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Analytics-Driven Differentiation in B2B Markets: Integrating the Resource-Based View and Dynamic Capabilities Theory

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Abstract
Data analytics has become a strategic imperative for B2B organisations seeking sustainable product and service differentiation. Yet a critical research gap persists regarding how B2B firms systematically leverage analytics capabilities drawn from CRM, ERP, and IoT data to create value-based and solution-based differentiation. This study integrates the Resource-Based View (RBV) and Dynamic Capabilities frameworks to examine how analytics capabilities enable B2B organisations to develop and sustain differentiated value propositions across complex supply chain ecosystems. Employing a mixed-methods approach combining 18 semi-structured interviews with B2B practitioners across manufacturing, industrial technology, and professional services, followed by a survey of 347 B2B firms analysed using PLS-SEM, our findings reveal three interconnected analytics capabilities driving differentiation: predictive market sensing, prescriptive solution orchestration, and supply chain intelligence integration. Quantitative analysis confirms that data analytics capability significantly influences both value-based and solution-based differentiation, with dynamic capabilities mediating this relationship. We propose a Data Analytics-Driven Differentiation (DADD) framework explicating how B2B firms transform heterogeneous data into VRIN analytics capabilities. Theoretically, the study extends RBV and dynamic capabilities literature; managerially, it provides actionable guidance for designing adaptive, customer-centric, analytics-driven differentiation strategies.

Key Words: Data analytics, B2B marketing, Product differentiation, Resource-Based View, Dynamic capabilities, Predictive analytics, Supply chain analytics, PLS-SEM

Introduction
The B2B landscape is undergoing a profound transformation driven by exponential data growth, with global spending on big data and business analytics projected to reach $215.7 billion by 2027 (IDC, 2023). As markets become increasingly commoditised, B2B organisations face a strategic imperative to leverage data analytics, encompassing predictive, prescriptive, and supply chain analytics to differentiate their offerings (Ulaga & Reinartz, 2011; Davenport & Harris, 2017).

B2B differentiation is fundamentally distinct from B2C contexts, extending beyond product features to encompass value-based differentiation, demonstrating superior economic value and solution-based differentiation, integrating products, services, and knowledge into customised solutions (Ulaga & Eggert, 2006; Storbacka, 2011). Despite analytics' strategic significance, existing research predominantly focuses on B2C applications (Lilien, 2016). Theoretically, the Resource-Based View (Barney, 1991) and Dynamic Capabilities framework (Teece, 2007) together illuminate what analytics capabilities matter and how organisations dynamically deploy them, yet critical gaps persist regarding specific analytics-differentiation pathways, inter-organisational analytics operations, and the dynamic capabilities' mediating role (Bendig et al., 2018; Kohtamäki et al., 2021).

This study addresses these gaps through a sequential mixed-methods design: 18 in-depth interviews with B2B practitioners across manufacturing, industrial technology, and professional services, followed by a survey of 347 B2B firms analysed using PLS-SEM. The research makes three contributions: developing and validating a Data Analytics-Driven Differentiation (DADD) framework specifying distinct pathways to value-based and solution-based differentiation; advancing dynamic capabilities theory by demonstrating how sensing, seizing, and transforming mediate the analytics-differentiation relationship; and extending RBV by conceptualizing integrated CRM, ERP, and IoT analytics capabilities as VRIN resources enabling sustainable competitive advantage across supply chain networks.

2. Literature Review

2.1. Data Analytics in B2B Markets

Data analytics involves the systematic computational analysis of data to discover patterns and support decision-making (Davenport & Harris, 2017). In B2B markets, this spans from descriptive and diagnostic approaches to predictive modelling and prescriptive optimisation (Lepenioti et al., 2020). Firms increasingly draw on heterogeneous data sources: Customer Relationship Management (CRM) for relational data, Enterprise Resource Planning (ERP) for operational data, and Internet of Things (IoT) sensors for real-time performance tracking. Integrating these systems creates unique capabilities from customer lifetime value prediction to predictive maintenance, though challenges like data silos and governance complexities often persist (Lilien, 2016).

2.2. Resource-Based View (RBV)

The Resource-Based View (RBV) posits that sustained competitive advantage derives from resources that are Valuable, Rare, Inimitable, and Non-substitutable (VRIN) (Barney, 1991). Data analytics capabilities qualify as critical VRIN resources. They create value through superior decision-making, remain rare due to complex infrastructure-talent requirements, achieve inimitability through path-dependent organisational routines, and resist substitution via unique configurations (Akter et al., 2016). In B2B contexts, these characteristics are amplified by inter-organisational collaborative intelligence and data sharing embedded in deeply rooted, trust-based partnerships (Kohtamäki et al., 2021).

2.3. Dynamic Capabilities

While RBV explains advantage at a specific point, the Dynamic Capabilities framework addresses how firms modify resources to navigate changing environments (Teece, 2007). In analytics contexts, this involves three core dimensions: sensing emerging patterns across CRM, ERP, and IoT data environments; seizing opportunities by translating analytical insights into differentiated value propositions; and transforming organisational routines and analytical models to maintain evolutionary fitness (Bendig et al., 2018). These dynamic processes are essential in turbulent B2B supply chains requiring continuous strategic adaptation.

2.4. Product/Service Differentiation in B2B Markets
B2B differentiation takes two distinct forms. Value-based differentiation relies on demonstrating superior economic value relative to competitive alternatives, requiring rigorous quantification supported by predictive and prescriptive analytics (Ulaga & Eggert, 2006). Solution-based differentiation integrates products, services, and relational processes into customised bundles to solve complex customer problems, requiring deep integration of CRM, ERP, and IoT insights (Storbacka, 2011; Tuli et al., 2007). Both differentiation strategies demand substantial, dynamically orchestrated analytical capabilities to effectively manage multi-element offerings across complex supply chain ecosystems.

2.5. Hypotheses Development
Building on these theoretical foundations, we develop hypotheses regarding the relationships among data analytics capabilities, dynamic capabilities, and B2B differentiation.
2.5.1. Data Analytics and Value-Based Differentiation
Predictive analytics enables B2B firms to forecast demand and model economic value by leveraging CRM, ERP, and IoT data (Anderson et al., 2006). Prescriptive analytics recommends optimal pricing and communication strategies (Lepenioti et al., 2020), while supply chain analytics identifies cost-reduction opportunities, enhancing total delivered economic value (Chae et al., 2014). Collectively, these capabilities provide the foundation for articulating and demonstrating superior value propositions. Therefore:
H1: Data analytics capability positively influences value-based differentiation in B2B markets.

2.5.2. Data Analytics and Solution-Based Differentiation
Solution-based differentiation requires integrating multiple elements into customised offerings to address complex needs (Tuli et al., 2007). Predictive analytics anticipates customer requirements, while CRM and ERP data provide visibility essential for seamless delivery. Furthermore, IoT sensor data supports outcome-oriented solutions like predictive maintenance (Ng & Wakenshaw, 2017), and prescriptive analytics optimises solution configurations by modelling scenarios to maximise customer value (Storbacka, 2011). Therefore:
H2: Data analytics capability positively influences solution-based differentiation in B2B markets.

2.5.3. Data Analytics and Dynamic Capabilities
Analytics capabilities provide the informational infrastructure supporting dynamic capability processes. Sensing is enhanced when firms systematically scan diverse data to detect emerging patterns (Bendig et al., 2018). Seizing is supported by evidence-based recommendations for strategic resource allocation. Transforming is facilitated by continuously monitoring strategy effectiveness and identifying adaptation needs, ultimately improving overall organisational agility and decision quality (Gupta & George, 2016). Therefore:
H3: Data analytics capability positively influences dynamic capabilities (sensing, seizing, transforming) in B2B organisations.

2.5.4. Dynamic Capabilities and Differentiation
Dynamic capabilities enable firms to adapt competitive strategies. Sensing identifies new differentiation opportunities based on evolving customer needs, seizing implements offerings

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that capture these identified opportunities, and transforming ensures strategies remain effective by continuously reconfiguring resources (Teece, 2007). In relational B2B contexts, these capabilities are vital for continuously renewing differentiation to maintain market relevance (Storbacka & Nenonen, 2015). Therefore:
H4a: Dynamic capabilities positively influence value-based differentiation in B2B markets.
H4b: Dynamic capabilities positively influence solution-based differentiation in B2B markets.

2.5.5. Mediating Role of Dynamic Capabilities
We posit that dynamic capabilities mediate the relationship between analytics and differentiation. While analytics provide informational resources, they must be dynamically orchestrated to produce sustained competitive advantage (Teece, 2007). Analytical insights that remain unacted upon through dynamic processes such as failing to seize sensed opportunities or transform organisational routines, will not translate into meaningful differentiation (Akter et al., 2016; Wamba et al., 2017). Therefore:
H5a: Dynamic capabilities mediate the relationship between data analytics capability and value-based differentiation.
H5b: Dynamic capabilities mediate the relationship between data analytics capability and solution-based differentiation.

Hypothesis	**Relationship**	**Direction**
H1	Data Analytics Capability → Value-Based Differentiation	Positive
H2	Data Analytics Capability → Solution-Based Differentiation	Positive
H3	Data Analytics Capability → Dynamic Capabilities	Positive
H4a	Dynamic Capabilities → Value-Based Differentiation	Positive
H4b	Dynamic Capabilities → Solution-Based Differentiation	Positive
H5a	Data Analytics Capability → Dynamic Capabilities → Value-Based Differentiation	Mediation
H5b	Data Analytics Capability → Dynamic Capabilities → Solution-Based Differentiation	Mediation

Table 1 summarizes the hypothesized relationships in the conceptual framework.

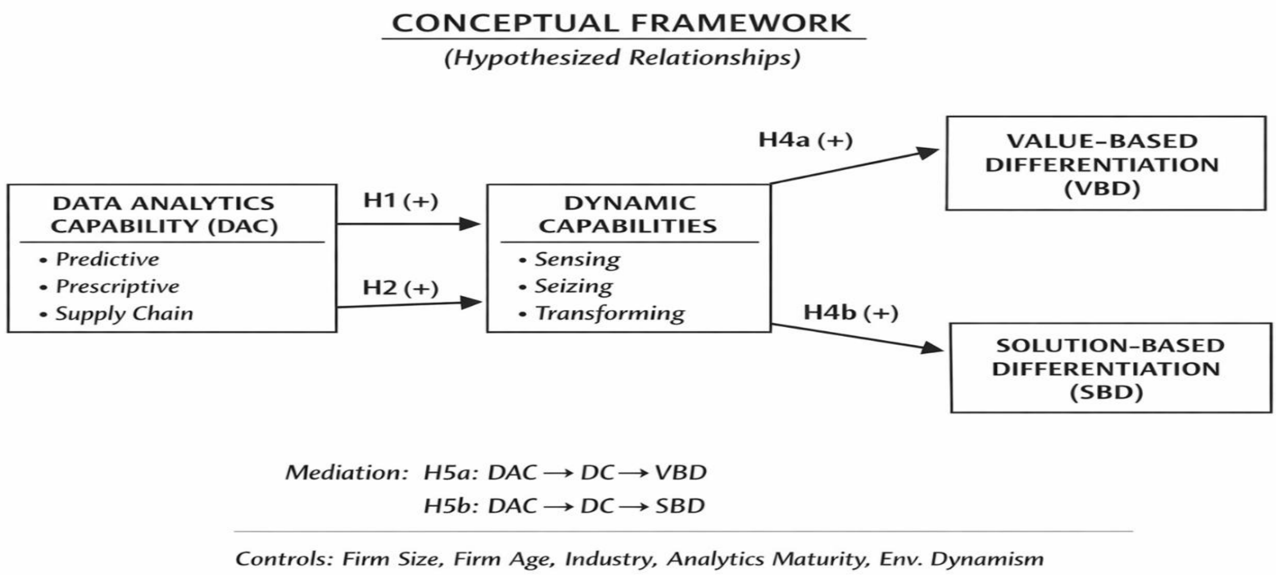

FIGURE 1: Conceptual Framework (Hypothesised Model)

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Figure 1 presents the conceptual framework and hypothesised relationships among data analytics capability, dynamic capabilities, and B2B differentiation outcomes

3. Research Methodology

3.1. Research Design

Given the nascent state of research on analytics-driven differentiation in B2B markets and the need to both explore underlying mechanisms and test theoretical relationships, we adopted a sequential exploratory mixed-methods design (Creswell & Plano Clark, 2018). This approach combines qualitative and quantitative phases, with the qualitative phase informing and enriching the quantitative phase. This design is particularly appropriate when existing theory provides a foundational but incomplete framework that requires empirical enrichment before quantitative testing (Venkatesh et al., 2013).

The qualitative phase (Phase 1) employed semi-structured in-depth interviews to explore how B2B organisations develop and deploy analytics capabilities for differentiation, identify contextual factors and mechanisms, and refine the conceptual framework and survey instruments. The quantitative phase (Phase 2) employed a cross-sectional survey analysed using PLS-SEM to empirically test the hypothesised relationships in the DADD framework.

3.2. Phase 1: Qualitative Study

3.2.1. Sampling and Informants

Informants for the qualitative phase were selected through purposive sampling (Patton, 2002), targeting senior professionals with direct experience in both B2B marketing/strategy and data analytics implementation. Selection criteria required informants to hold managerial or senior specialist positions, have a minimum of five years of B2B marketing or strategy experience, and possess direct involvement in analytics-driven differentiation initiatives within their organisations.

We recruited 18 expert informants from three industry sectors at the forefront of B2B analytics-driven differentiation: manufacturing (n=7), industrial technology (n=6), and professional services (n=5). These sectors were selected because they represent diverse B2B contexts with varying degrees of analytics maturity, supply chain complexity, and differentiation imperatives. Table 2 summarises informant backgrounds.

Informant	Gender	Position	Industry Sector	B2B Experience	Analytics Experience	Primary Data Sources
I1	Male	VP Analytics & Strategy	Manufacturing – Automotive	15 years	8 years	CRM, ERP, IoT
I2	Female	Chief Data Officer	Industrial Technology – Automation	12 years	10 years	ERP, IoT, CRM
I3	Male	Director, Solutions Marketing	Manufacturing – Chemicals	18 years	6 years	CRM, ERP
I4	Female	Head of Customer Intelligence	Professional Services – Consulting	10 years	7 years	CRM

I5	Male	Supply Chain Analytics Manager	Manufacturing – Electronics	14 years	9 years	ERP, IoT
I6	Male	CEO	Industrial Technology – IoT Platforms	20 years	12 years	IoT, CRM, ERP
I7	Female	Marketing Analytics Director	Professional Services – IT Services	11 years	8 years	CRM, ERP
I8	Male	Product Manager, Predictive Solutions	Manufacturing – Heavy Equipment	16 years	7 years	IoT, ERP
I9	Male	Head of Digital Transformation	Industrial Technology – Energy	22 years	5 years	ERP, IoT
I10	Female	Director, Value Engineering	Manufacturing – Precision Instruments	13 years	6 years	CRM, IoT
I11	Male	Chief Strategy Officer	Professional Services – Logistics	17 years	9 years	ERP, IoT, CRM
I12	Male	Analytics Consultant (B2B Focus)	Professional Services – Analytics	8 years	8 years	CRM, ERP
I13	Female	VP Operations & Analytics	Manufacturing – Packaging	14 years	7 years	ERP, IoT
I14	Male	Business Intelligence Lead	Industrial Technology – Semiconductors	19 years	10 years	ERP, CRM, IoT
I15	Male	Director, Outcome-Based Services	Manufacturing – HVAC/Industrial	15 years	6 years	IoT, CRM
I16	Female	Head of Partner Analytics	Industrial Technology – Telecom Equipment	12 years	8 years	CRM, ERP
I17	Male	Senior Manager, Pricing Analytics	Industrial Technology – Software	10 years	7 years	CRM, ERP
I18	Male	Global Account Analytics Manager	Industrial Technology – Engineering	16 years	5 years	CRM, ERP, IoT

Table 2: Background of Qualitative Informants

Source: Authors' own work.

Informants were recruited through the researchers' professional networks, industry conferences (e.g., B2B Marketing Summit, Industrial Analytics Conference), and LinkedIn outreach, followed by snowball sampling in which participants recommended additional qualified informants. Recruitment continued until theoretical saturation was achieved, with no substantively new themes emerging from the final three interviews (Bryman, 2016).

3.2.2. Data Collection

Data were collected between January and June 2024 through 18 semi-structured interviews, each lasting 45-75 minutes. The interview protocol, developed from the literature review, was pilot tested with two industry practitioners and one academic expert to ensure clarity and relevance. Questions addressed four areas: analytics capabilities and infrastructure, differentiation strategies, dynamic capability processes (sensing, seizing, and transforming), and challenges and enablers.

Interviews were conducted via Microsoft Teams and Zoom, recorded with participants' explicit permission, and transcribed verbatim. Field notes capturing contextual observations were maintained throughout. Follow-up clarifications were conducted via email when needed, and informants were invited to share supporting materials such as anonymised dashboards and strategic documents to enrich the dataset.

3.2.3. Qualitative Data Analysis

Thematic analysis followed Braun and Clarke's (2006) six-phase approach. All three researchers independently read transcripts multiple times for familiarisation before systematically generating initial codes using NVivo software. Codes were collated into potential themes through iterative discussions and affinity diagramming. Themes were reviewed and refined through collaborative sessions to ensure coherence across the dataset, culminating in an analytical narrative providing interpretive insights.

Quality was ensured through member checking (informants verified key interpretations), triangulation across informants, industries, and supporting documents, and peer debriefing with academic colleagues (Spencer et al., 2003). Reliability was maintained through systematic coding procedures, a detailed audit trail, and inter-coder reliability checks among the three researchers, with discrepancies resolved through discussion and consensus.

3.3. Phase 2: Quantitative Study

3.3.1. Sampling and Data Collection

A cross-sectional survey targeted B2B organisations across manufacturing, industrial technology, and professional services with dedicated analytics functions. Key informants were senior managers responsible for analytics, marketing strategy, or product/service management, consistent with the competent informant approach (Kumar et al., 1993).

A structured questionnaire, developed from the literature review, qualitative findings, and established scales, was pretested with 15 practitioners and five academic experts for content validity and clarity. The survey was distributed via Qualtrics to 1,200 B2B professionals identified through professional databases (Dun & Bradstreet, LinkedIn Sales Navigator) and industry association lists. After two reminder waves over six weeks, 389 responses were received (32.4% response rate), yielding 347 usable responses after excluding incomplete submissions and failed attention checks.

Non-response bias was assessed by comparing early and late respondents using independent samples t-tests (Armstrong & Overton, 1977), revealing no significant differences (all $p > 0.05$). Common method bias was evaluated using Harman's single-factor test, where the first factor explained only 28.7% of total variance (below the 50% threshold), and the marker variable technique (Podsakoff et al., 2003), confirming no significant method factor effects. Neither bias posed a substantial threat to data integrity.

3.3.2. Measurement

All constructs were measured using multi-item reflective scales adapted from established instruments and refined based on qualitative findings. Items were rated on 7-point Likert scales (1 = strongly disagree; 7 = strongly agree).

Data Analytics Capability (DAC) was measured as a second-order construct with three dimensions: Predictive Analytics Capability (PAC, 4 items adapted from Akter et al., 2016; Gupta & George, 2016), Prescriptive Analytics Capability (PRC, 4 items developed from literature and qualitative findings), and Supply Chain Analytics Capability (SCAC, 4 items adapted from Chae et al., 2014; Wamba et al., 2017). Sample items include "Our organisation effectively uses predictive models to forecast B2B customer demand and behaviour" (PAC), "Our analytics systems recommend optimal decision alternatives for complex B2B problems" (PRC), and "Our analytics capabilities provide real-time visibility across our B2B supply chain network" (SCAC).
Dynamic Capabilities (DC) were measured as a second-order construct with three dimensions adapted from Wilden et al. (2013) and Pavlou and El Sawy (2011): Sensing (4 items), Seizing (4 items), and Transforming (4 items). Sample items include "We systematically scan our analytics outputs to identify new market opportunities" (Sensing), "We rapidly mobilise resources to capitalise on analytics-identified opportunities" (Seizing), and "We continuously reconfigure our analytics processes and organisational routines in response to market changes" (Transforming).

Value-Based Differentiation (VBD) was measured using 5 items adapted from Ulaga and Eggert (2006) and Terho et al. (2012). Sample items include "Our offerings are differentiated based on demonstrable superior economic value to B2B customers" and "We systematically quantify and communicate the total cost of ownership advantages of our offerings."
Solution-Based Differentiation (SBD) was measured using 5 items adapted from Storbacka (2011) and Tuli et al. (2007). Sample items include "We differentiate by integrating products, services, and knowledge into customised solutions for B2B customers" and "Our solutions are designed to address complex, cross-functional customer problems rather than individual product needs."
Control variables included firm size (number of employees), firm age, industry sector, analytics maturity (years of formal analytics operations), and environmental dynamism (4 items adapted from Jaworski & Kohli, 1993).

3.3.3. Quantitative Data Analysis
PLS-SEM was selected as the primary analytical method for several reasons consistent with methodological guidance (Hair et al., 2019). First, PLS-SEM is appropriate for exploratory-confirmatory research where theory is being extended rather than merely confirmed. Second, PLS-SEM effectively handles complex models with second-order constructs and mediating relationships. Third, PLS-SEM is robust with non-normal data distributions and performs well with sample sizes of the magnitude obtained. Fourth, PLS-SEM maximises explained variance in dependent constructs, aligning with our focus on understanding the determinants of differentiation outcomes.
The analysis was conducted using SmartPLS 4.0 software in two stages following established procedures (Hair et al., 2019). The first stage assessed the measurement model (reliability, convergent validity, and discriminant validity). The second stage assessed the structural model (path coefficients, significance levels, R^2 values, effect sizes f^2, and predictive relevance Q^2). Mediation effects were tested using bootstrapping with 5,000 subsamples to generate bias-corrected confidence intervals (Preacher & Hayes, 2008).

4. Qualitative Findings

The qualitative analysis revealed five overarching themes illuminating how B2B organizations develop and deploy analytics capabilities for differentiation, providing empirical grounding for the quantitative hypotheses.

Theme 1: Integrated Data Infrastructure as the Foundation. Informants emphasised that integrating heterogeneous data-CRM, ERP, and IoT into a unified infrastructure constitutes a strategic capability. Bridging "islands of data" creates holistic customer views and a VRIN resource, as one informant noted: "nobody can buy fifteen years of customer interaction data integrated with ERP production history and IoT performance data."

Theme 2: Predictive Analytics for Value-Based Differentiation. Predictive analytics emerged as the primary engine for value-based differentiation. Organisations combine customer operational data with IoT metrics to forecast the total cost of ownership precisely. One executive explained that presenting a "precise financial model" based on thousands of comparable installations consistently wins deals over standard pitches.

Theme 3: Prescriptive Analytics and Supply Chain Intelligence for Solutions. Customised solution design requires prescriptive algorithms modelling demand forecasts and usage patterns to recommend optimal configurations. Supply chain analytics extends visibility to the "customer's customer," enabling firms to orchestrate solutions optimizing the entire value chain.

Theme 4: Dynamic Capabilities as the Vital Bridge. Informants stressed that superior algorithms alone are insufficient. The critical differentiator is "organisational muscle" dynamically sensing emerging patterns, rapidly mobilising cross-functional teams to seize opportunities, and transforming procedures to sustain advantages.

Theme 5: Inter-Organisational Analytics Collaboration. Differentiation increasingly depends on trust-based analytics collaboration across ecosystems. Organisations co-develop predictive models with customers and exchange metrics with partners, fostering supply chain-embedded differentiation that is highly inimitable due to its reliance on collaborative intelligence and relational trust.

These themes collectively demonstrate that analytics-driven differentiation requires integrated infrastructure, advanced analytical methods, dynamic organisational capabilities, and deep inter-organisational collaboration.

Theme	**Core Concept**	**Key Mechanism**	**Theoretical Alignment**
1. Integrated Data Infrastructure	CRM+ERP+IoT integration as a strategic capability	Path-dependent, firm-specific data configurations create VRIN resources	RBV (Barney, 1991)
2. Predictive Analytics for Value Differentiation	Quantified economic value demonstration	Predictive models enable precision in value quantification	Value-based selling (Terho et al., 2012)
3. Prescriptive & Supply Chain Analytics for Solution Differentiation	Customised solution design and optimization	Prescriptive models and supply chain intelligence enable solution configuration	Solution business (Storbacka, 2011)
4. Dynamic Capabilities as Bridge	Sensing-seizing-transforming cycle	Analytics insights are only actionable through dynamic capability processes	DC (Teece, 2007)
5. Inter-Organizational	Cross-boundary	Shared data, co-	Network capabilities (Möller &

Analytics Collaboration	analytics co-creation	developed models, ecosystem-embedded analytics	Halinen, 2017)

Table 3: Summary of Qualitative Themes
Source: Authors' own work.

5. Quantitative Results
5.1. Respondent Profile
Table 4 summarises the demographic profile of survey respondents. The sample represents a balanced distribution across manufacturing (39.5%), industrial technology (34.3%), and professional services (26.2%). The majority of respondents held senior positions: C-suite (18.4%), VP/Director (41.8%), and Senior Manager (31.7%). Firm sizes ranged from medium (100–499 employees, 22.8%) to large (500–4,999 employees, 41.5%) and very large (5,000+ employees, 35.7%). Analytics maturity ranged from 2–4 years (26.5%) to 5–9 years (42.1%) and 10+ years (31.4%).

Characteristic	**Category**	**n**	**%**
Industry	Manufacturing	137	39.5
	Industrial Technology	119	34.3
	Professional Services	91	26.2
Position	C-Suite	64	18.4
	VP/Director	145	41.8
	Senior Manager	110	31.7
	Manager/Specialist	28	8.1
Firm Size	100–499 employees	79	22.8
	500–4,999 employees	144	41.5
	5,000+ employees	124	35.7
Analytics Maturity	2–4 years	92	26.5
	5–9 years	146	42.1
	10+ years	109	31.4

Table 4: Respondent Demographics (n = 347)

5.2. Measurement Model Assessment
The measurement model was assessed for reliability, convergent validity, and discriminant validity following established PLS-SEM criteria (Hair et al., 2019).
Reliability: Composite reliability (CR) values for all constructs exceeded the 0.70 threshold, ranging from 0.873 to 0.941. Cronbach's alpha values ranged from 0.841 to 0.927, confirming internal consistency.

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Convergent validity: All item loadings exceeded 0.70, and Average Variance Extracted (AVE) values for all constructs exceeded the 0.50 threshold, ranging from 0.617 to 0.782, confirming that constructs explain more than half the variance of their indicators.

Discriminant validity: The Heterotrait-Monotrait (HTMT) ratio was assessed for all construct pairs. All HTMT values were below the conservative 0.85 threshold, confirming discriminant validity (Henseler et al., 2015). Additionally, the Fornell-Larcker criterion was satisfied, with each construct's square root of AVE exceeding its correlations with other constructs.

Construct	**Items**	**Loadings Range**	**Cronbach's α**	**CR**	**AVE**
Predictive Analytics Capability (PAC)	4	0.78–0.89	0.862	0.906	0.708
Prescriptive Analytics Capability (PRC)	4	0.76–0.87	0.841	0.893	0.677
Supply Chain Analytics Capability (SCAC)	4	0.79–0.91	0.878	0.916	0.732
Sensing	4	0.81–0.90	0.883	0.919	0.740
Seizing	4	0.77–0.88	0.856	0.902	0.698
Transforming	4	0.80–0.92	0.893	0.926	0.758
Value-Based Differentiation (VBD)	5	0.74–0.88	0.891	0.921	0.700
Solution-Based Differentiation (SBD)	5	0.77–0.91	0.907	0.931	0.730
Environmental Dynamism (Control)	4	0.72–0.85	0.841	0.873	0.617

Table 5: Measurement Model Results

Note: All loadings are significant at $p < 0.001$. Second-order constructs (DAC, DC) confirmed through a repeated indicators approach.

	PAC	**PRC**	**SCAC**	**Sensing**	**Seizing**	**Transforming**	**VBD**	**SBD**
PRC	0.74							
SCAC	0.68	0.71						
Sensing	0.63	0.67	0.59					
Seizing	0.58	0.65	0.61	0.78				
Transforming	0.55	0.60	0.64	0.73	0.81			
VBD	0.61	0.57	0.52	0.54	0.56	0.48		
SBD	0.54	0.63	0.59	0.58	0.62	0.57	0.69	

Table 6: Discriminant Validity – HTMT Ratios

Note: All HTMT values < 0.85, confirming discriminant validity.

5.3. Structural Model Assessment

The structural model was assessed using bootstrapping with 5,000 subsamples to test path coefficients, significance levels, R^2 values, effect sizes (f^2), and predictive relevance (Q^2).

Hypothesis	**Path**	**β**	**t-value**	**p-value**	**Decision**

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H1	DAC → VBD	0.287	4.826	<0.001	Supported
H2	DAC → SBD	0.241	3.947	<0.001	Supported
H3	DAC → DC	0.564	11.283	<0.001	Supported
H4a	DC → VBD	0.382	6.194	<0.001	Supported
H4b	DC → SBD	0.439	7.521	<0.001	Supported

Table 7: Structural Model Results – Direct Effects

Explained Variance (R^2):

- Value-Based Differentiation: $R^2 = 0.423$ (moderate-substantial)
- Solution-Based Differentiation: $R^2 = 0.467$ (moderate-substantial)
- Dynamic Capabilities: $R^2 = 0.318$ (moderate)

Predictive Relevance (Q^2): All endogenous constructs showed Q^2 values well above zero (VBD: $Q^2 = 0.287$; SBD: $Q^2 = 0.321$; DC: $Q^2 = 0.234$), confirming the model's predictive relevance (Hair et al., 2019).

Effect Sizes (f^2):

- DAC → VBD: $f^2 = 0.102$ (small-medium)
- DAC → SBD: $f^2 = 0.083$ (small-medium)
- DAC → DC: $f^2 = 0.467$ (large)
- DC → VBD: $f^2 = 0.187$ (medium)
- DC → SBD: $f^2 = 0.258$ (medium-large)

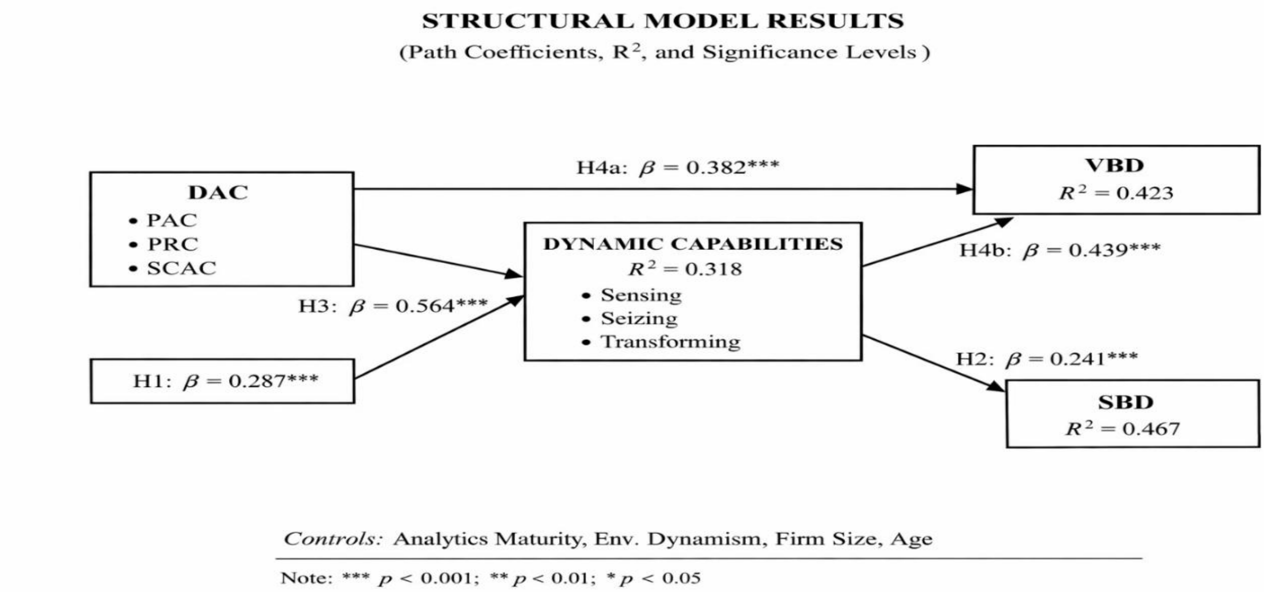

FIGURE 2: Structural Model Results (PLS-SEM with β values)

5.4. Mediation Analysis

Mediation effects were tested using bootstrapping with 5,000 subsamples and bias-corrected 95% confidence intervals (Preacher & Hayes, 2008).

Hypothesis	Indirect	Indirect	95% CI	t-	p-	VAF	Decision

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	Path	Effect (β)		value	value		
H5a	DAC → DC → VBD	0.215	[0.154, 0.284]	5.847	<0.001	42.8%	Supported (Partial Mediation)
H5b	DAC → DC → SBD	0.248	[0.181, 0.322]	6.312	<0.001	50.7%	Supported (Partial Mediation)

Table 8: Mediation Analysis Results

Note: VAF = Variance Accounted For by mediation. Total effects: DAC → VBD total = 0.502; DAC → SBD total = 0.489.

The results reveal that dynamic capabilities partially mediate the relationship between data analytics capability and both forms of differentiation. Notably, the mediation is stronger for solution-based differentiation (VAF = 50.7%) than for value-based differentiation (VAF = 42.8%), suggesting that solution-based differentiation depends more heavily on the dynamic capability processes that translate analytics resources into actionable strategy.

5.5. Control Variable Effects

Among control variables, analytics maturity showed a significant positive effect on both VBD ($\beta = 0.118$, $p < 0.01$) and SBD ($\beta = 0.134$, $p < 0.01$). Environmental dynamism showed a significant positive effect on SBD ($\beta = 0.097$, $p < 0.05$) but not on VBD ($\beta = 0.062$, $p = 0.187$). Firm size and firm age showed no significant effects. Industry sector (manufacturing vs. services) showed a marginally significant effect on SBD ($\beta = 0.084$, $p < 0.10$), suggesting that manufacturing firms may have a slight advantage in solution-based differentiation, potentially due to IoT-enabled data richness.

5.6. Multi-Group Analysis

To examine whether the structural relationships vary across industry sectors, we conducted a PLS multi-group analysis (PLS-MGA) comparing manufacturing firms ($n = 137$) and industrial technology/professional services firms ($n = 210$). Results showed that the path from DAC → SBD was significantly stronger in manufacturing ($\beta = 0.317$) than in technology/services ($\beta = 0.196$), with a significant difference ($\Delta\beta = 0.121$, $p < 0.05$). This suggests that IoT-rich manufacturing environments offer stronger analytics-driven solution differentiation opportunities. Other paths did not differ significantly across groups.

6. Discussion and the DADD Framework

6.1. Discussion of Findings

The combined qualitative and quantitative findings converge to provide a comprehensive understanding of how analytics drives B2B differentiation via dynamic capabilities. Supporting H1 and H2, alongside qualitative Themes 2 and 3, data analytics significantly drives both differentiation forms. Specifically, predictive analytics enables value-based differentiation through precise economic quantification, whereas prescriptive and supply chain analytics facilitate solution-based differentiation through optimal configuration and cross-boundary integration.

Strong support for H3, corroborated by Theme 4, confirms that analytics infrastructure fundamentally undergirds dynamic capabilities, empowering organisations to sense market opportunities, seize them, and continuously transform processes. Crucially, confirming H5a and H5b, dynamic capabilities partially mediate the analytics-differentiation relationship, with notably stronger mediation for solution-based differentiation. This demonstrates that complex,

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knowledge-intensive solution orchestration relies more heavily on dynamic organisational processes to translate insights into customised offerings. Aligning with Theme 5, inter-organisational analytics collaboration emerges as a distinctive B2B differentiation mechanism. Co-developing analytics models with partners and integrating dashboards across supply chains creates deeply embedded relational capabilities that extend beyond organisational boundaries to secure sustainable competitive advantage.

6.2. The DADD Framework

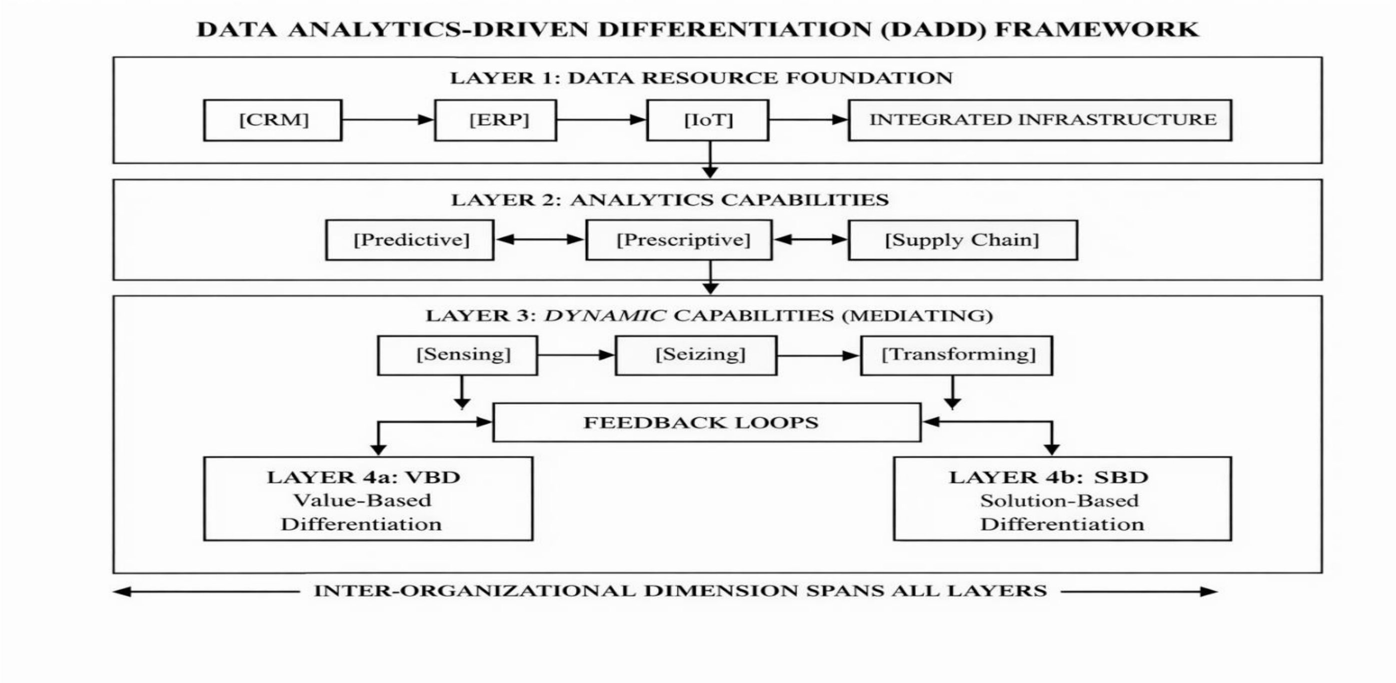

FIGURE 3: Data Analytics-Driven Differentiation (DADD) Framework

Figure 3 presents the Data Analytics-Driven Differentiation (DADD) framework that integrates our theoretical and empirical findings. The framework depicts a dynamic, iterative process through which B2B organizations transform heterogeneous data resources into sustained competitive differentiation.

The framework comprises four interconnected layers:

Layer 1 Data Resource Foundation: Heterogeneous data sources, CRM, ERP, and IoT sensors-constitute the raw resource base. Their integration into a unified analytical infrastructure creates firm-specific, path-dependent data assets satisfying VRIN criteria.

Layer 2 Analytics Capabilities: Three interconnected capabilities-predictive (forecasting, value modelling), prescriptive (optimisation, scenario modelling), and supply chain analytics (cross-boundary visibility, demand sensing), transform raw data into actionable intelligence, representing the operational manifestation of VRIN data resources.

Layer 3 Dynamic Capabilities (Mediating Mechanism): Sensing detects opportunities in analytics outputs, seizing implements analytics-informed differentiation strategies, and transforming reconfigures processes and partnerships to sustain advantages. These capabilities translate analytics intelligence into strategic action.

Layer 4 Differentiation Outcomes: Value-based differentiation (quantified economic superiority, TCO advantages) and solution-based differentiation (customised architectures,

integrated product-service bundles, supply chain-embedded solutions) are continuously refined through feedback loops.
Inter-Organisational Dimension: Analytics collaboration with customers and supply chain partners-shared data, co-developed models, ecosystem-level analytics-spans all layers, representing a distinctive B2B differentiation feature.
Feedback Loops: The framework is cyclical rather than linear. Differentiation outcomes generate new data feeding back into the resource foundation, triggering renewed cycles of analytics, dynamic capability activation, and differentiation refinement.

7. Theoretical Contributions

First, it extends RBV and analytics capability literature (Barney, 1991; Gupta & George, 2016) by conceptualising and empirically validating integrated data analytics capability as a VRIN resource driving sustainable B2B differentiation. By disaggregating analytics capabilities, we demonstrate distinct pathways: predictive analytics primarily enables value-based differentiation through quantification precision, while prescriptive and supply chain analytics enable solution-based differentiation through optimisation and cross-boundary integration. Qualitative findings further identify inter-system data integration architecture (CRM+ERP+IoT) as a new VRIN resource category characterised by firm-specific, path-dependent configurations.
Second, the study advances dynamic capabilities theory (Teece, 2007) by revealing differential mediation patterns in the analytics-differentiation relationship. The finding that dynamic capabilities mediate more strongly for solution-based differentiation than value-based differentiation provides nuanced theoretical insight: translating analytics into customised solutions demands more intensive organisational engagement in sensing, seizing, and transforming than quantifying economic value propositions. Qualitative evidence further extends dynamic capabilities theory to the inter-organisational level, where these processes increasingly operate across organisational boundaries.
Third, the study enriches B2B marketing literature (Ulaga & Eggert, 2006; Lilien, 2016) by developing the DADD framework a coherent, cyclical model connecting data resources, analytics capabilities, dynamic processes, and differentiation outcomes. The identification of inter-organisational analytics collaboration as a distinctive, highly inimitable differentiation mechanism contributes a novel dimension, revealing that the most sustainable B2B differentiation is embedded in analytics ecosystems creating collective intelligence that exceeds individual firm capabilities.

8. Managerial Implications

This study offers six actionable implications for B2B leaders seeking to leverage data analytics for differentiation.
First, invest in an integrated data infrastructure rather than standalone analytics tools. Integration of CRM, ERP, and IoT data sources into a unified analytical platform creates differentiation foundations that competitors cannot easily replicate. B2B leaders should prioritise breaking down data silos and investing in integration architectures connecting relational, operational, and real-time performance data into a coherent analytical ecosystem.
Second, align analytics capabilities with specific differentiation objectives. Organisations pursuing value-based differentiation should prioritise predictive analytics, enabling precise value quantification and ROI-based selling. Those pursuing solution-based differentiation should prioritise prescriptive and supply chain analytics supporting optimal solution

configuration and outcome-based offerings. Analytics investments should strategically align with the firm's primary competitive positioning.

Third, develop dynamic capability processes that translate analytics insights into strategic action. This means establishing cross-functional teams that regularly scan analytics outputs for differentiation opportunities (sensing), creating rapid decision-making protocols that translate opportunities into initiatives within defined timeframes (seizing), and implementing continuous improvement mechanisms embedding analytics-driven learning into organisational routines (transforming).

Fourth, cultivate inter-organisational analytics collaboration with strategic partners and customers. B2B leaders should design collaborative arrangements including shared analytics dashboards providing mutual operational visibility, co-developed predictive models integrating data from both parties, and joint innovation processes co-designing differentiated solutions. These relationships should be treated as strategic assets requiring dedicated investment in trust-building and data governance.

Fifth, build analytics-driven value selling and solution selling capabilities. Commercial teams need training in using predictive models, customer-specific value calculators, and ROI simulations for value-based differentiation, alongside prescriptive analytics outputs and supply chain intelligence for solution-based differentiation. Organisations should develop analytics literacy among customer-facing teams and create compelling tools that translate analytical capabilities into differentiation narratives.

Sixth, adopt continuous learning and adaptation regarding analytics-driven differentiation. Organisations must institutionalise feedback loops channelling market outcomes and competitive intelligence back into analytics systems, triggering new sensing-seizing-transforming cycles. Leaders should establish quarterly analytics-differentiation reviews assessing alignment between current capabilities and evolving market realities, adjusting investment priorities accordingly.

9. Limitations and Future Research

While this study makes substantive contributions, several limitations should be acknowledged, each suggesting promising future research avenues.

First, the cross-sectional quantitative design limits causal inference, capturing associations at a single point rather than establishing temporal precedence. Future research should employ longitudinal designs, including panel surveys and longitudinal case studies, to examine how analytics capabilities, dynamic capabilities, and differentiation outcomes co-evolve over time, including time lags between analytics investments and observable differentiation outcomes.

Second, while the sample spans manufacturing, industrial technology, and professional services, findings may not generalise to all B2B sectors. Future research should extend the investigation to construction, agriculture, healthcare supply chains, and commodity-based industries where analytics infrastructure and differentiation dynamics may differ substantially, revealing important boundary conditions moderating the analytics-differentiation relationship.

Third, examining analytics capability as a composite construct may obscure nuances regarding individual analytics types' relative contributions and complementarities. Future research should examine interaction effects for example, whether prescriptive analytics amplifies predictive analytics' differentiation impact, informing more precise investment allocation decisions.

Fourth, extending the investigation to the individual level would illuminate how analytics leadership, data literacy, and managerial cognition influence interpretation of analytics outputs, revealing micro-foundations of sensing, seizing, and transforming processes. Analytics culture as a moderating or mediating factor also deserves deeper investigation.

Fifth, inter-organisational analytics collaboration emerged prominently in qualitative findings but was not fully operationalised quantitatively. Future research should develop validated measures and examine governance mechanisms supporting effective collaboration through dyadic and network-level research designs.

Sixth, competitive dynamics and imitation risks associated with analytics-driven differentiation were not explicitly examined. Future research should investigate conditions under which analytics-driven differentiation is sustainable versus temporary, employing game-theoretic and competitive dynamics perspectives.

Seventh, emerging technologies, including generative AI, large language models, and autonomous analytics systems, are rapidly reshaping analytics capabilities. Future research should examine how these technologies alter the analytics-differentiation relationship and transform the dynamic capability cycle in B2B markets.

Eighth, potential dark sides of analytics-driven differentiation deserve investigation, including when analytics-driven standardisation undermines relational trust dimensions or when over-reliance on quantitative analytics crowds out qualitative market intelligence and intuitive expertise, providing a more balanced perspective.

10. Conclusion

This study examined how B2B organisations leverage data analytics capabilities to achieve product and service differentiation, with dynamic capabilities as a mediating mechanism. Through a sequential mixed-methods design combining 18 expert interviews and a survey of 347 B2B firms analysed using PLS-SEM, the study develops and validates the Data Analytics-Driven Differentiation (DADD) framework.

Findings demonstrate that integrated data analytics capability, encompassing predictive, prescriptive, and supply chain analytics drawn from CRM, ERP, and IoT sources, significantly drives both value-based and solution-based differentiation. Dynamic capabilities partially mediate this relationship, with particularly strong mediation for solution-based differentiation, underscoring the organisational processes required to translate analytical intelligence into customised offerings. Qualitative findings further reveal inter-organisational analytics collaboration as a distinctive, inimitable differentiation mechanism extending across supply chain ecosystems.

Theoretically, the study extends RBV by identifying integrated analytics infrastructure as a new VRIN resource category, advances dynamic capabilities theory by revealing differential mediation patterns, and enriches B2B marketing literature through the DADD framework. Managerially, the framework provides evidence-based guidance for designing analytics-driven differentiation strategies that are adaptive, customer-centric, and continuously renewed through dynamic capability processes. As B2B markets continue their digital transformation, the ability to systematically convert heterogeneous data into sustained differentiation will increasingly define competitive success.

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