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Research paper

Analytics Culture and Absorptive Capacity as Mediators of Big Data Value Creation in SMEs

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Abstract

This paper examines the ways small and medium firms derive value from big data analytics. It notes that many firms invest in analytics technology. Yet many struggle to turn data into strategic value. The research asks whether analytics culture and absorptive capacity help. Analytics culture involves using data in daily decisions. Absorptive capacity involves finding, learning, and using outside knowledge. The model tests human and technological analytics capabilities. It tests analytics culture and absorptive capacity as mediators. The results show that both mediators matter. Analytics culture amplifies the effect of capabilities on business value. Absorptive capacity strengthens this effect. Together, these factors help firms translate analytics investments into measurable outcomes. The findings add new empirical evidence for SMEs. Results show that technology alone is not enough. Firms need culture and learning routines. Managers should develop analytics mindsets and promote knowledge sharing and external learning. These steps help align analytics with organizational goals and results. The model demonstrated strong fit and predictive accuracy. The mediators partly explain the process through which capabilities lead to value. The research provides clear recommendations for managers in SMEs. Leaders should align technology, people, and processes. Training and hiring matter. Leaders should reward knowledge sharing. Firms should develop routines to learn from partners. The research adds to theory and practice. Limitations include the single-country, cross-sectional design. Future work should use other countries and longitudinal data.

Keywords: *SME; Big Data; Analytics; Reliability; Culture.*

1. Introduction

This paper studies big data analytics in small and medium-sized firms. Big data analytics (BDA) refers to collecting and using very large and complex data sets[1]. Firms use BDA to gain insights that guide better decisions. Data comes from many sources, like sensors, mobile devices, social media, logs, and transactions[2]. In today's digital economy, BDA is seen as a powerful driver of change in strategy, process, and performance. Prior research highlights that BDA transforms the way organizations operate, compete, and deliver value[3]. Still, BDA does not always bring the expected value. Many firms invested heavily in data systems and analytic tools[4]. Yet firms face difficulties when trying to turn data into tangible business value. There are technical barriers, including system integration and data quality. There are managerial barriers, including a lack of leadership commitment. There are organizational and cultural barriers that reduce the ability to act on insights[5]. These challenges show that BDA alone is not enough. Another issue is that as BDA spreads across many industries, its advantage weakens. When most firms use similar tools, it is hard to stand out from competitors[6]. To move beyond parity, firms need to combine analytics with creativity, culture, and unique routines. This requires fresh ways to reconfigure resources and link BDA to business strategy.

Most research so far has looked at large companies. Small- and medium-sized enterprises (SMEs) remain under-studied[7]. SMEs usually lack the financial and human resources of big firms. Firms face unique challenges in adopting and benefiting from BDA. As a result, it is unclear if lessons from large companies apply to SMEs[8]. The paper highlights this knowledge gap and provides evidence on ways for SMEs to capture value from analytics. It focuses on two organizational factors that go beyond technology. The first is analytics culture. This refers to a culture in which decisions rely on facts and data rather than only intuition or experience[9]. It involves values, norms, and behaviors that support the use of analytics. A strong analytics culture requires leaders and staff to rely on evidence[10]. The second factor is absorptive capacity. BDA frequently depends on external platforms, tools, and partnerships[11]. Absorptive capacity allows a firm to integrate outside resources with internal knowledge. It supports faster learning and better use of analytics outcomes. These two factors are linked to BDA capabilities. BDA capabilities include both technological and human elements[12]. Technological capability involves having the right infrastructure, tools, and data systems. Human capability involves having managers and staff with the skills to manage and analyze data[13]. Both are important, but might not be enough on their own. The paper argues that culture and absorptive capacity mediate the link between capabilities and value. The research uses a survey of 447 Canadian SMEs. Respondents include executives, managers, and analytics professionals. The data is analyzed with partial least squares structural equation modeling (PLS-SEM)[14]. This method allows testing of both direct and indirect effects in the model. It is well-suited for complex models and medium-sized samples[15]. The key contributions of the paper are:

The research focuses on SMEs, a group frequently overlooked in BDA research. Data were collected from 447 Canadian SMEs, providing robust empirical support.

- Analytics culture and absorptive capacity are examined as mediators, representing a novel approach in SME research. Findings indicate that culture and learning routines enhance the value of analytics, offering clear managerial guidance.
- The work links BDA capability research to resource-based and dynamic capability perspectives.

The introduction makes clear that technology and skills are necessary but not enough. SMEs need to commit to data-driven practices and to continuous learning from outside[16]. In this way, analytics investment is converted into a strategic advantage.

2. Background

The paper begins by defining BDA. BDA involves collecting, curating, and analyzing very large and mixed data sets. Firms use BDA to get useful and actionable insights. Good insights affect firm performance. The section cites prior work that links BDA to performance and decision-making [26], [24]. The paper then describes four main pillars of BDA. The pillars are data, technology, people, and organizational culture [17], [19]. Data is the raw input. Technology is the set of tools and platforms. People bring skills and judgment. Culture shapes the way people use data. It is stressed that a single pillar alone is not enough. The work draws on the resource-based view (RBV) of the firm. RBV says that unique and valuable resources give firms an edge [21], [20]. Dynamic capabilities are used to explain the ways firms adapt and renew routines over time [22]. The IT capability perspective is used to show the ways technology supports performance [23]. Finally, organizational culture is used to show the influence of shared norms on the use of analytics. Data is an intangible resource [17]. Firms need the right infrastructure to collect and store it. Human skills are needed to interpret results and to take action [26]. Thus, data alone will not produce value without tech and people.

BDA capabilities are defined (BDAC). BDAC refers to the ability to assemble, integrate, and use Big-Data-specific resources [17]. BDAC is multi-dimensional. It includes technological capabilities and human (management and staff) capabilities [24]. Technological capability covers hardware, software, platforms, and integration experience [23]. Human capability covers analytic skills, managerial competence, and soft skills, including communication and teamwork. The two capability types need to align and work together. The paper emphasizes the interplay between human and technical capabilities. Technical tools need skilled people to operate them. Managers need to translate analytics into decisions. Skilled staff need to extract insights that matter to the business. When both capabilities are present, a firm-specific bundle forms that is hard to copy. This concept links back to RBV and dynamic capabilities [21, 22].

Analytics culture is a set of norms and values that favor data-driven decision-making [25]. It shows up when leaders and teams use data routinely. A strong analytics culture reduces reliance on hunches. Building this culture requires leadership, training, and incentives [26]. Closely related is absorptive capacity. This is a firm’s ability to find, absorb, and use external knowledge. Cohen and Levinthal first framed this concept [18]. Absorptive capacity matters because much BDA technology and knowledge come from outside the firm. Firms need to acquire external data, tools, or methods. Firms need to assimilate this knowledge and put it to work. Absorptive capacity supports continuous learning and helps firms renew analytics routines.

Table 1: Comparison of BDA Value Creation between Large Firms and SMEs

Aspect	Large Firms [2], [7], [15], [20]	SMEs [5], [8], [16]
Resource Availability	High financial and human resources; formal data teams	Limited budgets; multitasking staff roles
Analytics Infrastructure	Advanced IT systems and centralized data warehouses	Basic or cloud-based tools; often outsourced analytics
Decision-Making Process	Structured and data-driven, guided by policies	Flexible, experience-based, and adaptive
Learning and Innovation	Formalized R&D and structured learning routines	Informal, experiential learning through collaborations
Cultural Orientation	Established analytics culture reinforced by leadership	Evolving data mindset; depends on individual champions
Value Creation Path	Direct technology-to-performance linkage	Mediated through culture, adaptability, and absorptive capacity

3. Methodology

The research strategy involved both qualitative and quantitative steps. First, a set of exploratory interviews was conducted. After that, a large-scale survey was launched to collect data from Canadian SMEs. In total, 447 usable responses were gathered, which offered a solid empirical base for analysis. The research focused on small- and medium-sized enterprises. For this paper, the firms needed between 20 and 499 employees. This definition follows the Canadian standard for SME classification. Using a market research firm made the sample both broad and reliable. The process began with ten in-depth case interviews with SMEs. The insights from these conversations shaped the wording and structure of the survey questions. Once a draft survey was ready, it was reviewed by five academic researchers with expertise in big data analytics. Feedback was taken from managers who had joined the interviews. A pretest with 12 SMEs followed.

Figure 1 presents a conceptual framework that links BDA strengths with corporate business advantage through both direct and indirect paths. On the left side, BDA strengths are shown as two main elements: technology and infrastructure strengths, and staff-level and executive BDA capabilities. These two factors form the foundation for organizations to develop and apply analytics resources. The framework shows a direct link between these strengths and corporate strategic value. Value is created directly for the business. This happens without relying on other factors. The middle section of the figure introduces intermediary variables that shape the indirect path toward corporate business advantage. These include analytical mindset and adaptive capacity, which represent the organization’s ability to process, interpret, and use data effectively. An analytical mindset feeds into adaptive capacity, showing the ways culture and thinking styles support learning and flexibility. The model suggests that these intermediary variables help in transferring the effects of BDA strengths toward strategic outcomes. On the right side, corporate strategic value appears as the outcome influenced by both direct and mediated effects. The structure shows that organizations gain stronger value when both technical and human factors work together. This balance shows technical efficiency. It shows the role of learning and adaptability in creating value.

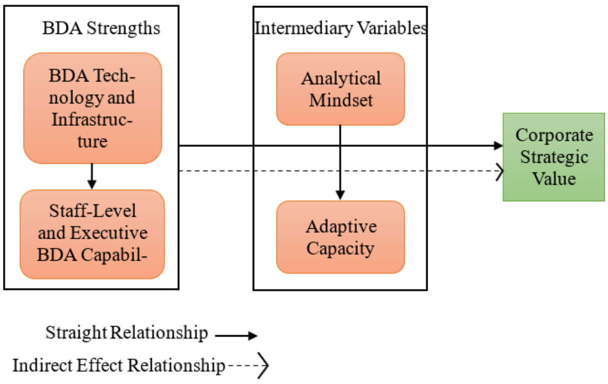

Fig. 1: Conceptual Model.

The final questionnaire relied on multi-item Likert scales. Respondents indicated agreement with statements on a 1-to-7 scale, with 1 representing strong disagreement and 7 representing strong agreement. Each construct—technological capability, human capability, analytics culture, absorptive capacity, and strategic business value—was measured through multiple reflective items. No new scales were created from scratch. Instead, measures were adapted from established prior research, adding to the reliability and validity of the research. Since the survey was cross-sectional and based on self-reports, the risk of common method bias was acknowledged. Several steps were taken to limit this problem. Confidentiality was assured to respondents. Clear and well-validated measures were used. Questions were separated by construct to avoid confusion. Only knowledgeable respondents were allowed to complete the survey. For statistical checks, Harman's single-factor test was applied. Results showed that a single factor did not dominate variance. A marker variable test was applied, confirming that the main findings were not distorted by common method variance.

The analysis was conducted using PLS-SEM with SmartPLS 3.3.7. This choice was justified because PLS-SEM works well with complex models, moderate sample sizes, and non-normal data distributions. It is widely used in studies of big data analytics capabilities. The analysis followed the usual two-step approach: first, testing the measurement model for reliability and validity. Second, test the structural model for hypothesized relationships. The measurement model was carefully assessed. Internal consistency reliability was tested using Cronbach's alpha and composite reliability (CR). Both statistics exceeded the threshold of 0.70, with all constructs reporting values greater than 0.80. Convergent validity was tested with average variance extracted (AVE), and all constructs had AVE values above 0.50. Discriminant validity was checked through cross-loadings and the Fornell–Larcker criterion. In both cases, results showed that constructs were distinct from one another. These findings confirmed that the measurement model was sound. The focus then shifted to the structural model. In PLS-SEM, endogenous latent variables are explained by exogenous variables through structural paths. The general equation for a structural model is expressed as:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{1}$$

Here, η is the vector of endogenous constructs is the matrix of relationships among endogenous variables. Γ is the effect of exogenous constructs. ζ is the residual error. For the key outcome of this research, strategic business value, the model is simplified as:

$$\mathrm{SV} = \beta_1 \mathrm{TechCap} + \beta_2 \mathrm{HumanCap} + \beta_3 \mathrm{AnalyticsCult} + \beta_4 \mathrm{AbsorpCap} + \zeta \tag{2}$$

Here, SV is the strategic business value, TechCap is technological capability, HumanCap is human capability, AnalyticsCult is analytics culture, and AbsorpCap is absorptive capacity. The coefficients β_i capture the strength of each path. The model fit was assessed using indices suitable for PLS-SEM. The standardized root mean square residual (SRMR) was reported as 0.047, which is below the threshold of 0.08. The normed fit index (NFI) was 0.88, which is considered strong. The RMS-theta value was 0.11, which falls below the acceptable cutoff of 0.12. These indicators suggest that the model fit the data well. The structural model reported explained variance through R^2. The R^2 values for the endogenous constructs ranged between 0.565 and 0.638, which is considered substantial. Predictive relevance was assessed with Stone–Geisser's Q^2. Values above 0.25 are considered good, and reported Q^2 values exceeded this threshold for the endogenous constructs. Together, these results indicate the model has strong explanatory and predictive power. Multicollinearity was checked using variance inflation factors (VIF). The formula for VIF is:

$$\mathrm{VIF}_j = \frac{1}{1 - R_j^2} \tag{3}$$

Here, R_j^2 is obtained from regressing predictor j on the other predictors. All VIF values reported were between 1.7 and 3.7. These values are well below the cutoff of 5, meaning there was no serious collinearity. For hypothesis testing, bootstrapping was used. This resampling approach produces robust standard errors and confidence intervals. Path coefficients, t-statistics and p-values were reported. Significance was assessed at common cutoffs like $p \le 0.05$. The bootstrapping method supported mediation testing. Mediation was tested using indirect effects. For example, the indirect effect of technological capability on strategic value through analytics culture is calculated as $\hat{a}\hat{b}$. Here $\hat{a}$

is the effect of technological capability on analytics culture and $\hat{b}$ is the effect of analytics culture on strategic value. If the bootstrapped confidence interval for $\hat{a}\hat{b}$ does not include zero, then mediation is supported. The Sobel test was used as an additional check. The Sobel z statistic is given as:

$$z = \frac{\hat{a}\hat{b}}{\sqrt{\hat{b}^2 s_{\hat{a}}^2 + \hat{a}^2 s_{\hat{b}}^2}} \tag{4}$$

Here, $s_{\hat{a}}$ and $s_{\hat{b}}$ are the standard errors of $\hat{a}$ and $\hat{b}$. A z value greater than 1.96 in absolute terms suggests significance at the 5% level. Using both bootstrapping and Sobel tests strengthened confidence in the mediation results. It was verified that demographics, including age, gender, and managerial experience, did not bias responses. The marker variable was tested again, and correlations remained stable. These steps strengthen the reliability of the findings. The careful design helps make the findings credible and replicable. The use of PLS-SEM allows testing of both direct and indirect paths, making it possible to examine the mediating roles of analytics culture and absorptive capacity. The overall approach aligns with best practices in management and information systems research.

4. Results

The first part of the results focuses on the reliability and validity of the constructs. The constructs are technological capabilities (TechCap), human capabilities (HumanCap), analytics culture (AC), absorptive capacity (ACap), and strategic business value (SBV). Each Cronbach's alpha is above 0.80. Each composite reliability is above 0.80. Every AVE value is above 0.50. These results indicate strong reliability and convergent validity. Discriminant validity was confirmed through cross-loading tests and the Fornell–Larcker criterion. In both tests, the constructs met the accepted thresholds, indicating that each construct measures something distinct. Table 2 presents the reliability and validity values.

Table 2: Reliability and Validity of Constructs

Construct	Cronbach's Alpha	Composite Reliability	AVE
TechCap	0.89	0.92	0.67
HumanCap	0.91	0.94	0.71
AC	0.87	0.91	0.65
ACap	0.90	0.93	0.69
SBV	0.88	0.92	0.66

These numbers show that each construct is measured well. TechCap has alpha 0.89 and composite reliability 0.92. Both are much higher than the minimum threshold of 0.70. The AVE values, including 0.67 and 0.71, indicate that the constructs capture more than half of the variance of the items. This confirms that the measurement model is strong and valid. After confirming measurement validity, the structural model was tested. Fit indices were checked first. The SRMR is 0.047. The NFI is 0.88. The RMS-theta is 0.11. Each value meets the recommended thresholds, indicating that the model fits the data well. Table 3 presents these fit and explanatory measures.

Table 3: Model Fit and Explanatory Power

Measure	Value	Threshold
SRMR	0.047	< 0.08
NFI	0.88	> 0.80
RMS-theta	0.11	< 0.12
Q^2 values	> 0.25 (all constructs)	> 0.25
R^2 (range)	0.565--0.638	> 0.33

The values show that the model not only fits well but also predicts outcomes effectively. R^2 of 0.638 is considered high in social science research. The Q^2 values confirm that the model is not only descriptive but predictive. Collinearity was tested. The VIF values ranged from 1.7 to 3.7, which are below the threshold of 5. The final part of the results tested the hypotheses about direct and mediated relationships. Direct paths between capabilities and strategic business value were strong. For mediation, AC and ACap were tested as mediators. The analytics culture was found to mediate both TechCap to SBV and HumanCap to SBV. Absorptive capacity mediated HumanCap to SBV but did not mediate TechCap to SBV. The tests were based on bootstrapping methods and supported by Sobel's test. In all but one case, Sobel's test statistics exceeded 1.96. The exception was the mediation of HumanCap through AC, which had weaker Sobel support but still passed the bootstrapping test. Table 4 explains the mediation results of AC and ACap.

The results reveal that absorptive capacity mediates human but not technological capabilities. This difference can be understood through both theoretical and contextual perspectives. From the resource-based view (RBV), human capabilities are intangible and socially embedded resources that depend on learning and knowledge integration. Absorptive capacity strengthens this process by allowing employees to identify, assimilate, and apply external knowledge effectively. In contrast, technological capabilities are mainly infrastructure-oriented and less dependent on social learning routines. For SMEs, this pattern also reflects resource constraints. Many small firms lack formal R&D or external collaboration structures. This reduces opportunities to transform technology-driven insights through absorptive processes. Human expertise remains flexible and adapts faster through informal learning and partnerships. Thus, absorptive capacity enhances the effect of human capabilities by promoting learning agility and knowledge sharing. This influence on technological capability remains limited because technology value depends more on system efficiency than on knowledge assimilation.

Table 4: Mediation Results of AC and ACap

Path	Mediator	Result
TechCap → SBV	AC	Supported
HumanCap → SBV	AC	Supported (Sobel weak)
TechCap → SBV	ACap	Not Supported
HumanCap → SBV	ACap	Supported

Table 4 shows that analytics culture is a strong mechanism linking both technological and human capabilities to strategic value. Absorptive capacity plays a selective role. It works as a mediator for human capabilities, but not for technological capabilities. This pattern shows that culture and absorptive learning processes are essential parts of value creation in firms. Figure 2 shows the values of Cronbach's Alpha, CR, and AVE. Cronbach's Alpha values are all above 0.78, which indicates strong internal consistency. The highest Cronbach's Alpha is observed in human capabilities at around 0.87. While the lowest appears in absorptive capacity at about 0.78. Composite Reliability values are steadily higher than Cronbach's Alpha across all constructs. Human capabilities again show the highest CR value close to 0.91. It is followed by technological capabilities and analytics culture, both above 0.85. The lowest CR value is absorptive capacity at approximately 0.82, though it is still within an acceptable range. Cronbach's Alpha demonstrates acceptable reliability, though it is slightly lower than CR. AVE values remain below 0.75 in all cases, showing that the explained variance is moderate but acceptable for model validation. Strategic business value shows similar reliability with Cronbach's Alpha close to 0.82, CR around 0.86, and AVE near 0.72. It is slightly better in variance extraction compared to the others. Human and technological capabilities show higher reliability. Absorptive capacity and analytics culture are lower but acceptable.

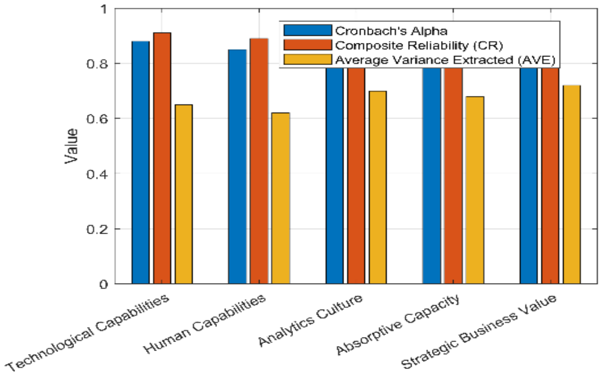

Fig. 2: Reliability & Validity Metrics Per Construct.

Figure 3 presents the R^2 values for AC, absorptive capacity (AB), and SBV. These values represent the proportion of variance explained by the model for each construct. Analytics culture shows an R^2 value of about 0.56, meaning that the model accounts for 56 percent of its variation. Absorptive capacity records a higher R^2 value of nearly 0.61, while strategic business value has the strongest explanatory result with an R^2 of about 0.64. All three values exceed the 0.50 benchmark. It indicates that the model explains more than half of the variance for each construct and provides acceptable predictive strength. Strategic business value shows the highest variance. It is more predictable than the other two. Absorptive capacity follows closely, suggesting that the model is effective in capturing most of the variation for this construct. Analytics culture, although slightly lower, still reflects a strong explanatory result above the minimum required threshold. The R^2 difference is small (0.08), showing model balance. The model predicts all constructs well, with a stronger effect on strategic business value.

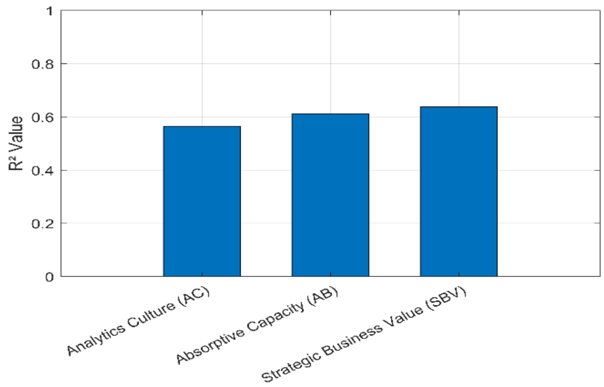

Fig. 3: R^2 Values for Endogenous Constructs.

Figure 4 presents the Q^2 values for AC, AB, and SBV. Q^2 measures predictive relevance, indicating the model's ability to predict data for each construct. Analytics culture records the lowest Q^2 value of about 0.41. It indicates that the model has a moderate predictive ability for this construct. Absorptive capacity performs slightly better, with a Q^2 value near 0.45 showing improved predictive relevance. Strategic business value stands out with the highest Q^2 value of about 0.49, reflecting stronger predictive accuracy compared to the other two. All three values are above the threshold of 0.35, indicating that the model demonstrates a good level of predictive strength in all constructs.

Strategic business value is predicted most effectively, suggesting that the model captures more variation in business value outcomes. Absorptive capacity follows closely, which shows that the model provides good predictive power for this construct. Analytics culture, while slightly lower, still reflects strong predictive ability above the acceptable level. The gap between the lowest and highest Q^2 values is less than 0.10, which shows that the model is balanced in predicting the three constructs. The model explains variance. It shows strong predictive power. Strategic business value has the highest relevance.

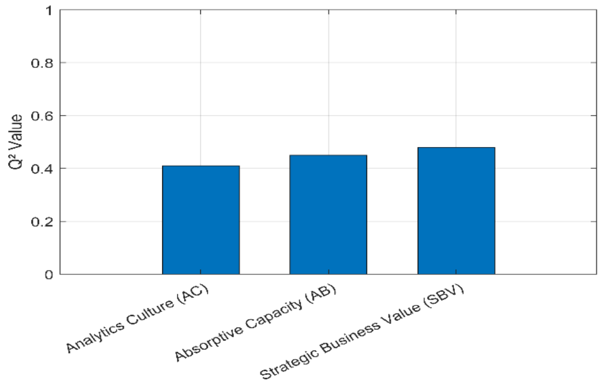

Fig. 4: Q^2 Values for Predictive Relevance.

Figure 5 displays Cronbach's Alpha, CR, and AVE for five constructs. It includes technological capabilities (TC), human capabilities (HC), AC, absorptive capacity (AB), and SBV. Cronbach's Alpha values remain within 0.85 to 0.90, confirming good steadiness among items. Human capabilities show the lowest Alpha at about 0.85, while analytics culture reaches the highest at nearly 0.90. Composite Reliability is reliably higher than Cronbach's Alpha for all constructs, ranging between 0.89 and 0.92. Strategic business value performs best with a CR above 0.92, reflecting very strong reliability. Average Variance Extracted records lower values compared to the other two measures, ranging from 0.62 to 0.72. Human capabilities show the lowest AVE at about 0.62, while strategic business value shows the highest at nearly 0.72. CR values show a reliable pattern and remain the strongest, proving that the model has stable measurement properties. Cronbach's Alpha values are acceptable, showing reliable internal agreement of the items used. AVE values, though lower, remain within a satisfactory range, indicating that each construct explains a reasonable portion of variance in its measures. The model is statistically sound. Strategic business value is the most reliable construct. Other dimensions meet the required reliability and validity.

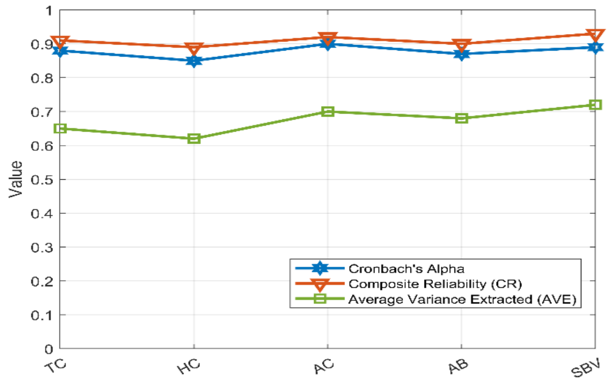

Fig. 5: Reliability & Validity Trends Across Constructs.

Figure 6 presents the explanatory power (R^2) and predictive relevance (Q^2) for three constructs. For the analytics culture, the R^2 value is about 0.56, indicating that 56 percent of its variance is explained by the model. Absorptive capacity has an R^2 value of 0.61, while strategic business value reaches the highest with 0.64. Q^2 values show predictive relevance. Analytics culture has a Q^2 value of about 0.41, absorptive capacity is slightly higher at 0.45, and strategic business value records the highest at 0.49. R^2 values are steadily higher than 0.50, showing that the model explains more than half of the variance in all constructs. Strategic business value shows the strongest explanatory power and predictive accuracy, which suggests that the model is most effective in capturing business value outcomes. Absorptive capacity performs strongly, with both R^2 and Q^2 values above the required thresholds. Analytics culture, although slightly lower, still demonstrates solid explanatory and predictive capability. The differences among the three constructs are not very large, with only a 0.08 gap in Q^2 and the same in R^2. The figure shows that the model explains variance well. It predicts data with high accuracy. The model is robust for measuring analytics culture, absorptive capacity, and strategic business value.

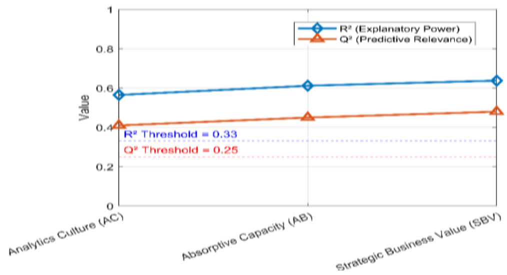

Fig. 6: Sequential Explanatory Power Across the Causal Chain.

Figure 7 shows the direct, indirect, and total effects across four paths. Path 1 has a direct effect of about 0.50 and an indirect effect of 0.20, which together produce a total effect of 0.70. Path2 records a direct effect of around 0.40 and an indirect effect of 0.35, leading to the highest total effect at nearly 0.75. In Path3, the direct effect is stronger at about 0.60, while the indirect effect is lower at 0.10, giving a total effect close to 0.70. Path 4 shows the lowest values among all paths, with a direct effect of 0.30, an indirect effect of 0.25, and a total effect of about 0.55. Path2 is a clear example in which both direct and indirect effects are nearly equal, explaining why it has the strongest overall impact. Path1 and Path3 are driven mainly by direct effects, with only small additions from indirect effects. Path4 is more balanced, but its lower values in both direct and indirect measures result in the weakest total effect. In Figure 7, the strength of both direct and indirect effects shows how analytics culture and absorptive capacity enhance value creation processes. The stronger indirect effects in Path 2 indicate that when firms encourage data-driven mindsets and continuous learning, the impact of analytics capabilities on strategic outcomes is significantly amplified. This finding suggests a practical implication: managers should design initiatives that promote cross-functional collaboration and training programs. This allows employees to interpret and apply analytics insights in daily operations.

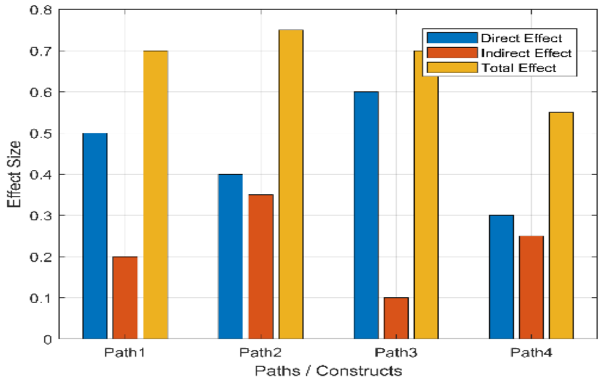

Fig. 7: Mediation Strength.

Figure 8 shows the stepwise build-up of variance explained (R^2) for three constructs. Construct 1 starts at about 0.30 in Step 1, increases to about 0.40 in Step 2, and reaches 0.55 in Step 3. Construct 2 begins lower at 0.25, moves up to 0.35 in Step 2, and reaches 0.50 in Step 3. Construct 3 begins at a higher point of 0.40, rises to 0.50 in Step 2, and reaches the highest value of 0.65 in Step 3. Construct 2 shows steady improvement across steps but remains the lowest overall. Construct 3 reliably performs best across all steps. At Step 2, the gap is 0.15 between Construct 2 (0.35) and Construct 3 (0.50). At Step 3, the gap increases slightly to 0.15 again, between Construct 2 (0.50) and Construct 3 (0.65). Construct 1 remains in the middle position throughout, showing a gradual and steady rise. The gradual increase in R^2 across steps reflects how combining technological and human capabilities with mediating factors progressively strengthens the model's explanatory power. Theoretically, this supports the resource-based view by showing that layered integration of resources (technology, people, and learning routines) yields higher value creation potential. For practitioners, the result emphasizes the importance of maturity stages in analytics adoption—starting from technological readiness, advancing to human capability development, and finally embedding data-driven culture and learning mechanisms.

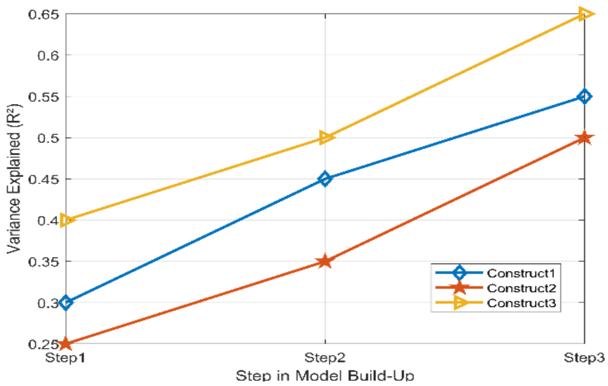

Fig. 8: Variance Explained (Stepwise Build-Up).

5. Discussions

The discussion brings the results to life. The focus is restated on what was tested. The research examined the creation of value in SMEs through technological and human analytics capabilities. It examined whether analytics culture and absorptive capacity act as bridges from capability to value. Survey data from 447 Canadian SMEs were used, and PLS-SEM was applied. The discussion links these results to theory and practice. The core finding is simple. Both technological capability and human capability help firms create strategic value from big data analytics. This indicates that tools and platforms matter. It indicates that managers and skilled staff matter. Absorptive capacity plays a key role. It helps firms learn from outside and apply new knowledge. The discussion then moves to managerial implications. The first practical message is that technology purchases alone will not guarantee value. Firms should invest in training and in managerial skills that translate analytics into decisions.

Senior leaders should promote a data mindset. Support should be shown through both words and actions. Practical steps include creating cross-functional teams, running small analytics pilots, and rewarding data sharing. SMEs should start with focused use cases. Partnering with universities, vendors, or industry consortia helps access skills and data. Using lightweight tools and cloud services lowers upfront costs. The role of absorptive capacity is highly relevant here. When SMEs quickly learn from partners, external BDA assets are utilized without heavy internal investment.

The discussion lists limitations and directions for future work. It is also important to note that BDA challenges vary across SME industries. For example, retail SMEs often face issues related to customer data volume, real-time decision-making, and privacy regulations, requiring a stronger analytics culture and data governance. Manufacturing SMEs, on the other hand, deal with sensor-based operational data and integration challenges between legacy systems and new digital platforms. Service-oriented SMEs may struggle more with intangible data sources and skill shortages in interpreting analytics insights. These sectoral differences suggest that the effectiveness of analytics culture and absorptive capacity may depend on the nature of data and industry processes. Managers should therefore tailor BDA strategies to their specific sectoral realities, balancing technology investments with human and learning-oriented initiatives. Recognizing these variations enhances the practical relevance and transferability of the study's findings.

6. Conclusions

The purpose was to show the ways SMEs capture value from BDA. The research finds that both technological and human capabilities matter. These capabilities help firms create strategic business value. Analytics culture and absorptive capacity increase the effectiveness of those capabilities. An analytics culture helps people use data in daily decisions. Absorptive capacity helps firms learn from outside and reuse new knowledge. Together, these factors amplify the benefits of BDA investments. Firms need to align tools with people and routines. Managers should cultivate a data-driven mindset across the company. Investment in training and rewarding knowledge sharing is important. Firms should create routines to acquire and apply external knowledge. For SMEs, partnerships and focused pilots help when internal resources are limited. These practical steps help small firms gain strategic gains without huge budgets. Theoretical contributions are outlined. The paper extends BDA capability research to SMEs. It highlights absorptive capacity as a key mechanism. It confirms analytics culture as a mediator between capabilities and value. These findings add to resource-based and dynamic capability views in BDA research. Although this research focused on Canadian SMEs, the insights may also apply to firms in other regions with certain contextual adjustments. Differences in regulatory environments, digital infrastructure, and data governance practices influence how analytics culture and absorptive capacity create value. Future studies can extend this framework to multiple countries, comparing variations across contexts. Cross-national research, such as that reviewed in [7], highlights those institutional and cultural factors significantly shape SME data adoption and learning behavior. A structured multi-country framework could thus validate the model's robustness across diverse settings. The research is cross-sectional and uses Canadian firms, which limits causal claims and broad generalization. Longitudinal and cross-country research is recommended. Testing other moderators, including industry or AI adoption, is suggested. The closing message is that BDA value creation is socio-technical. Firms need to align technology, skills, culture, and learning to gain real value. Small firms succeed by focusing on people, culture, and partnerships.

References

[1] A. C. Ikegwu, H. F. Nweke, C. V. Anikwe, U. R. Alo, and O. R. Okonkwo, "Big data analytics for data-driven industry: a review of data sources, tools, challenges, solutions, and research directions," Cluster Computing, vol. 25, no. 5, pp. 3343–3387, 2022. https://doi.org/10.1007/s10586-022-03568-5.

[2] D. Blazquez and J. Domenech, "Big data sources and methods for social and economic analyses," Technological Forecasting and Social Change, vol. 130, pp. 99–113, 2018. https://doi.org/10.1016/j.techfore.2017.07.027.

[3] R. Jiwat and Z. L. Zhang, "Adopting big data analytics (bda) in business-to-business (b2b) organizations–development of a model of needs," Journal of Engineering and Technology Management, vol. 63, p. 101676, 2022. https://doi.org/10.1016/j.jengtecman.2022.101676.

[4] E. Raguseo, "Big data technologies: An empirical investigation on their adoption, benefits and risks for companies," International Journal of Information Management, vol. 38, no. 1, pp. 187–195, 2018. https://doi.org/10.1016/j.ijinfomgt.2017.07.008.

[5] E. Bryan, Q. Bernier, M. Espinal, and C. Ringler, "Making climate change adaptation programmes in sub-saharan africa more gender responsive: insights from implementing organizations on the barriers and opportunities," Climate and Development, vol. 10, no. 5, pp. 417–431, 2018. https://doi.org/10.1080/17565529.2017.1301870.

[6] G. Stalk, Jr, P. Evans, and L. E. Shulman, "Competing on capabilities," Own the Future: 50 Ways to Win from the Boston Consulting Group, pp. 41–51, 2012. https://doi.org/10.1002/9781119204084.ch5.

[7] N. A. Dela Cruz, A. C. B. Villanueva, L. A. Tolin, S. Disse, R. Lensink, and H. White, "Protocol: Effects of interventions to improve access to financial services for micro-, small-and medium-sized enterprises in low-and middle-income countries: An evidence and gap map," Campbell Systematic Reviews, vol. 19, no. 3, p. e1341, 2023. https://doi.org/10.1002/cl2.1341.

[8] A. Pearce, D. Pons, and T. Neitzert, "Implementing lean—outcomes from sme case studies," Operations Research Perspectives, vol. 5, pp. 94–104, 2018. https://doi.org/10.1016/j.orp.2018.02.002.

[9] H. Wu, "Intuition in investment decision-making across cultures," Journal of Behavioral Finance, vol. 23, no. 1, pp. 106–122, 2022. https://doi.org/10.1080/15427560.2020.1848839.

[10] K. Ramakrishna, S. Balaji, and M. S. Kumar, "The impact of hr analytics on organisational culture and employee engagement.," Journal of Advanced Zoology, vol. 45, no. 6, 2024. https://doi.org/10.53555/jaz.v45i6.4851.

[11] H. D. Jonsdottir, "The utilization of bda in digital marketing strategies of international b2b organizations from a dynamic capability´ s perspective: A qualitative case study," 2024.

[12] P. Korherr and D. Kanbach, "Human-related capabilities in big data analytics: a taxonomy of human factors with impact on firm performance," Review of Managerial Science, vol. 17, no. 6, pp. 1943–1970, 2023. https://doi.org/10.1007/s11846-021-00506-4.

[13] R. N. Lussier and J. R. Hendon, Human resource management: Functions, applications, and skill development. Sage publications, 2025.

[14] J. Hair and A. Alamer, "Partial least squares structural equation modelling (pls-sem) in second language and education research: Guidelines using an applied example," Research Methods in Applied Linguistics, vol. 1, no. 3, p. 100027, 2022. https://doi.org/10.1016/j.rmal.2022.100027.

[15] L. C. Vieira, M. L. Handojo, and C. O. Wilke, "Medium-sized protein language models perform well at transfer learning on realistic datasets: Lc vieira et al.," Scientific Reports, vol. 15, no. 1, p. 21400, 2025. https://doi.org/10.1038/s41598-025-05674-x.

[16] N. Kling, S. Haugk, and H. Gebauer, "Towards a data-driven organisation: Making data a strategic knowledge asset in smes," Journal of the Knowledge Economy, pp. 1–19, 2025. https://doi.org/10.1007/s13132-025-02631-x.

[17] M. Gupta and J. F. George, "Toward the development of a big data analytics capability," Information & Management, vol. 53, no. 8, pp. 1049–1064, Dec. 2016. https://doi.org/10.1016/j.im.2016.07.004.

[18] W. M. Cohen and D. A. Levinthal, "Absorptive capacity: A new perspective on learning and innovation," Administrative Science Quarterly, vol. 35, no. 1, pp. 128–152, 1990. https://doi.org/10.2307/2393553.

[19] A. Braganza, L. Brooks, D. Nepelski, M. Ali, and R. Moro, "Resource management in big data initiatives: Processes and dynamic capabilities," Journal of Business Research, vol. 70, pp. 328–337, Jan. 2017. https://doi.org/10.1016/j.jbusres.2016.08.006.

[20] B. Wernerfelt, "The resource-based view of the firm: Ten years after," Strategic Management Journal, vol. 16, no. 3, pp. 171–174, 1995. https://doi.org/10.1002/smj.4250160303.

[21] J. Barney, “Firm resources and sustained competitive advantage,” Journal of Management, vol. 17, no. 1, pp. 99–120, 1991. https://doi.org/10.1177/014920639101700108.
[22] D. J. Teece, “Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance,” Strategic Management Journal, vol. 28, no. 13, pp. 1319–1350, 2007. https://doi.org/10.1002/smj.640.
[23] A. S. Bharadwaj, “A resource-based perspective on information technology capability and firm performance: An empirical investigation,” MIS Quarterly, vol. 24, no. 1, pp. 169–196, 2000. https://doi.org/10.2307/3250983.
[24] S. F. Wamba, S. Akter, A. Edwards, G. Chopin, and D. Gnanzou, “Big data analytics and firm performance: Effects of dynamic capabilities,” Journal of Business Research, vol. 70, pp. 356–365, 2017. https://doi.org/10.1016/j.jbusres.2016.08.009.
[25] D. Kiron, P. K. Prentice, and R. B. Ferguson, “The analytics mandate,” MIT Sloan Management Review, vol. 55, no. 4, pp. 1–25, 2014.
[26] G. Cao, Y. Duan, and G. Li, “Linking business analytics to decision making effectiveness: A path model analysis,” IEEE Transactions on Engineering Management, vol. 62, no. 3, pp. 384–395, Aug. 2015.r. https://doi.org/10.1109/TEM.2015.2441875.