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BIG DATA ANALYTICS, ARTIFICIAL INTELLIGENCE, DIGITAL MARKETING, AND BUSINESS PERFORMANCE

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Abstract
Big data analytics (BDA), artificial intelligence (AI), and digital marketing are creating a new paradigm in business management that is changing the way companies gather market intelligence, understand customers, develop strategies, and acquire competitive advantage. The current existing studies, however, are fragmented with very limited focus on the transformation of data-driven capabilities into AI-powered marketing intelligence and then into the value of the customers and the business. This paper introduces an integrated conceptual framework that connects BDA capability, AI enabled marketing intelligence, digital marketing capability, marketing agility, customer experience, customer trust, responsible data governance and business performance. The framework borrows the concepts from the resource-based view, dynamic capabilities theory, and the theory of resource orchestration, which essentially defines BDA as the analytical platform, AI as a mechanism that enhances intelligence, and digital marketing as the platform to turn intelligence into action in the market. The framework suggests that BDA capability supports AI-powered marketing intelligence that further develops digital marketing capability and marketing agility that leads to better customer experiences, personalization, engagement and business performance. It also suggests that the readiness of organizations to adopt AI and their digital maturity affects the development of capabilities, and that good data management and customer trust enable the realisation of value from data. The framework adds a capability-based data-to-value view, and offers theoretically informed propositions for future empirical studies.

1. INTRODUCTION

The digitalization of economic activity has changed the nature of the relationship between organizations, markets, technologies and customers. In the digital environment, today's companies have to deal with many structured and unstructured information sources created in digital environments, such as websites, mobile applications, electronic commerce platforms, social media, search engines, customer relationship management systems, connected devices, digital advertising networks, online reviews, and others (Kraus et al., 2021). Organizations have never before had the opportunity to see, analyse, predict and shape customer behaviour. Meanwhile, managers' strategic dilemma has grown significantly more complicated (Rane et al., 2024). The question is not just where are you going to get the information at this point, but how are you going to deal with the combination of heterogeneous information and find patterns that make sense, turn them into intelligence in time, apply intelligence in marketing practice, and create value for customers and the organization. Research on digital transformation also highlights the need of building new assets, capabilities, organizational structures and performance metrics, where digital technologies begin to be integrated into business models and organizational processes (Hanelt et al., 2021).

The advent of big data analytics (BDA) has been one of the key capacities that organizations have to cope with this. The scale, speed, heterogeneity and complexity of the information that can be collected and analyzed is what sets big data apart from traditional organizational information (Prakash, 2024). Consumer analytics is of special significance because of the way that companies can now watch consumer behavior at ever greater detail and near real time in today's digital environments. In a seminal study Erevelles, Fukawa and Swayne (2020) presented a first conceptualization of big data consumer analytics as a process that can be leveraged by organizations to gather evidence of consumer activity, derive consumer insights from that data, and apply those insights to improve their organizations' dynamic and adaptive capabilities. They have a resource-based view that stresses that the utility of big data is not just about data availability, but also the physical, human, and organizational resources that enable firms to leverage big data. Likewise, Wedel and Kannan concluded that the nature of data-rich environments has now shifted the marketing analytics needs and saw personalization, marketing-mix optimization, privacy and data security as significant challenges in current marketing organisations (Ibrahim et al., 2025).

The importance of BDA is further bolstered by studies that show analytics capability to be a driver of organizational performance. Wamba et al. (2020) found that the business value of analytics is related to the organizational capacity to translate analytical assets into dynamic processes, which are the firm's capabilities for adaptation. The same has been seen in the discussion of the business value of BDA, which should be achieved not for the sake of technology but for strategic business value, as said by Grover et al. (2014). While these studies set an important theoretical benchmark, they also point to an ongoing research challenge: the state of having analytical capability does not explain exactly how analytical information results in action that is market facing in a business world that is increasingly AI driven.

Artificial intelligence, or AI, has played a major role in this metamorphosis. Ooi et al. (2025) present a set of increasingly sophisticated mechanisms that enable organizations to process information and make decisions with the help of machine learning, deep learning, natural language processing, recommendation systems, computer vision, predictive models, conversational AI and generative AI. AI has applications in marketing, such as customer segmentation, targeting and prediction, personalization, recommendation, campaign optimization, customer service automation, sentiment analysis, content development, lead scoring, churn prediction, and customer lifetime value estimation (Bhardwaj et al., 2024). Davenport et al. stated that AI would have a significant impact on marketing strategy and consumer behaviour and highlighted that it would not only change the way things are done but also on the topic of privacy, bias, ethics and how humans interact with AI-driven systems in the future (Davenport et al., 2020). Huang and Rust then formulated a strategic framework to differentiate between mechanical, thinking, and feeling AI, and illustrated the various types of AI that could assist in marketing research, segmentation, targeting, positioning, and marketing actions (Huang and Rust, 2021). While these contributions have significantly increased knowledge and understanding of AI in marketing, the marriage between AI marketing capability and the wider big-data infrastructure that provides AI systems with information is still largely unfulfilled. Digital marketing is one more critical element of the shift. Digital marketing is the means by which big data analytics and AI are able to get to customers (Ziakis and Vlachopoulou, 2023). Businesses can use search advertising, social marketing, email marketing, mobile marketing, content marketing, e-commerce, recommendation systems, CRM, marketing automation and omnichannel communication to take their analytical insights to the market (Hasan, 2025). If, for instance, the organization has an AI model that predicts customer churn, but is unable to translate said prediction into a timely and appropriate intervention, then the value of the AI is limited. Likewise, a recommendation system won't mean much if the system can't be incorporated into customer journeys and can't be communicated via the right channels. Intelligence generation and intelligence deployment, therefore, are essential in understanding the concept of digital business value (Zeebaree, 2025).

This dynamic is further complicated and expanded by the fast evolution of generative AI. While traditional AI focuses on recognizing patterns, making predictions, and guiding decisions, generative AI can generate text, images, conversational responses, product descriptions, advertising copy, and more, all within the realm of marketing communications (Trigka and Dritsas, 2025). The creative and execution stage of marketing is then gaining its influence, alongside the analytical phase, in the era of AI. In addition to opportunities for scale, speed, experimentation, and personalization, there are also concerns about misinformation, brand consistency, privacy, intellectual property, algorithmic bias, and inappropriate automation (Garg, 2025). However, as AI becomes more prevalent in marketing research, the potential value of AI should be seen in conjunction with the readiness of the organization, customers' perceptions of AI, ethical considerations, and human management and oversight (Kehinde, 2025). Although these research fields are advancing quickly, there is a significant body of literature that is dispersed in an important regard. Research on big data has mainly focused on analytical capability, dynamic capabilities, organization agility, innovation and firm performance (Mikalef et al., 2018). Customer interaction, personalisation, automation, segmentation, targeting and strategic use of AI in marketing have all been explored. The studies on digital transformation have focused on the organizational structure (Potwora et al., 2024), business models, capabilities, and technological change (Potwora et al., 2024). Organizations' capacity to sense and react quickly to market changes has been studied in the context of marketing-agility. Theory integration between these literatures is incomplete, but at the same time, they overlap to a great extent (Ameen and Tarba, 2025). Specifically, there is comparatively little focus on the stream of events that turns data resources to analytical capabilities, analytical capability to AI-enabled intelligence, AI-enabled intelligence to marketing action, marketing action to customer value and customer value to organizational performance (Abrokwah-Larbi and Awuku-Larbi, 2024).

In this paper, an integrated data-to-dynamic-advantage framework is discussed to fill this gap. Big data analytics capability is the basic organizational capability that enables high quality and integrated information, AI-enabled marketing intelligence the process by which information is made into prediction, recommendation, classification and generation, digital marketing capability the organizational ability to deploy intelligence across all customer facing channels, marketing agility the ability to quickly translate marketing intelligence into action, customer experience and personalization the process of creating value for customers and business performance the ultimate organizational outcome. Importantly, the framework does not consider privacy and ethics as external constraints but as components of responsible data governance and customer trust. The reasoning here is that customer value generated by marketing features via AI can be more likely to be sustainable if trust is bolstered by responsible governance.

The paper offers a number of contributions. First, it links the various threads of research together within one theoretical structure. Second, it goes beyond the direct technology vs. performance relationship by focusing on the organizational processes that convert technology to value. Third, it brings into the framework the upstream part of the BDA capability and the downstream part—the marketing agility, customer experience, trust and business performance. Fourth, it establishes the capability for responsible data governance as a strategic value enabler, and not just a compliance tool. Last but not least, it formulates ten propositions for further empirical testing. The rest of the paper outlines the theoretical underpinning for the framework, critically reviews current research, proposes relationships, and discusses theoretical and management implications, further research opportunities, and implications for organizations that aim to achieve sustainable competitive advantage in the current and future market where data and Artificial Intelligence are becoming more and more important.

2. Literature Review and Theoretical Foundation

The theoretical structure of proposed framework starts with resource-based view (RBV), that is, the concept of competitive advantage is based upon the valuable resources and capabilities that organizations could develop and deploy strategically. Barney's base-level RBV theory suggests that resources can help them achieve sustained competitive advantage if they have characteristics of being valuable, rare, difficult to imitate and effectively organized. In today's digital world, however, RBV's approach to data and AI needs conceptual evolution (Barney and Clark, 2007). Furthermore, data is now more accessible to competitors, cloud infrastructure can be bought by several companies, commercial AI models can be purchased, and digital advertising can be acquired by a number of companies. It is important, therefore, to not assume that technology or data alone constitutes a competitive advantage, sustainable or otherwise. The strategically relevant resource is rather to be seen as the organisational ability to integrate data, technology, analytical skills, managerial knowledge, customer knowledge and organisational processes in a way that is difficult to duplicate by other organisations (Beverungen et al., 2022; Van Der Vlist et al., 2024).

This is in line with the BDA capability literature. The concept of BDA ability is a mixture of tangible, human and intangible resources rather than just a technological resource was conceptualized by Gupta and George. Wamba et al. later found that the ability to create BDA can affect performance, while the findings showed that analytical resources are more valuable when integrated into the organizational processes, thus giving empirical evidence of how analytical resources can influence performance via dynamic capabilities. Grover et al. also highlighted the strategic importance of BDA as the way of converting the analytical resources as organizational value (Grover et al., 2018). The message is that companies should not be concerned about having big data, they should be concerned about having the ability to produce organizationally relevant knowledge and/or action.

This argument is market-specificly complemented by big data consumer analytics. According to Erevelles et al. (2016), big data can revolutionize marketing by providing companies with the opportunity to monitor consumer activities, uncover previously unknown information and use the resulting information to help build adaptability. This is particularly significant as consumer information is not valuable on its own, but rather when it can be used to discover meaningful patterns and relate those patterns to marketing decisions (Kitchens et al., 2018). However, a company can store millions of customer records and not have much competitive advantage if these records are not well organized, incomplete, inaccurate, or not used in decision making. Hence data quality, data integration, analytical skills, organization culture and managerial interpretation should be recognized as elements of BDA capability (Fisher, 2009).

The dynamic capabilities approach builds on this argument by tackling the issue of environmental uncertainty. Teece et al. (1994) defined dynamic capabilities as organization skills that they used to integrate, develop and reconfigure their internal and external capabilities to meet shifting environments. This is especially true when it comes to digital marketing as there could be a fast-changing landscape in terms of customer preferences, competitor strategies, technologies, platforms, and market conditions. When it comes to making decisions, some may rely on historical analytics in stable environments, while others need continuous sensing, interpretation, experimentation, and adaptation in dynamic digital environments. The capability to be agile in marketing thus proves to be an essential linking pin between analytical intelligence and responding to an organisation (Homburg and Wielgos, 2022). Empirical evidence supporting the linkage of analytics and dynamic capability has already been found. The study by Wamba et al. showed that process-oriented dynamic capabilities are a mediator between BDA capability and firm performance (Bhatti et al., 2025). In more recent conceptual research, the BDA capability has been specifically associated with marketing agility and firm performance: the ability to leverage big data positively for firms can lead to greater capability to respond rapidly to the opportunities and threats of the market (Vesterinen et al., 2025). Kalaignanam et al. defined marketing agility as how fast an organization can sense the market and act on marketing decisions as the conditions change (Hughes and Chandy, 2021).These results help bolster the case made in the current framework for analytical intelligence turning into a strategy when organizations can act on it quickly.

Another important theory is resource orchestration theory. Managers structure, bundle and use resources to leverage the value of data, AI and digital marketing technologies (Zhu et al., 2026). Structuring is the process of acquiring and organizing technological infrastructure, technological data assets, human expertise and governance. The resources are then consolidated into higher-level processes like predictive analytics, recommendation systems, customer intelligence, marketing automation, and AI-driven decision-making (Yang et al., 2026). Leveraging is using these capabilities that create customer and business value. This view can account for the fact that two organizations with the same technological resources can produce very different outcomes. Differences probably stem from managerial capacity to integrate the technology into the organization's processes and market strategy, rather than from the technology itself.

This argument is further strengthened by the marketing analytics literature that reveals a need for organizations to rethink the process of making marketing decisions in data-rich environments. Wedel and Kannan noted that analytics is becoming more critical to marketing-mix optimisation, personalisation and customer-level decision making, and also pointed out the need for privacy and data security (Wedel and Kannan 2016).The marketing analytics perspective becomes then an important link between BDA and digital marketing. However, with the advent of AI, this bridge now needs to incorporate automated prediction, learning, recommendation, generation, and interaction (Theodorakopoulos et al., 2025).

The overall framework can be viewed as an intelligence transformation capability, enabled by AI. While BDA can make information accessible and analytically manageable, AI can go further, enabling organisations to detect intricate patterns, make predictions, automate repetitive decisions, understand natural language, make recommendations, and generate content. Huang and Rust's framework is useful in distinguishing between mechanical, thinking, and feeling types of AI, and associating them with various marketing activities (2021). Davenport et al. (2020) also argued that AI will change the marketing strategy and customer behaviors, and highlighted that AI would be best suited to complement, rather than supplant, human decision makers.

The current model builds on this idea by focusing on how AI fits into the analytic capability to marketing execution. AI should not be seen as a substitute for BDA or digital marketing. Rather, AI is an intermediate layer of intelligence that converts information created with data into predictions, recommendations, decisions and outputs. This is significant because it is a major reason why AI can have limited value if not backed by proper data capability, and why complex AI models that do not integrate with marketing can be technologically impressive but strategically ineffective.

This makes digital marketing the deployment capability in the framework. With digital marketing, businesses can leverage intelligence at each customer touchpoint. For instance, predictive customer analytics can be linked to customised email, focused advertising, product recommendations, dynamic website experiences, mobile notifications or even customer-service interventions (Mou, 2024). The strategic benefit of

AI therefore depends on whether or not organizations have the organizational processes in place to get AI going. The above logic can be represented as a sequence of transformations:

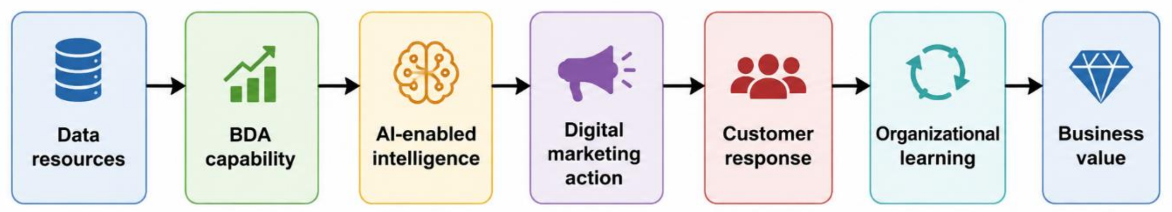

Figure 1. Integrated data-to-business value pathway from data resources through BDA capability, AI-enabled intelligence, digital marketing action, customer response, organizational learning, and business value.

In reality the sequence is not linear. Instead, the responses of the customers produce new data that re-enters the analytical system. Digital marketing is then a system for learning, not a one-way communication. This feedback-loop viewpoint is an important enhancement to the traditional marketing funnel perspective because the organisation is constantly enriching its understanding of the customer based on their behavioural reaction (Palmucci et al., 2025). CX plays an integral role in this shift. Lemon and Verhoef believed that the customer experience is built at many touch points and throughout the customer journey. For digital environments, AI can impact such experiences as providing greater relevance, lowering search costs, decrease response time, enhance recommendations and deliver personalized communication (Lemon and Verhoef, 2016). But, AI can also make perceived authenticity a problem, be frustrating when things go wrong with automated systems, or raise concerns about surveillance. So, it's not a one-size-fits-all situation between AI and customer experience. One specific instance of this tension is personalization. With the help of data-rich marketing, companies can gain insight into consumer preferences, buying behaviors, browsing habits and behavioral traits (Kim et al., 2025). These data can be used to create personalised suggestions and messages using AI. Personalization was one of the important applications of marketing analytics identified by Wedel and Kannan (2016). But personalization also has a paradox: as it helps make content more relevant, it also raises customers' awareness of the need for privacy and surveillance.

This is a subject that has been brought to the fore by recent research. The systematic literature review of AI in digital marketing conducted by Saura, Škare, and Ozretić Došen highlights privacy and ethical issues raised by behavioral analytics, real-time tracking, personalized content and other data-driven approaches (Cappuccio et al., 2024). This evidence bolsters the need to include the concepts of customer trust and responsible data governance within the theoretical model. Click-through rate and conversion thus is not the only metric used to measure the strategic effectiveness of personalisation. It should also be assessed based on customer perception of fairness, transparency, privacy, legitimacy (El-Annan and Hassoun, 2025). These relationships are embedded in the context of digital transformation in the organisation. In this report, Verhoef et al. clearly differentiate between digitization, digitalization and digital transformation and stress that transformation is a change in business models, organizational structures, capabilities and performance measurement, in addition to digitization and digitalization (Verhoef et al., 2021). To explore this aspect of digital transformation in greater depth, this study takes a closer look at the marketing capability component of digital transformation. Big data and AI are not technical initiatives but business initiatives. They need to be supported by structures that enable intelligence to shape strategic and operational decisions.

The literature therefore suggests that the strategic value of big data, AI, and digital marketing depends on a chain of mutually reinforcing capabilities. BDA provides the information foundation; AI transforms information into intelligence; digital marketing deploys intelligence; marketing agility enables rapid response; customer experience and personalization create customer value; trust and governance determine the legitimacy and sustainability of those interactions; and organizational learning converts market responses into new knowledge. The proposed framework integrates these elements into a unified theoretical model.

Table 1. Comparison of Major Research Streams and Contribution of the Proposed Framework

Research stream	Primary theoretical concern	Main contribution of prior research	Remaining limitation	Extension provided by the present framework
Big data analytics capability	How data and analytics generate organizational value	Establishes BDA as an organizational capability associated with performance	Limited integration with AI-enabled marketing processes	Positions BDA as the foundational data and analytical layer
Big data consumer analytics	How customer data generate market insights	Connects consumer analytics with adaptive capabilities	Limited attention to contemporary generative and intelligent AI	Extends consumer analytics into AI-enabled intelligence
AI in marketing	How AI supports marketing research, strategy and actions	Explains automation, prediction, segmentation, targeting and personalization	Often treats AI as the central technology without fully modeling upstream data capability	Positions AI as an intelligence transformation mechanism
Digital marketing	How firms interact with customers through digital channels	Explains customer engagement and digital channel management	Does not always explain how analytical intelligence becomes action	Positions digital marketing as the intelligence deployment layer
Dynamic capabilities	How organizations adapt to changing environments	Explains sensing, seizing and reconfiguration	Often insufficiently specific about AI-enabled marketing mechanisms	Connects AI-enabled intelligence with marketing agility
Marketing agility	How firms rapidly respond to changing markets	Establishes speed, iteration and responsiveness as marketing capabilities	Limited integration with responsible AI and customer trust	Positions agility as a mechanism connecting intelligence with action
Personalization	How firms tailor customer interactions	Demonstrates potential for relevance and customer value	Privacy and surveillance concerns may offset benefits	Integrates personalization with trust and governance

Responsible AI	How AI risks can be controlled	Highlights privacy, fairness, transparency and accountability	Often conceptualized primarily as risk management	Repositions governance as a value-enabling capability
Digital transformation	How organizations restructure around digital technologies	Establishes organizational and strategic dimensions of transformation	Broad frameworks may not specify marketing-level mechanisms	Provides a detailed data-to-marketing-to-performance pathway
Proposed study	How data become sustainable business value	Integrates resources, capabilities, intelligence, marketing and customer outcomes	—	Provides an integrated data-to-dynamic-advantage architecture

This work assumes that business value does not come from data or AI technology itself. Value, rather, is created in a series of changes of capabilities. While big data creates an ever-wider information environment, the strategic value of this environment can only be determined by an organization's ability to have the infrastructure, human know-how, analysis processes and organizational culture to convert all the information in that environment into useful intelligence. This conceptualisation aligns with the previous research in BDA, which shows that there are several dimensions of resources involved in analytics capability and that the impact of analytics capability on performance happens via organizational resources (Carayannis et al., 2017). The initial one in the framework is, therefore, the conversion of BDA capabilities into AI-powered marketing intelligence.

Companies that have a high BDA capability are better suited to gather, merge, clean, format, and analyze customer data. These organisations can supply the AI systems with more meaningful and trustworthy inputs and can also create the data pipelines to enable continuous learning (Wang et al., 2019). In contrast, companies with a disjointed data structure might not be able to leverage AI despite having powerful algorithms. The quality of data thus impacts the quality of AI-generated insights (Dzreke, 2025). Therefore, it is important to consider AI as a complement to, and not a replacement for, BDA capability. This thinking results in the first proposition:

Proposition 1: Being capable of big data analytics is a positive factor in an organization's capacity to develop an AI-powered marketing intelligence solution.

The second connection is between the ability of AI intelligence and digital marketing. Prospects, churn likelihood, product suggestions, sentiment scores, content recommendations, audience categorization, campaign projections, and more, are all examples of intelligence that can be created with AI. But, intelligence alone is not strategic unless there are organizational processes in place to incorporate intelligence into marketing. Digital marketing capability is the capability to use digital channels and platforms to turn intelligence into customer facing activities. Organizations that can embed the output of AI into customer relationship management (CRM), ads, content, e-commerce, social media and the omnichannel experience should have the best chance to unlock the value of AI. This argument can be applied to the AI-marketing literature as well. Based on the study by Huang and Rust (2021), AI can assist with marketing research, segmentation, targeting, positioning and marketing actions (King, 2025). The current system introduces a perspective on capability of the organization, stating that AI results must be integrated into digital marketing systems, before they can impact customers. Thus:

Proposition 2: The use of AI for marketing intelligence has a positive impact on digital marketing ability.

The third relationship is related to marketing agility. Modern markets are dynamic, with customers' expectations constantly evolving, competition, technologies and communication environments are all very dynamic. Marketing organizations need to have the ability to process information in a timely fashion and to act on the insights. Kalaignanam et al., (2021) describe marketing agility as a back and forth process between creating meaning for the market and executing marketing activities quickly. By automating data processing, identifying patterns, forecasting customer responses, and facilitating quick experimentation, AI can help to accelerate this cycle. BDA offers the information, and AI enhances both the speed and the depth of the interpretation. Agility does not, however, rise out of the void with the help of AI (Haque et al., 2025). Organizations need to have structures that enable rapid decision-making, while marketing teams need to be ready and capable of implementing AI-driven insights. This is why marketing agility is a capability, not a technology. The framework thus suggests:

Proposition 3: When organization processes allow the quick translation of intelligence into marketing decisions, then the presence of AI in marketing intelligence positively affects marketing agility.

The fourth relationship is to do with personalisation and value to the customer. By leveraging AI, companies can transition from predictive customer segments to the prediction of each customer. Recommendations can vary by customer based on the context, time, what they have bought and how, and how they have reacted to the content. This customization can save customers the cost of searching for information, make the content more relevant and make it easier for customers to use. However, personalization itself does not have any value (Kudapa, 2024). The same technology can lower satisfaction and trust, if it is seen as intrusive, manipulative, or too much. The framework thus defines personalisation as a value-creation process that is conditional. The benefit of personalization should be greater if the customers feel that the practices of the organisation are legitimate and transparent. This results in a proposition of the following form:

Proposition 4: When customers feel the personalisation is relevant, transparent, and not intrusive, AI-enabled personalisation capability can have a positive impact on customer value.

Another way that AI can impact business performance is by helping to improve marketing agility. In a flash, the company can find out about new trends in the market, tweak campaigns, tweak targeting, react to competitor activity, and try out new products. Recent studies have specifically linked BDA capability to marketing agility and company performance, indicating that a quick response is a critical lever in how analytics can generate value (Vesterinen et al., 2025). The present framework builds on this thinking and makes sense of AI intelligence as a vital mechanism in which BDA can further increase agility. Marketing agility must also be viewed as a dynamic capability as it enables organisations to sense, act, assess and adapt over and over again. An organization that starts an AI-based campaign that it can't rapidly change if the customers are responding to it may not come out with as much benefit as an organization that can experiment continuously. Accordingly:

Proposition 5: Marketing agility is a mediator between AI-enabled marketing intelligence and business performance.

Another important mediating mechanism is customer experience. Using digital technologies can enhance the experience, by making it more responsive, frictionless, recommending more accurately, and making it more consistent, across channels. An AI-powered system can be able to identify customers' needs even before they are able to express them. Predictive service interventions, customized suggestions, chatbots, and automated support can, therefore, enhance customer journeys. However, AI can also lead to bad user experiences when AI systems do not grasp the context, make irrelevant suggestions, or block customers from getting human support. AI in marketing is only as effective as it is when it works alongside human managers and customer interactions, as Davenport et al. have noted (2020). Therefore, the framework does not assume that automation is better than a human interaction. Rather, it suggests that AI generates added value when it enhances the customer's experience.

Proposition 6: AI-enabled digital marketing capability is indirectly linked to business performance through customer experience.

The framework also places customer trust as a key boundary condition. Trust is defined as the trustworthiness of the customer on the part of the organization to employ information and intelligent systems appropriately, reliably, fairly, and responsibly. Uncertainty can also be introduced into AI-powered marketing when it becomes unclear how decisions are made or what information has been leveraged. While AI can be effective in creating personalized experiences, it can also generate negative reactions if customers feel it's being intrusive or manipulative, even if the information is correct. The recent study on Artificial Intelligence (AI) and digital marketing ethics highlights the significance of this issue. Saura et al. found that there are significant relationships between behavioral analytics, real-time tracking and surveillance, personalized content, privacy and ethical issues (Saura et al., 2021). This suggests that there must be an equitable way of using data with technology.

Proposition 7: Customer trust positively moderates the impact of AI's personalization capability on customer value.

Data governance is then a strategic capability. Governance encompasses privacy protection, data security, transparency, accountability, fairness, appropriate consent, model monitoring, and human oversight. In traditional views, governance can be seen as a barrier to technological innovation. The current scheme suggests an alternative interpretation: good governance can support innovation by creating the conditions for customers and other stakeholders to embrace the interactions enabled by AI (Guillen-Aguinaga et al., 2025). A firm that is transparent about how data is being collected and utilized, has appropriate controls, regularly checks for algorithmic bias, and has accountability could earn more trust than that of a firm that has the same technological capability without transparency. Governance can then enhance the legitimacy of AI-powered marketing and increase the chances of the positive results of AI for customers (Misra, 2025).

Proposition 8: AI driven digital marketing capability and customer trust are positively moderated by responsible data governance.

Another essential contingency is the readiness of the organization for AI. Technology infrastructure, data quality, competent staff, management buy-in, organizational learning, financial investment and strategic alignment are some of the key factors for AI adoption. There is a large variation between organizations in these dimensions. This suggests that organizational readiness can cause variations in the levels of AI enabled intelligence that the same BDA capability can provide (Jöhnk et al., 2021). It's not just about the technology infrastructure being in place. Staff must have enough knowledge of AI to understand what it produces, its constraints, and be able to apply suggestions to management decisions. Organizational structures are also important, as managers need to foster experimentation while holding people accountable. Therefore:

Proposition 9: Organizational AI readiness positively moderates the relationship between big data analytics capability and AI-enabled marketing intelligence.

The last contingency is environmental dynamism. In a volatile market, the value of intelligence information is even more critical, as it becomes outdated rapidly compared to the times of other markets. In a more dynamic environment, the ability of AI to process real-time information and identify emerging patterns should therefore be more strategic in value. However, in relatively stable markets, the incremental value of real-time intelligence could be less. This is in line with the dynamic capability theory that posits that the value of adaptive capabilities is attributed to the 'environmental conditions' (Alshurideh et al., 2024). It is also consistent with recent BDA research that has drawn the attention of the community to the importance of the environmental conditions in shaping the relationship between analytics and performance. Accordingly:

Proposition 10: Environmental dynamism has a positive impact on the connection between AI-driven marketing intelligence and marketing agility.

These propositions collectively generate a theoretical model with multiple stages. The upstream part is about resource development – organizations develop BDA capability and AI readiness. The middle part is about intelligence transformation – data is transformed into AI-based marketing intelligence and then utilized by digital marketing capabilities. Organizational adaptation aspect relates to marketing agility, which refers to the ability of organizations to quickly convert knowledge into action. The customer component relates to personalization, experience, trust and customer value (Olayinka, 2021). The final part has to do with business results, such as growth in revenues, profitability, customer retention, innovation, marketing efficiency and competitive advantage. Responsible governance permeates these phases of the process, as its effects are felt on the legitimacy and sustainability of the whole transformation process.

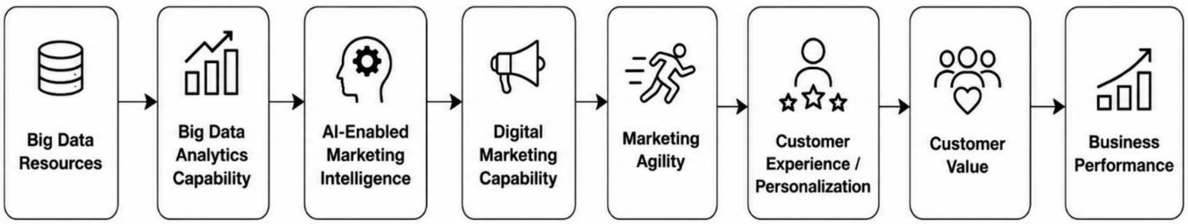

Figure 2. ***Proposed Integrated Data-to-Dynamic-Advantage Framework***

4. Discussion

The key theoretical innovation of the proposed framework is the virtual abandonment of a simple technology-performance relationship. Much of the hype about big data and AI seems to suggest that these tools and systems will give organizations a competitive edge upon acquisition of the data or implementation of the technology. This assumption is contrary to the strategic management's capability-based logic. Empirically, Wamba et al. found that BDA has an impact on performance through organizational dynamic capabilities (2017), while Grover et al. insisted that the strategic value of BDA is not only through the technological aspects, but also by value realization (2017). This logic is now applied to digital marketing, where AI-driven intelligence, marketing capability, agility, customer experience and trust are seen as overlapping tools for value creation.

The first key theoretical implication is the role of AI in the digital capability architecture. Previous research on AI in marketing research has identified its potential applications in the areas of marketing research, marketing segmentation, targeting and positioning, marketing personalization, and customer interaction (Huang and Rust, 2021). AI systems are reliant on data and processes, however. The proposed framework puts BDA capability ahead of AI marketing intelligence, highlighting the need for AI to be effective, which can be partly attributed to the quality of the information that the organisation can provide in the right time, place and context and in a reliable way. Therefore, the relationship between AI readiness and BDA capability should be studied together and not separately from the business performance.

The second one has to do with the role of digital marketing. Digital marketing is often seen as a channel or as a specific form of communication but in the current framework it is seen as a capability of digital organisation deployment. This distinction is of theoretical significance because there is no automatic market value for intelligence. An AI model can tell a person is likely to buy a product, but the organization needs to know how, when and via which channel to approach the person. Digital marketing is thus an organizational face-to-face with intelligence and customer action. The third contribution is with regard to marketing agility. The marketing agility has been identified as a key organisational capacity for dealing with rapidly changing markets, as found in previous studies. Kalaignanam et al. (2021) developed a concept of agility as a process of quick 'iteration' between market sensemaking and marketing execution. This process is enhanced by incorporating the proposed framework, which introduces an AI-powered intelligence perspective. AI can speed up the sensemaking element through its ability to analyse and synthesise vast amounts of data as well as making predictions, and digital marketing systems can speed up the execution element. This can lead to a continuous sense–decide–act–learn cycle.

As the fourth contribution, it's worth exploring customer value. The technology oriented models typically equate the performance of companies with their technology competencies. The framework instead proposes to take customer experience and personalisation between marketing capabilities and business performance. Theoretically it is significant because the final result of any organization depends on the reactions of customers. A marketing technology that makes things more efficient inside the company but hurts the customer's trust may not give an advantage that can last over time. On the other hand, higher levels of relevance, convenience and satisfaction can lead to better retention and customer lifetime value.

The fifth contribution is the combination of trust and responsible governance. In the world of AI-driven marketing, privacy and ethical considerations have come to the fore. Saura et al.'s analysis shows that personalization, tracking, behavioural analytics, surveillance, privacy and ethics are entangled in a complicated relationship when it comes to digital marketing and AI (Saura et al., 2021). The present study transcends an external perspective on these concerns as regulatory matters. Responsible governance is defined as a strategic capacity able to generate trust, which enhances value realisation. This is a shift in managerial discourse on governance from What organisations cannot do to What organisations need to do to create sustainable value.

The sixth contribution is related to Generative AI. Traditional marketing AI was mostly used for prediction, classification and recommendations. Generative AI is a new capability that adds to the capability architecture's content production and conversational interaction capabilities. This establishes a new relationship between intelligence and execution as the AI system can now generate a marketing communication with increasing frequencies. This does not mean that there is no need for organization. Rather, it accentuates brand governance, human oversight, factual verification, content quality, customer-data protection, and alignment of strategy. The study framework also extends the resource-based theory by arguing that competitive advantage in the context of AI pertaining to marketing will probably be more likely to be derived from resource complementarity than from individual technologies. Information is useless if it doesn't have someone with analytical skills to use it. Good data is essential to AI. Marketing is required for analytics to be of any value. Personalization, if not based on trust, can cause the resistance of customers. Without innovation, governance can lead to rigidity within the organization. The key to the competitive advantage is the coordination of complementary resources.

This argument has some interesting implications for managers. AI adoption must not be seen through the lens of organizations doing AI technology procurement. As always, the first question is what strategic problems need to be addressed with better intelligence, or quicker adaptation. They should then review their data architecture, analytical skills, digital marketing platforms, governance, and decision-making processes to determine if they can support AI. This series will be more likely to yield strategic value than the acquisition of AI tools and hoping for a transformation in performance. The study also indicates that there is a need to assess marketing effectiveness with AI at various levels within organizations. With a highly-accurate model, the results can be poor as the model cannot be expected to generate business outcomes if it is not implemented or if the customers are not receptive to the recommendations. Organizations should, therefore, consider the quality of data, the performance of their models, the returns on their marketing activities, the customer experience, customer confidence, financial results, and governance results at the same time.

Table 2. Constructs, Theoretical Logic, Roles, and Proposed Relationships

Construct	Definition in the proposed framework	Theoretical foundation	Role in framework	Expected relationship
Big Data Analytics Capability	Organizational ability to acquire, integrate, process and analyze heterogeneous data	RBV; dynamic capabilities	Foundational antecedent	Positive influence on AI-enabled intelligence
Organizational AI Readiness	Technological, human, managerial and cultural preparedness for AI	Capability perspective	Moderator	Strengthens BDA → AI relationship
AI-Enabled Marketing Intelligence	Ability to transform data into predictions, recommendations, classifications and generated marketing knowledge	Dynamic capabilities; AI marketing	Core mediator	Influences digital marketing and agility
Digital Marketing Capability	Ability to deploy intelligence through digital customer-facing activities	Resource orchestration	Mediator	Converts intelligence into market action
Marketing Agility	Ability to rapidly sense, decide, execute and adapt marketing actions	Dynamic capabilities	Mediator	Converts intelligence into adaptive action
Personalization Capability	Ability to dynamically tailor marketing content, offers and interactions	Customer-value theory	Mediator	Influences customer value
Customer Experience	Overall cognitive, emotional and behavioral evaluation of customer interactions	Customer experience theory	Mediator	Influences customer value and performance
Customer Trust	Customer confidence in the reliability, fairness, privacy and legitimacy of AI-enabled interactions	Trust/privacy perspective	Moderator	Strengthens personalization → value
Responsible Data Governance	Privacy, transparency, security, fairness, accountability and human oversight	Responsible AI	Cross-cutting moderator/enabler	Strengthens trust

Environmental Dynamism	Rate and unpredictability of market, technological and competitive change	Dynamic capabilities	Moderator	Strengthens intelligence → agility
Business Performance	Financial, market, customer and strategic organizational outcomes	RBV; dynamic capabilities	Ultimate dependent outcome	Result of integrated capability system

The framework further recommends a shift from a channel perspective of digital marketing to a system perspective of digital marketing. In traditional digital marketing, companies tend to handle the search, social media, email, advertising, websites, and customer relationship management (CRM) as somewhat independent marketing efforts. AI and BDA provides opportunities to tie these channels together with a single customer intelligence architecture. Recommendations in one channel can be affected by a customer interaction in another channel, and customer responses in one channel can continually add or refine the customer's knowledge and understanding of the organisation. This is a shift from multichannel digital marketing to an intelligent, adaptive and connected marketing system.

Customer lifetime value management is a prime example of the strategic importance of this shift. AI-powered systems can forecast the value of a customer over time and customize decisions on acquiring, serving, and communicating with them, rather than optimizing one-off transactions. This can enable companies to allocate their marketing resources on the fly. But applying customer-level predictions has significant implications for fairness and transparency, especially when algorithms are used to decide who will be offered an offer, discount, service, or be included in a promotion.

The framework, therefore, delivers a more comprehensive view of digital marketing performance. While click, impressions, conversion, return on advertising spend are traditional metrics, customer lifetime value, retention, satisfaction, trust, complaint rates, personalisation rates and governance indicators are important measures that need to be considered alongside these traditional metrics. While a high short-term conversion rate can be the result of intrusive personalization, it may not be a sustainable approach if it leads to harming long-term customer relationships.

The framework also emphasizes the need for collaboration between humans and AI. Davenport et al. suggest that AI is likely to be more effective when it is used in conjunction with people rather than in place of them (Davenport et al., 2020). This is also a valid argument in line with the proposed model since intelligence and action are not very effective at recognizing patterns, and humans can still be better suited to understand the organizational context, ethical considerations, strategic goals, and unusual customer situations. Therefore, it is important that future AI-powered marketing systems are built with the right balance of human and machine capabilities.

This research also has implications for small & medium enterprises. While large organizations might have more resources, data and analysis expertise, SMEs could make up for this with cloud-based analytic tools, outside AI vendors, niche platforms and partnerships. But reliance on external sources can pose data sovereignty, interoperability, cyber security, and strategic control issues. The capability-based framework implies that SMEs should build up the organizational capacity to orchestrate external technologies and not try to replicate the technological capabilities of larger companies.

The value of these capabilities is also influenced by environmental dynamism. Organizations need to be quick on their feet in fast-changing markets. The use of AI-powered systems could offer substantial benefits as they can continuously analyze data and identify emerging trends. However, in environments that are not as volatile, gains from advanced AI may be less than the cost and complexity. Hence, it is important to align environmental conditions and technological investments to maximize the expected benefits.

Finally, the study proposes that sustainable advantage is contingent on the ability to create a continuous learning architecture at the organization level. Data is created through digital interactions, the data is converted to intelligence which is then used to drive marketing action, customers respond, new data is created and the process continues. The speed and effectiveness of organizational learning may become as important as the possession of information in the future to gain competitive advantage, rather than just the possession of the information itself.

5. Theoretical and Managerial Implications

This study builds on the resource-based view theory by focusing on the theoretical importance of data and AI as part of a more comprehensive capability system. It's not just data that makes data strategic; it's when the organization can integrate data with infrastructure, people, analytical processes, market expertise, and governance. This will further emphasize the notion that technological tools that are part of the organizational routines and learning processes are not easy to replicate.

This study further extends Dynamic Capabilities theory, defining the role of Digital Intelligence in the marketing subprocesses of sensing, seizing and reconfiguration. But, BDA adds information on customer and market conditions which is strength for the sensing. AI enhances interpretation and prediction. Digital marketing is the way to seize by turning intelligence into market action. Marketing agility facilitates re-configurability by allowing reconfiguration of the marketing strategy when customers or competitors change. Therefore, the proposed model is more detailed in explaining the operation of dynamic capabilities in an AI enabled marketing environment. The resource orchestration perspective is also extended in that the framework specifies which resources are to be structured and bundled. Organizational capabilities need to be assembled from data assets, analytical infrastructure, AI systems, human expertise, marketing platforms and governance systems. This means that Digital Transformation needs to be seen as an organizational design challenge and not as a technology implementation challenge. The structure can be seen as a combination of customer experience, personalization, trust and digital capacity in one value-creation process from a marketing theory perspective. While past studies have shown the value of personalization and AI in the customer experience, the current research highlights the significance of customer value from a technological perspective and from a relational perspective. While a personalised interaction can be important, it will not be valued if felt as intrusive by customers.

The first implication for managers is to create a solid data foundation prior to attempting to scale AI. Data quality, integration, ownership, security and access should be seen as strategic data issues. The second is that enterprises should hire people with analytical and AI skills who can convert technical outputs into business decisions. The third implication is that marketing and technology are not distinct, but should be part of a collaborative effort. The fourth implication would be the need to tie AI projects to the business goals, whether that is customer retention, conversion, customer lifetime value, marketing efficiency, or innovation. The fifth implication is that responsible governance should be embedded in the design process and not be added on afterward when an AI system has been implemented.

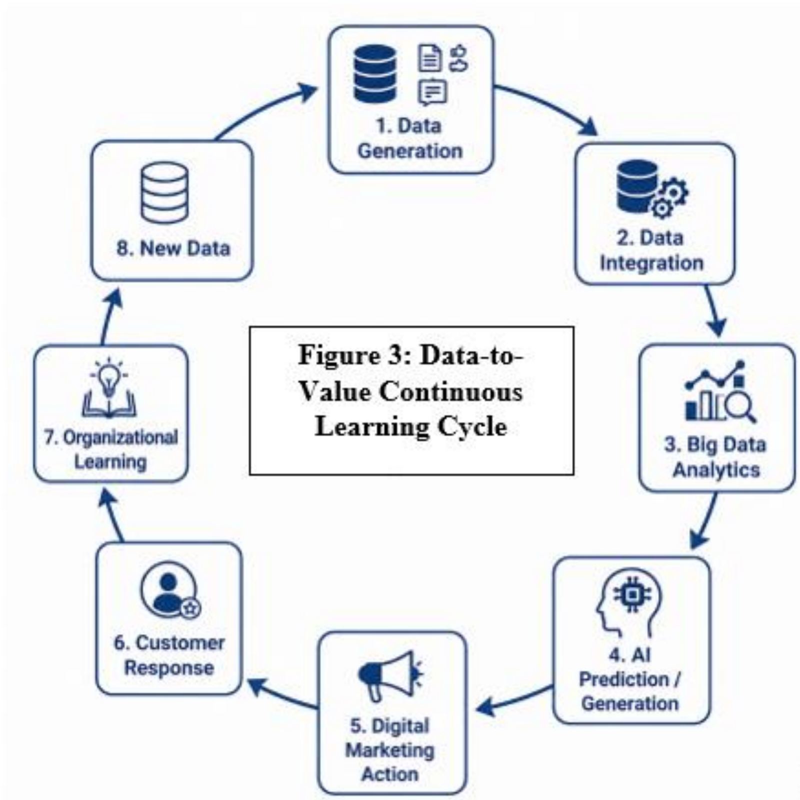

Figure 3. Data-to-Value Continuous Learning Cycle

Managers should also reconsider performance measurement. An AI system should not be considered successful merely because its predictive accuracy is high. The organization should evaluate whether predictions lead to better decisions, whether those decisions improve customer outcomes, whether customers trust the process, and whether the resulting benefits exceed implementation and governance costs. This suggests a hierarchy of measurement extending from data quality and AI accuracy to marketing effectiveness, customer outcomes, financial performance, and strategic adaptability.

6. Future Research Directions

There are multiple opportunities for empirical research in the conceptual framework. The first one is quantitative validation via structural equation modeling. BDA capability, AI-enabled marketing intelligence, digital marketing capability, marketing agility, customer experience, trust, governance and business performance were operationalized and examined the direct, mediating and moderating relationships hypothesized in the model. Modeling with partial least squares could be considered for exploratory theory development in the development of structure, while the model fit assessment and theory confirmation were considered for modeling using covariance-based methods.

Longitudinal studies would be even more powerful as they would follow participants over time as they learn to be more capable with AI. Companies can go through a series of experiments, pilot projects, integration, scaling and institutionalization. Negative or positive performance outcomes may not be seen right away following technology use. A longitudinal study could thus investigate if there is a mediation effect between investing in AI and long-term performance.

It would also be useful to carry out comparative studies amongst industrial sectors. In sectors like healthcare, banking, insurance, and telecommunications, where organizations handle highly sensitive data, customer trust can be critical. Personalization and recommendation systems might become more important in the retail and e-commerce sectors. Predictive maintenance, supply-chain analytics and B2B marketing can be a point of focus for manufacturing companies. Studies specific to the industry may thus identify if the proposed framework needs to be adapted to the context.

There is also a need to differentiate between predictive AI and generative AI in future studies. While predictive AI has a profound impact on estimation and decision-making, generative AI also has a significant impact on content creation and customer engagement. Therefore the ways that these technologies can affect marketing performance can vary. While generative AI can enhance productivity and experimentation, it can also lead to risks related to hallucination, brand consistency, IP, and customer disclosure.

Another significant research area is AI agents and ever more independent marketing systems. The difference between intelligence and action could become more blurred as artificial intelligence systems can plan and carry out series of actions. The framework could then be explored further for the possibility of autonomous AI agents as a new organizational capability and the governance model of managing these agents. Empirically, customers' trust should also be paid more attention. Trust can be different for various customers, cultures, industries, and experience with technology. Researchers were given the opportunity to investigate how transparency, explain ability, privacy controls, human oversight and perceived fairness support the personalization and customer value nexus. Last, but not least, future studies should explore the issue of competitive convergence or competitive differentiation brought about by AI. Technology capabilities can be more easily copied if commercially available AI tools are readily accessible. It may therefore be expected that the competitive advantage becomes more and more related to proprietary data, to the capability to learn and integrate, to customer relationships, to brand trust, and to responsible governance. This is especially relevant for determining if AI can provide a long-term competitive edge in a fast-changing technological landscape.

7. Conclusion

The intersection of big data analytics (BDA), artificial intelligence (AI), and digital marketing is an unprecedented shift in how business is managed today. There are more and more ways for organisations to gather and analyse a wide variety of data from their customers and markets, and AI can turn that data into predictions, recommendations, automated decisions and personalised content. Digital marketing is then the medium by which this intelligence is converted to actions that are taken by the customer. But the use of technology is not sufficient to provide a competitive advantage. This paper suggests an integrated data-to-dynamic-advantage framework, where BDA capability serves as the base, providing marketing intelligence through the support of AI, actionable decision-making through the use of AI, implementation through digital marketing, and agility through rapid organizational response to digital marketing. All of these collectively improve personalization, customer experience, customer value, and ultimately, financial and strategic performance. The structure combines dispersed and fragmented views from BDA, AI marketing, digital transformation, marketing analytics and dynamic capabilities. It is most notable for its ability to move away from thinking in terms of technology and towards thinking in terms of business capability and value. Technologies including big data, AI and digital marketing are only valuable if they're orchestrated with processes, human expertise, customer relationships and strategy. Beyond that, sustainable AI-powered marketing in an era where personalization and automated decision-making rely on sensitive customer data hinges on responsible data governance and customers' trust. The framework focuses on the value creation process that starts with data that generates potential; follows with analytics that creates insight; continues with the use of AI to generate intelligence; moves to digital marketing to convert intelligence into action; then customer experience to create value, and finally responsible governance to sustain the value. This view should give a basis for future empirical studies and give a direction to managers for creating adaptive and reliable organisations based on data.

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