Reframing the Consumer Buying Process: A Big Data Analytics Perspective

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ABSTRACT

The rise of Big Data Analytics (BDA) has transformed how organisations engage with consumers, yet its integration into established consumer decision-making frameworks remains underdeveloped, particularly in emerging markets. Traditional models of the consumer buying process outline five stages; need recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behaviour. While foundational, these models were conceived in an era with limited digital data and do not fully capture the role of analytics in shaping consumer behaviour today.

This study proposes a reframed model *The Consumer Buying Process: A Big Data Analytics Perspective* that embeds BDA across five redefined stages: Predictive Need Identification, Guided Discovery, Evidence-Based Evaluation, Conversion Optimisation, and Retention & Advocacy. A qualitative, constructivist grounded theory approach was employed, drawing on semi-structured interviews with thirty-two marketing and data professionals across South Africa's banking, financial services, telecommunications, and media sectors. Thematic analysis revealed how BDA enables predictive insights at the need stage, personalisation during discovery, sentiment-driven comparative evaluation, optimisation of purchase outcomes through recommender systems and dynamic pricing, and post-purchase lifecycle management using churn prediction and loyalty analytics.

The findings demonstrate a shift from reactive to proactive consumer engagement strategies, positioning BDA not as supplementary but as a strategic enabler across the consumer lifecycle. The study contributes theoretically by extending consumer behaviour frameworks in the age of Marketing 5.0 and practically by offering guidance for firms in South Africa and other emerging markets seeking to embed analytics into decision-making processes.

Keywords: Big Data Analytics, Consumer Decision-Making, Marketing 5.0, Customer Experience, Data-Driven Marketing, Emerging Markets, South Africa

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1. INTRODUCTION

Consumer decision-making has been a central focus of marketing research for decades, with models such as Engel–Kollat–Blackwell (Engel et al., 1995) and Kotler and Keller's five-stage framework (Kotler & Keller, 2016) shaping much of the foundational understanding of how consumers recognise needs, gather information, evaluate alternatives, purchase, and reflect post-purchase. These models, however, were developed in contexts where consumer data was limited, feedback loops were slow, and firm–consumer interactions followed largely one-way communication patterns. In contrast, the contemporary marketplace is characterised by unprecedented volumes of consumer data, rapid technological advancements, and increasingly complex decision journeys (Wedel & Kannan, 2016).

Big Data Analytics (BDA) has emerged as a transformative capability in this landscape, allowing firms to leverage structured and unstructured data through predictive modelling, artificial intelligence, and real-time insights (Chen et al., 2012; Wamba et al., 2015). While developed markets have progressed in embedding BDA into marketing practice, firms in emerging economies such as South Africa face distinct challenges, including data costs, regulatory frameworks like the Protection of Personal Information Act (POPIA), and organisational capacity constraints (Munyoka & Manzira, 2020). This duality of opportunity and constraint underscores the need to revisit consumer decision-making models through the lens of BDA and Marketing 5.0 (Kotler et al., 2021).

1.1 CONSUMER DECISION-MAKING AND MARKETING 5.0

Traditional consumer behaviour models conceptualised the decision-making process as a linear sequence, with each stage informing the next. While these models remain useful, they do not fully capture the realities of today's consumer journeys, which are often non-linear, multi-channel, and influenced by real-time interactions (Lemon & Verhoef, 2016). Digital technologies, mobile connectivity, and the proliferation of online platforms have created decision-making pathways that are fluid rather than sequential, requiring firms to adapt their approaches accordingly.

Marketing 5.0 provides a framework for understanding this transformation. It represents a paradigm where advanced technologies including BDA, artificial intelligence, natural language processing, and robotics are deployed in tandem with human-centred values to deliver personalised, inclusive, and ethical consumer experiences (Kotler et al., 2021). Within this paradigm, the consumer journey is not simply a series of behavioural steps but an ecosystem of data-driven touchpoints. Firms are expected to use analytics not only to observe behaviour but also to anticipate and shape it, aligning with the broader trend of predictive and prescriptive marketing (Davenport et al., 2020).

BDA plays a critical role in operationalising Marketing 5.0. At the need recognition stage, analytics enables firms to detect latent needs through browsing histories, purchase patterns, or even social media sentiment. During information search, predictive and real-time analytics help personalise recommendations and reduce consumer effort. In the evaluation stage, tools such as sentiment analysis, AI-driven comparisons, and crowd-sourced reviews are filtered and structured for consumer relevance. For the purchase stage, recommender systems and conversion optimisation techniques allow for seamless transaction experiences. Finally, in the post-purchase stage, churn prediction models and customer experience analytics help firms sustain long-term loyalty and advocacy (Chatterjee et al., 2021).

However, the Marketing 5.0 paradigm also raises critical questions about privacy, trust, and inclusivity. Emerging markets such as South Africa face additional complexities. While digital adoption is high, especially via mobile devices (Goldstuck, 2023), systemic barriers such as high data costs, uneven digital literacy, and regulatory frameworks present unique challenges. Furthermore, consumers in these markets may prioritise affordability and access differently from those in developed economies, necessitating context-specific applications of BDA. Thus, the integration of analytics into consumer decision-making must balance technological sophistication with ethical responsibility and local realities.

1.2 RESEARCH GAP

Despite its transformative potential, the integration of BDA into consumer decision-making models remains underexplored in both theory and practice. Existing scholarship often positions analytics as a support tool for discrete marketing functions such as segmentation, targeting, or campaign evaluation without systematically mapping its influence across the entire consumer journey (Erevelles et al., 2016). Moreover, much of the existing empirical work is drawn from developed markets, where data infrastructure, organisational readiness, and regulatory conditions differ significantly from those in emerging economies.

South Africa provides a particularly compelling setting for such inquiry. The country has seen rapid digital adoption and the growth of data-driven marketing practices in sectors such as banking, financial services, telecommunications, and media. Yet, firms continue to struggle with issues such as siloed data, talent shortages, and the cost of advanced analytical technologies (Munyoka & Manzira, 2020). These contextual dynamics highlight both the potential for innovation and the barriers to implementation. This study addresses this gap by examining how BDA can be systematically integrated into each of the five decision stages, offering insights that are both theoretically grounded and contextually relevant.

1.3 STUDY PURPOSE AND OBJECTIVES

The overarching purpose of this study is to develop a conceptual model that integrates Big Data Analytics into the five stages of consumer decision-making, advancing both marketing theory and practice. The specific objectives are to:

- Explore how BDA is operationalised across each stage of the consumer decision-making process.
- Identify the enablers and barriers that influence the adoption of BDA in South African firms.
- Propose a conceptual model that synthesises empirical insights and theoretical perspectives to guide marketing scholarship and practice.

2. LITERATURE REVIEW

The literature review positions this study within established research, critically examines prior work on consumer decision-making and Big Data Analytics (BDA), and identifies the theoretical foundations that guide the development of the proposed conceptual model.

2.1 CONSUMER BUYING DECISION MODELS

The study of consumer behaviour has long been underpinned by models that conceptualise how individuals recognise needs, gather information, evaluate alternatives, purchase, and engage post-purchase. The Engel–Kollat–Blackwell model (Engel et al., 1995) was one of the earliest frameworks to formalise decision-making as a sequential process, while Kotler and Keller (2016) refined the five-stage model need recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behaviour that remains influential in marketing literature.

Although these models provide useful insights, they were developed in an era characterised by limited consumer data and relatively simple market structures. Decision-making was often linear and could be mapped predictably from need identification to purchase. However, the rise of digital channels has created more complex, fragmented journeys. Lemon and Verhoef (2016) argue that consumers today move across channels fluidly, engage in iterative evaluation processes, and are influenced by peer-generated content as much as by firm-led communication.

Recent studies suggest that digital technologies have blurred the boundaries between decision stages. For example, consumers may simultaneously search for information and evaluate alternatives while engaging with digital platforms (Court et al., 2009). This shift highlights the need to reconsider traditional decision-making models, particularly in contexts where firms can access real-time data to predict or shape consumer behaviour.

2.2 BIG DATA ANALYTICS IN MARKETING

The emergence of BDA has been described as a transformative force in marketing, enabling firms to capture, store, and analyse unprecedented volumes of data (Chen et al., 2012). Defined by the “three Vs” volume, velocity, and variety Big Data goes beyond traditional datasets to include unstructured data from social media, transaction records, mobile applications, and sensors (Gandomi & Haider, 2015). BDA refers to the application of statistical, computational, and machine learning techniques to derive actionable insights from these datasets (Wamba et al., 2015).

In marketing, BDA has been used to enhance segmentation, targeting, and positioning by enabling more granular understanding of consumer preferences and behaviours (Erevelles et al., 2016). Predictive analytics, for example, can identify potential churn before it occurs, while prescriptive models recommend personalised offers that increase conversion rates (Davenport et al., 2020). Firms have also leveraged real-time analytics to optimise digital advertising spend, track consumer sentiment, and refine customer journeys.

Despite these advances, several challenges remain. First, integrating analytics into decision-making processes often requires organisational change, including breaking down silos between marketing and IT functions (Akter et al., 2016). Second, ethical considerations around privacy, transparency, and algorithmic bias have become pressing concerns, especially in light of regulatory frameworks such as the General Data Protection Regulation (GDPR) and South Africa’s Protection of Personal Information Act (POPIA) (Toufaily et al., 2021). Finally, while firms in developed economies have access to advanced infrastructure and talent, firms in emerging markets frequently struggle with data quality, cost, and skills shortages (Munyoka & Manzira, 2020).

These challenges suggest that BDA is not yet fully embedded into consumer decision-making, particularly in emerging markets. This gap provides the rationale for developing a model that systematically integrates analytics into each stage of the decision journey.

2.3 THEORETICAL FRAMEWORKS

The development of a Data-Driven Consumer Buying Model is informed by several theoretical perspectives.

2.3.1 Resource-Based View (RBV)

The Resource-Based View posits that firms achieve competitive advantage by leveraging unique, valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). In the context of BDA, data and analytics capabilities can be considered strategic resources when they are embedded into organisational processes and decision-making. Firms that effectively integrate analytics into consumer engagement may thus create sustained competitive advantage (Gupta & George, 2016).

2.3.2 Dynamic Capabilities Theory

Teece (2007) extends RBV by emphasising that resources alone are insufficient; firms must also develop dynamic capabilities to sense opportunities, seize them, and reconfigure resources in response to changing environments. BDA enables such dynamic capabilities by providing real-time insights that allow firms to adapt marketing strategies rapidly. For example, predictive analytics can sense emerging consumer needs, while prescriptive models enable firms to seize opportunities through targeted offers.

2.3.3 Technology Adoption and Diffusion

Models of technology adoption, such as the Technology Acceptance Model (Davis, 1989) and Diffusion of Innovations (Rogers, 2003), highlight the conditions under which new technologies are accepted by organisations and individuals. In marketing contexts, adoption of BDA is influenced by factors such as perceived usefulness, ease of use, organisational readiness, and cultural acceptance (Akter et al., 2016). In emerging markets, additional barriers such as infrastructure, cost, and digital literacy play a critical role (Dwivedi et al., 2021).

2.3.4 Marketing 5.0 Paradigm

The Marketing 5.0 paradigm provides the most direct lens for situating BDA within consumer decision-making. It emphasises the fusion of advanced technologies and human-centred values, advocating for marketing practices that are personalised, inclusive, and ethical (Kotler et al., 2021). By embedding BDA into each decision stage, firms can align technological capabilities with consumer expectations for relevance, trust, and engagement. This paradigm is particularly salient in emerging markets, where issues of inclusivity and access are critical.

2.4 SYNTHESIS

The literature reveals three critical insights that frame this study. First, traditional consumer decision-making models provide a useful foundation but must be revisited in light of non-linear, multi-channel journeys. Second, BDA has demonstrated potential to enhance marketing practice but has not been systematically mapped to the consumer decision process. Third, theoretical perspectives such as RBV, Dynamic Capabilities, and Marketing 5.0 suggest that analytics can serve as both a strategic resource and a dynamic enabler, but empirical work in emerging markets remains limited.

Taken together, these insights underscore the need for a conceptual model that integrates BDA into the five stages of consumer decision-making, grounded in the South African context. This model seeks to advance theory by extending consumer behaviour frameworks into the era of BDA and Marketing 5.0, while also offering practical guidance for firms navigating the opportunities and constraints of emerging markets.

3. METHODOLOGY

The methodology outlines the research design, sampling approach, data collection, analysis procedures, and ethical considerations that guided this study. Given the study’s objective to develop a conceptual model integrating Big Data Analytics (BDA) into the five stages of consumer decision-making a qualitative approach was adopted to capture rich insights from practitioners directly engaged in marketing and analytics functions.

3.1 RESEARCH DESIGN

This study employed a qualitative, constructivist grounded theory design. Grounded theory was selected because it enables the development of theory inductively from empirical data rather than imposing pre-existing models (Glaser & Strauss, 1967). The approach was appropriate for addressing the central research question of how BDA is integrated into the consumer decision-making process, as the phenomenon is underexplored and requires context-sensitive interpretation (Charmaz, 2014). Qualitative methods are particularly useful for capturing practitioner perspectives in dynamic contexts such as emerging markets, where standardised quantitative instruments may not fully account for cultural and organisational nuances (Creswell & Poth, 2018). The grounded theory design thus provided flexibility to identify themes, develop categories, and iteratively build towards a conceptual model.

3.2 POPULATION AND SAMPLING

The study population comprised marketing and data professionals working in South African firms across four industries: banking, financial services, telecommunications, and media. These sectors were chosen because of their high levels of digital adoption and data intensity, making them relevant contexts for studying BDA integration into marketing decision-making. A purposive sampling strategy was applied to ensure participants possessed relevant expertise in marketing strategy, analytics, or digital transformation (Palinkas et al., 2015). Inclusion criteria required that participants:

- Occupy senior or mid-level roles in marketing, analytics, or IT functions.
- Be directly involved in decisions or projects relating to BDA.

Exclusion criteria ruled out individuals without direct exposure to data or marketing responsibilities. A total of 32 professionals participated in the study, with representation across the four industries. This sample size was deemed sufficient to achieve thematic saturation, where no new insights emerged from additional interviews (Guest et al., 2006).

3.3 DATA COLLECTION INSTRUMENTS

Data were collected through semi-structured interviews, guided by an interview schedule developed from the study's research objectives and relevant literature. Semi-structured interviews were appropriate as they provided consistency in addressing key themes while allowing flexibility to probe deeper into participant experiences (Kallio et al., 2016).

- The interview guide included open-ended questions aligned to the six research objectives, covering:
- Evolution of BDA in marketing strategy.
- Influence of BDA on consumer engagement and decision-making.
- Application of BDA in marketing initiatives.
- Organisational changes required for BDA adoption.
- Barriers and challenges to leveraging analytics.
- Strategic outlook and recommendations.

Interviews were conducted online via Zoom and Microsoft Teams over a three-month period, reflecting the geographic distribution and time constraints of participants. Each interview lasted 30–45 minutes and was recorded with participant consent. To ensure validity, the interview guide was piloted with two professionals before full deployment, and minor adjustments were made for clarity. Reliability was supported by the use of a consistent protocol and interviewer training (Yin, 2018).

3.4 DATA ANALYSIS

Data were analysed using a thematic coding process consistent with grounded theory (Corbin & Strauss, 2015). Transcripts were first subjected to open coding, where initial codes were assigned to meaningful text segments. These codes were then grouped into categories during axial coding, linking concepts across consumer decision-making stages. Finally, selective coding integrated the categories into higher-level themes that informed the development of the conceptual model.

Atlas.ti software was used to manage data, code transcripts, and facilitate iterative analysis. Thematic saturation was achieved after approximately 28 interviews, though analysis continued across all 32 to ensure robustness.

Trustworthiness was established through multiple strategies:

Credibility: Use of member checking, where participants reviewed summaries of their responses.

Transferability: Rich descriptions of context and participant roles were included to aid interpretation in other settings.

Dependability and Confirmability: An audit trail was maintained, documenting coding decisions and analytical memos (Lincoln & Guba, 1985).

3.5 ETHICAL CONSIDERATIONS

Ethical approval for the study was obtained from the Research Ethics Committee of Nelson Mandela University Ethics Committee (Protocol Number: 0787 - REC-H 2022/07/15). Informed consent was obtained from all participants prior to interviews, with assurances provided regarding voluntary participation and the right to withdraw at any stage. Confidentiality was maintained by anonymising transcripts and removing identifying details of participants and their organisations. Data were securely stored on encrypted drives accessible only to the researcher. Compliance with South Africa’s Protection of Personal Information Act (POPIA) was ensured by limiting data use to the stated research purposes and protecting participant identities.

4. RESULTS

The results are presented thematically across the five stages of consumer decision-making. Thematic coding revealed how Big Data Analytics (BDA) was operationalised in practice, with sectoral differences and shared practices shaping the overall model.

4.1 NEED RECOGNITION

Participants described need recognition as the stage where analytics most clearly shifts firms from reactive to proactive marketing. Predictive models based on customer transaction data, browsing behaviour, and service usage allowed firms to detect latent needs. In the banking sector, analytics were widely used to identify customers likely to require credit facilities. As one banking executive explained:

> *"We track spending and income flows. When we see a pattern that suggests a customer's liquidity is tightening, our system flags them for personalised credit offers before they even apply."*

In telecommunications, network usage data helped firms anticipate demand for upgrades. A telecom analyst noted:

> *"When data usage consistently exceeds the customer's package, algorithms trigger upgrade suggestions. The goal is to match emerging needs with timely solutions."*

These findings indicate that BDA has transformed need recognition from a reactive to a predictive exercise, positioning firms as anticipators rather than responders. In summary, need recognition is increasingly shaped by predictive analytics, enabling firms to identify triggers before consumers explicitly articulate their needs.

4.2 INFORMATION SEARCH

The information search stage was characterised by personalisation. Firms deployed real-time recommendation engines and search optimisation analytics to reduce consumer effort and direct them to relevant options. Media companies described using clickstream and content analytics to personalise viewing recommendations. One participant highlighted:

> *"We analyse every click, pause, and rewind to tailor the landing page. The idea is that customers never feel lost; the right option is always in front of them."*

In financial services, chatbots driven by natural language processing guided customers through product comparisons. Participants emphasised how these tools replaced traditional, manual search processes. A cross-sector theme was the shift from consumer-driven search to firm-curated discovery. Instead of consumers actively gathering information, firms increasingly orchestrated the information flow using analytics. In summary, information search is moving from consumer-initiated exploration to firm-enabled discovery through personalisation and real-time guidance.

4.3 EVALUATION OF ALTERNATIVES

Evaluation was found to be heavily supported by sentiment analysis and AI-driven comparison tools. Firms used machine learning to aggregate reviews, benchmark competitors, and highlight features most relevant to target consumers. In telecommunications, comparative dashboards integrated competitor pricing data. As one analyst described:

> *"We don't expect customers to do the heavy lifting. We compare offers on their behalf and highlight why ours is better, sometimes even before they ask."*

Banks reported using sentiment analysis on social media to detect concerns about competing services. This allowed them to position their offerings proactively.

A striking finding was that firms sought not only to support consumer evaluation but also to influence the criteria by which alternatives were assessed. For example, a media company noted:

> *"If sentiment shows customers care most about value-for-money, our campaigns immediately pivot to emphasise that dimension in the comparison."*

In summary, evaluation is being reshaped by analytics that both inform and influence consumer criteria, shifting the balance of decision-making power toward firms while simultaneously simplifying the process for consumers.

4.4 PURCHASE DECISION

The purchase stage revealed analytics applications that were both operational and experiential. In e-commerce and media, recommender systems played a central role in upselling and cross-selling. A participant explained:

> *"When someone buys a data bundle, algorithms instantly suggest complementary offers like streaming packages. It's about maximising value per transaction."*

Dynamic pricing was particularly prevalent in telecommunications, where usage-based models allowed firms to tailor prices in real time. Fraud detection was also a recurrent theme in banking, where analytics secured purchase transactions. A banking participant said:

> *"Analytics is not just about nudging people to buy; it's also about protecting them. Fraud detection gives customers confidence to transact."*

These insights illustrate that analytics not only drives purchase optimisation but also ensures security and trust. In summary, BDA at the purchase stage enhances conversion efficiency while simultaneously safeguarding consumer confidence.

4.5 POST-PURCHASE BEHAVIOUR

Post-purchase engagement was the stage where participants reported the most sophisticated use of analytics. Firms relied heavily on retention analytics, loyalty scoring, and churn prediction. In telecommunications, churn models identified at-risk customers weeks in advance. One manager noted:

> *"We no longer wait for complaints. If a customer's usage pattern changes, or they suddenly stop engaging, we step in with proactive outreach."*

Media companies used recommendation engines not only for discovery but also to increase stickiness:

> *"Every time a user logs in, we tailor the experience. The goal is to keep them coming back until we become their default platform."*

In banking, post-purchase analytics were linked to lifetime value strategies. Executives described dashboards integrating credit use, repayment history, and engagement with additional services to guide cross-selling. Across industries, the focus was on shifting from transactional engagement to lifecycle management, with BDA forming the backbone of long-term consumer relationships. In summary, post-purchase is the most analytics-embedded stage, where retention, loyalty, and customer lifetime value are actively managed through predictive insights.

4.6 UNEVEN INTEGRATION OF BIG DATA ANALYTICS ACROSS THE CONSUMER BUYING PROCESS

A key observation emerging from the study is the uneven integration of Big Data Analytics (BDA) across the stages of the consumer buying process. Certain stages, particularly need identification and post-purchase behaviour, demonstrated advanced levels of analytics maturity. At the need stage, firms employed predictive analytics, transaction data, and social listening to anticipate emerging demands before consumers explicitly articulated them. Similarly, in the post-purchase stage, churn prediction models, customer experience dashboards, and loyalty scoring were widely used to retain customers, foster advocacy, and manage long-term engagement. These stages were prioritised because they directly influence revenue growth and customer lifetime value, making them strategic points for analytics investment.

In contrast, the evaluation of alternatives and purchase decision stages revealed a more hybrid approach, where human judgment and consumer input continued to play a dominant role alongside data-driven insights. While sentiment analysis, benchmarking tools, and recommender systems were deployed, their application was often constrained by the complexity of consumer trade-offs, personal preferences, and the centrality of trust in purchase decisions. As a result, analytics supported but did not fully replace traditional mechanisms of decision-making.

This uneven integration carries theoretical significance. From a Dynamic Capabilities perspective, firms appear stronger in sensing opportunities (need identification) and reconfiguring consumer relationships (post-purchase), but less mature in seizing opportunities (evaluation and purchase). From a Marketing 5.0 perspective, the findings illustrate progress towards proactive, personalised, and inclusive engagement, while also highlighting the persistence of stages where human involvement remains critical. The uneven integration of BDA across the consumer journey thus reflects both the transformative potential and current limitations of analytics in shaping consumer behaviour.

5. DISCUSSION

This study sought to integrate Big Data Analytics (BDA) into the five stages of consumer decision-making. The findings confirm that analytics is embedded across all stages need recognition, information search, evaluation, purchase, and post-purchase thus extending traditional consumer behaviour models and providing empirical grounding for a new conceptualisation.

5.1 EXTENDING CONSUMER DECISION-MAKING MODELS

The findings illustrate how consumer journeys have shifted from linear and consumer-driven to dynamic and analytics-enabled. Traditional frameworks such as the Engel–Kollat–Blackwell and Kotler–Keller models (Engel et al., 1995; Kotler & Keller, 2016) conceptualised decision-making as sequential and deliberate. In contrast, participants in this study described journeys shaped by predictive triggers, real-time recommendations, and automated comparisons. This reflects Lemon and Verhoef's (2016) view that contemporary journeys are iterative, multi-channel, and mediated by technology.

The findings show that firms are not merely facilitating consumer choices but actively influencing the criteria used for evaluation. For example, telecom and media firms used analytics to highlight features such as price or value-for-money, thereby shaping the dimensions consumers consider. This challenges assumptions of consumer agency embedded in earlier models and aligns with recent work that highlights the co-construction of consumer journeys through data (Anjorin et al., 2024).

5.2 RESOURCE-BASED VIEW: ANALYTICS AS A STRATEGIC ASSET

The Resource-Based View (RBV) posits that sustained competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). The results suggest that BDA capabilities fit these criteria when embedded into consumer engagement processes. Predictive models for need recognition, dynamic pricing algorithms for purchase, and churn prediction for retention all represent resources that are not easily replicated by competitors without equivalent data access, technological investment, and organisational expertise.

For example, banks leveraging transaction data to anticipate credit needs demonstrated how firm-specific datasets could be transformed into unique competitive advantages. Similarly, telecom firms' integration of consumption analytics into upgrade triggers created firm-level capabilities not easily transferable across contexts. This reinforces Gupta and George's (2016) argument that data capabilities become strategic when embedded in organisational routines.

5.3 DYNAMIC CAPABILITIES: ANALYTICS FOR AGILITY AND ADAPTATION

Dynamic Capabilities Theory emphasises the ability to sense opportunities, seize them, and reconfigure resources in turbulent environments (Teece, 2007). The results provide evidence that BDA enhances all three capacities.

- **Sensing:** Predictive analytics in need recognition and churn detection enabled firms to anticipate shifts in consumer behaviour.
- **Seizing:** Real-time recommendation engines and personalised promotions allowed firms to act immediately on these insights.
- **Reconfiguring:** Firms adapted campaigns, pricing strategies, and customer engagement processes based on analytics outputs, reflecting reconfiguration in action.

These findings resonate with Anning-Dorson (2025), who showed how data-driven dynamic capabilities support competitive adaptation in African markets. They suggest that analytics is not just a resource but a capability that enables agility in volatile environments such as South Africa.

5.4 MARKETING 5.0: TECHNOLOGY WITH HUMAN-CENTRICITY

Marketing 5.0 emphasises the fusion of technological sophistication and human-centric values (Kotler et al., 2021). The findings reflect this convergence. On the one hand, analytics automated key stages of decision-making, from information search to evaluation. On the other, participants highlighted the need to use analytics to support consumer trust and experience. For instance, fraud detection analytics in banking and proactive retention outreach in telecoms demonstrated how technology was applied in service of customer reassurance and relationship building. This aligns with Roy's (2025) notion of AI-capable relationship marketing, where analytics fosters long-term loyalty and trust. The findings also raise ethical questions. The shift from consumer-driven to firm-curated journeys reduces consumer effort but risks diminishing autonomy. This echoes Pillay and Struweg's (2023) concern that inclusivity and transparency are critical in emerging markets, where consumers face barriers such as data affordability and uneven digital literacy.

5.5 IMPLICATIONS FOR EMERGING MARKET CONTEXTS

The South African case highlights both opportunities and constraints. High mobile penetration and rapid digital adoption provided fertile ground for analytics-driven engagement. Yet systemic challenges including infrastructure gaps, cost barriers, and regulatory compliance under POPIA limited full integration.

Despite these challenges, firms demonstrated innovation by developing context-specific applications of BDA. Telecom firms, for example, adapted churn models to prepaid contexts, while banks leveraged localised transaction data to predict credit needs. These examples illustrate how firms in emerging markets may leapfrog traditional limitations by tailoring analytics to their unique operating environments, reinforcing the argument that BDA can serve as a driver of inclusive growth when responsibly applied.

5.6 THEORETICAL INTEGRATION

Together, the findings support a theoretical synthesis. BDA capabilities represent strategic resources (RBV) that are valuable, rare, and difficult to imitate. When applied dynamically, they serve as capabilities that allow firms to sense, seize, and reconfigure in real time (Dynamic Capabilities Theory). Finally, they align with Marketing 5.0, embedding technology into consumer journeys while striving to maintain human-centricity and ethics. This synthesis provides a foundation for the conceptual model proposed in this study the Data-Driven Consumer Buying Model which positions BDA as both a resource and a capability embedded across the consumer decision-making process.

5.7 THE DATA-DRIVEN CONSUMER BUYING MODEL

The proposed model represents an evolution from the traditional five-stage consumer decision-making framework into an analytics-embedded process. Rather than treating Big Data Analytics (BDA) as an adjunct to marketing, the model demonstrates how data capabilities are woven into every stage of the consumer journey, transforming how firms and consumers interact.

The first stage, traditionally referred to as Need Recognition, evolves into Predictive Need Identification. In this stage, BDA enables firms to anticipate consumer requirements before they are consciously recognised by individuals. Predictive modelling, transaction monitoring, and social listening tools allow organisations to sense emerging patterns and intervene early. This repositions firms as proactive agents shaping demand, rather than reactive responders.

The second stage, Information Search, becomes Guided Discovery. Here, analytics shifts the responsibility for exploration from the consumer to the firm. Recommendation systems, chatbots, and real-time search optimisation curate the information environment, presenting consumers with options tailored to their contexts. Guided discovery reduces effort for consumers while ensuring that firm-preferred pathways are foregrounded, marking a fundamental departure from consumer-led exploration.

The third stage, Evaluation of Alternatives, transforms into Evidence-Based Evaluation. With vast datasets and analytic techniques, firms aggregate reviews, conduct sentiment analysis, and generate comparative dashboards. These tools do not merely provide information; they actively structure the criteria upon which choices are evaluated. Consumers are no longer weighing options independently but are instead guided through a decision logic designed by analytics.

The fourth stage, Purchase Decision, is reframed as Conversion Optimisation. At this point, data and analytics converge to remove friction, secure trust, and maximise transaction efficiency. Dynamic pricing algorithms, recommender systems, and fraud detection technologies ensure that consumers not only complete transactions but do so confidently. Conversion optimisation integrates both the psychological and technical dimensions of decision-making, enhancing both convenience and security.

The final stage, Post-Purchase Behaviour, becomes Retention & Advocacy. Here, analytics sustains engagement by predicting churn, monitoring sentiment, and personalising experiences across the lifecycle. Firms can proactively identify dissatisfied customers and intervene with tailored solutions, while also amplifying advocacy through loyalty intelligence and referral analytics. This stage marks the transition from one-off transactions to enduring relationships grounded in predictive and prescriptive insights.

TABLE 1: DERIVED EVOLUTIONARY DD-CBM

Original Stage	BDA-Aligned Stage	Analytics Applications	Strategic Contribution
Need Recognition	**Predictive Need Identification**	Predictive modelling, Social listening, Transaction data analysis	Anticipates latent consumer needs; shifts firms from reactive responders to proactive demand shapers
Information Search	**Guided Discovery**	Recommendation systems, Chatbots, Real-time search optimisation	Curates' consumer information environment; reduces search friction; directs consumers along firm-preferred pathways
Evaluation of Alternatives	**Evidence-Based Evaluation**	Sentiment analysis, AI-driven comparisons, Benchmarking dashboards	Structures consumer choice through analytics; influences evaluation criteria; enhances decision confidence
Purchase Decision	**Conversion Optimisation**	Dynamic pricing, Recommender systems, Fraud detection tools	Maximises conversion efficiency; secures trust in transactions; integrates convenience with security
Post-Purchase Behaviour	**Retention & Advocacy**	Churn prediction models, Loyalty analytics, Customer experience (CX) dashboards	Extends engagement beyond transaction; builds loyalty and advocacy; enables lifecycle relationship management

These stages chart a journey into a new world of BDA-enabled marketing. The model is not a replacement of the classic consumer decision framework but an evolutionary reconfiguration that embeds analytics at the core. It illustrates how marketing in the era of Marketing 5.0 is not merely about technology adoption, but about reshaping the consumer–firm conversation into one where data continuously anticipates, guides, evaluates, optimises, and sustains engagement.

6. CONCLUSION

This study contributes to both theory and practice by proposing an evolutionary model that integrates Big Data Analytics into the five stages of consumer decision-making. By renaming and reframing these stages as Predictive Need Identification, Guided Discovery, Evidence-Based Evaluation, Conversion Optimisation, and Retention & Advocacy, the model illustrates how consumer journeys are being transformed into analytics-enabled processes. Theoretically, the model extends traditional consumer behaviour frameworks by embedding analytics as a cross-cutting enabler. It demonstrates how firms move beyond linear, consumer-led journeys to iterative, firm-curated pathways that are grounded in predictive and prescriptive insights. This aligns with the Resource-Based View, as analytics capabilities become rare and valuable organisational resources; with Dynamic Capabilities Theory, as firms use analytics to sense, seize, and reconfigure in real time; and with the Marketing 5.0 paradigm, which emphasises the fusion of technology and human-centric values.

The model provides firms with a roadmap to operationalise analytics across the consumer lifecycle. By adopting predictive and prescriptive tools, organisations can anticipate consumer needs, reduce search friction, influence evaluation criteria, secure transactions, and sustain long-term loyalty. At the same time, the model emphasises the need for responsible practices, including transparency, fairness, and inclusivity in analytics use—particularly relevant in emerging markets such as South Africa, where digital divides and regulatory compliance shape consumer experiences. While the study is limited to 32 professionals in four South African industries, its findings highlight both the opportunities and challenges of embedding analytics into consumer journeys. Future research should test this model quantitatively, extend it across markets, and integrate consumer perspectives to balance firm-driven insights with consumer autonomy. The Data-Driven Consumer Buying Model signals a shift from marketing as communication to marketing as continuous, analytics-enabled engagement. It demonstrates that the future of consumer decision-making lies not in the replacement of human judgement, but in its augmentation through data, shaping a new world where Big Data Analytics becomes the connective tissue of marketing practice.

DECLARATIONS

ETHICAL CONSIDERATIONS

This study was conducted in accordance with established ethical research practices. Ethical approval was obtained from the Nelson Mandela University Institute Research Ethics Committee prior to data collection. All participants were provided with an information sheet detailing the purpose of the study, their voluntary participation, and their right to withdraw at any time without prejudice. Informed consent was secured from each participant before interviews commenced. To ensure confidentiality, participant names, organisations, and other identifying details were anonymised in transcripts and publications, and all data were securely stored in password-protected files accessible only to the researcher.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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