creation evolves over time and what contingent factors may affect them differently. Such studies can shed light not only on causality, but also on how changes in the variables affect each other. In addition, the data are from a single developed country, so the findings may not be applicable to emerging or developing country contexts. Future research in other countries may reveal whether specific

contextual factors also shape the relationship between BDAC, EO and value creation. Another limitation is that this study assumes a linear relationship between EO and value creation, which may not always hold. Future research may explore non-linear or more complex relationships, or whether there is an optimal level beyond which further benefits may not accrue or may result in suboptimal resource allocation. Additionally, this study focuses on firm-level EO, however, the role of individual entrepreneurship [12] can be explored in future studies, particularly considering the growing interest in individual EO, which may have different mechanisms and may be quite different from firm-level EO [12].

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