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Big Data Analytics and Artificial Intelligence as Complementary Capabilities for Digital Marketing Performance: A Systematic Literature Review

Armina Rahmayanti; Tugiantoro
Master of Management Program, STIE Bhakti Pembangunan, Indonesia
Corresponding author: arminarahma78@gmail.com

Abstract
Purpose - This study synthesizes research on how Big Data Analytics (BDA) and Artificial Intelligence (AI) jointly contribute to digital marketing performance and identifies the organizational and customer-facing mechanisms through which value is realized. Design/methodology/approach - A PRISMA-guided systematic literature review was conducted using Scopus. The documented screening process identified 106 records, assessed 68 full-text reports, and retained 26 studies for qualitative synthesis. Because the studies differ substantially in constructs, contexts, research designs, and outcome measures, the evidence was integrated through descriptive profiling and thematic synthesis rather than statistical meta-analysis. Findings - The literature supports a complementary capability perspective. BDA provides the data integration, analytical infrastructure, and decision-information foundation, whereas AI extends this foundation through prediction, automation, recommendation, language processing, and personalization. Marketing performance is therefore best explained through a capability-conversion pathway in which customer insight, relevance, engagement, and organizational agility translate technological capabilities into outcomes. Data governance, privacy, and responsible use operate as important boundary conditions. Evidence for complementarity is stronger than evidence for a universal super-additive BDA-by-AI effect, which remains a proposition requiring direct empirical testing. Originality/value - The review develops an integrated capability-conversion-performance framework linking technological capabilities, organizational enablers, customer mechanisms, performance outcomes, and responsible governance. It also identifies priorities for longitudinal, real-time, cross-industry, SME, B2B, privacy, transparency, and human-AI research.

Keywords: big data analytics; artificial intelligence; digital marketing; marketing analytics; dynamic capabilities; systematic literature review

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1. Introduction

Digital transformation has altered both the information environment of marketing and the organizational capabilities required to compete within it. Digital platforms, mobile technologies, social media, and connected customer journeys generate high-volume and high-velocity information that can be translated into market knowledge when firms possess suitable analytical capabilities (Kannan & Li, 2017; Quinn et al., 2016; Vial, 2019; Verhoef et al., 2021). Within this environment, Big Data Analytics (BDA) and Artificial Intelligence (AI) have become closely related but analytically distinct capabilities. BDA concerns the acquisition, integration, processing, and interpretation of large and heterogeneous data, whereas AI enables learning, prediction, automation, natural-language processing, and adaptive decision support (Erevelles et al., 2016; Gupta & George, 2016; Huang & Rust, 2021).

The strategic relevance of BDA is not explained by data volume alone. Research on BDA capability emphasizes that business value depends on combinations of technological infrastructure, data quality, managerial skills, analytical talent, and alignment with business strategy (Akter et al., 2016; Gupta & George, 2016; Wamba et al., 2017). In marketing, these capabilities can deepen customer understanding, support segmentation and targeting, improve resource allocation, and make marketing decisions more responsive to changing market signals (Akter et al., 2021; Brewis et al., 2023; Wedel & Kannan, 2016). Accordingly, BDA is better treated as an organizational capability than as a stand-alone analytical tool.

AI extends this capability by converting complex data into predictions and actions at a scale and speed that would be difficult to achieve through manual analysis alone. Marketing applications include automated content and service processes, recommendation and targeting systems, predictive modeling, sentiment or language analysis, and personalization (Davenport et al., 2020; Huang & Rust, 2018; Huang & Rust, 2021). However, technological sophistication does not guarantee marketing performance. The ability to translate analytical outputs into market action depends on organizational agility, strategic alignment, and the capacity to integrate technological and human judgment (Mikalef et al., 2019; Shuradze et al., 2018; Sultana et al., 2022).

A further complication is that data-intensive and AI-enabled marketing creates tensions around privacy, transparency, and customer trust. Data collection may improve relevance and personalization, yet perceived misuse or opacity can erode customer responses and firm performance (Martin et al., 2017; Martin & Murphy, 2017; Quach et al., 2022). Consequently, research on BDA and AI in digital marketing must examine not only technological benefits but also organizational conversion mechanisms and responsible governance conditions.

Despite the rapid expansion of data-driven marketing research, three conceptual problems remain. First, BDA and AI are frequently examined as parallel technologies rather than as interdependent organizational capabilities. Second, technology adoption is often linked directly to performance without sufficiently specifying the organizational and customer-level mechanisms that convert analytical outputs into market outcomes. Third, the evidence remains uneven across industries, geographic settings, firm sizes, and governance conditions. Recent bibliometric research confirms the rapid growth and thematic diversification of digital marketing scholarship, but also illustrates its conceptual fragmentation (Ortegón-Cortázar et al., 2025). These features justify systematic synthesis rather than reliance on isolated empirical findings (Snyder, 2019; Tranfield et al., 2003).

Accordingly, this systematic literature review addresses four research questions. RQ1: How are BDA and AI capabilities conceptualized in digital marketing research? RQ2: Through which mechanisms are these capabilities associated with digital marketing performance? RQ3: Which organizational and governance conditions strengthen or constrain these relationships? RQ4: Which methodological, contextual, and theoretical gaps should guide future research? By answering these questions, the study develops an integrated capability-conversion-performance framework and distinguishes evidence-supported complementarity from stronger causal claims that remain to be tested.

2. Theoretical Background and Analytical Lens

2.1 Big Data Analytics as an organizational capability

BDA refers here to the organizational ability to acquire, integrate, analyze, and use large, diverse, and rapidly changing data for decision-making. The familiar characteristics of volume, variety, velocity, veracity, and value are useful for describing the data environment, but the capability perspective moves the analysis from data characteristics to the resources and routines required to create business value. Empirical and conceptual work consistently shows that analytical infrastructure alone is insufficient; human expertise, managerial coordination, strategic alignment, and data quality are integral components of BDA capability (Akter et al., 2016; Gupta & George, 2016; Wamba et al., 2017). This interpretation is also consistent with the Resource-Based View (RBV), which explains performance heterogeneity through valuable and difficult-to-replicate resource configurations rather than isolated technologies (Barney, 1991).

2.2 AI-enabled marketing capability

AI in marketing encompasses algorithmic systems that automate tasks, identify patterns, predict outcomes, generate recommendations, and process structured or unstructured information. Prior frameworks distinguish AI roles according to the type of task and intelligence required and emphasize its capacity to transform marketing activities and decision processes (Huang & Rust, 2018; Huang & Rust, 2021; Davenport et al., 2020). For this review, AI is conceptualized as an enabling capability that augments BDA by converting integrated data into scalable prediction, personalization, automation, and decision support. This distinction is analytically important: BDA provides the informational foundation, whereas AI expands the firm's capacity to learn and act on that foundation.

2.3 Complementarity through the RBV and Dynamic Capabilities Theory

BDA-AI integration is theoretically expected to create value because the two capabilities are complementary rather than interchangeable. The Resource-Based View (RBV) suggests that strategically valuable outcomes arise from resource configurations that are difficult to replicate, not from isolated technologies (Barney, 1991). Dynamic Capabilities Theory further explains how firms sense changes, seize opportunities, and reconfigure resources in volatile environments (Teece et al., 1997). Research on analytics capabilities links BDA to strategic alignment, innovation, and organizational agility (Brewis et al., 2023; Mikalef et al., 2019; Shuradze et al., 2018). Systems-theoretic evidence also indicates that combinations of digital resources can generate interaction effects (Dong & Yang, 2020). Nevertheless, complementarity should not be conflated with a statistically proven super-additive BDA-by-AI effect. The latter requires direct tests of the joint effect and is therefore treated here as a testable proposition rather than an established universal relationship.

2.4 Digital marketing performance as a multidimensional outcome

Digital marketing performance is not a single metric. The reviewed literature uses behavioral outcomes such as engagement and response, transaction outcomes such as conversion and sales, relationship outcomes such as retention and customer value, and internal outcomes such as decision speed and operational efficiency. Marketing analytics research recommends matching analytical capabilities to decision contexts and performance criteria rather than treating analytics adoption as performance in itself (Kannan & Li, 2017; Wedel & Kannan, 2016). The conceptual model used in this review therefore separates technological capabilities from capability-conversion mechanisms and observable marketing outcomes.

3. Method

3.1 Review design and reporting approach

The study uses a systematic literature review (SLR) to identify, evaluate, and synthesize research on BDA, AI, and digital marketing performance. Systematic reviews are appropriate when a research domain is fragmented across theories, methods, and contexts and when the objective is to develop an auditable synthesis rather than a selective narrative (Snyder, 2019; Tranfield et al., 2003). Reporting was aligned with the PRISMA 2020 logic of transparent identification, screening, eligibility assessment, and inclusion (Page et al., 2021). PRISMA was used as a reporting and selection framework; it should not be interpreted as evidence that the review is a clinical meta-analysis.

3.2 Data source and search strategy

Scopus was used as the sole bibliographic database because it provides broad multidisciplinary coverage and a consistent source for screening. The documented search combined the concepts 'Big Data Analytics', 'Artificial Intelligence', and 'Digital Marketing' using Boolean operators and returned 106 records. Reliance on a single database improves procedural consistency but may omit relevant studies indexed elsewhere. In addition, the archived search documentation did not retain the exact search date, complete TITLE-ABS-KEY query, or predefined publication-year window. These details are therefore not reconstructed post hoc and are reported as a reproducibility limitation.

The review distinguishes descriptive publication profiling from full bibliometric science mapping. The available review records support descriptive assessment of publication timing, disciplinary context, methods, and thematic patterns, but do not retain the software settings, network thresholds, co-citation maps, bibliographic coupling outputs, or other parameters required for a reproducible network-based bibliometric analysis. Accordingly, the present study uses descriptive profiling followed by thematic synthesis. This distinction is consistent with methodological guidance that treats performance analysis and science mapping as analytically distinct components of bibliometric research (Aria & Cuccurullo, 2017; Rialti et al., 2019).

3.3 Eligibility criteria

Eligibility criteria were defined to preserve direct relevance to the relationship among BDA, AI, digital marketing processes, and marketing-related outcomes. Studies were retained when they provided sufficient methodological or analytical information for comparison and were available in full text. Table 1 summarizes the inclusion and exclusion logic applied during screening.

Criterion	Include	Exclude
Topical relevance	Studies addressing BDA and/or AI within marketing or digital-marketing contexts and reporting evidence relevant to customer, organizational, or marketing outcomes.	Studies on BDA/AI without a clear marketing or digital-marketing connection.
Publication quality	Peer-reviewed journal articles indexed in Scopus.	Non-peer-reviewed material or records without adequate scholarly reporting.
Evidence/reporting	Studies with sufficient methodological and results information for thematic extraction and comparison.	Opinion pieces or studies with insufficient methodological or analytical information for comparison.
Accessibility	Full text available for eligibility assessment.	Reports not retrievable for full-text assessment (none were recorded).

Table 1. Eligibility criteria applied in the systematic review.

3.4 Screening and study selection

The screening process began with 106 Scopus records. No duplicate records were identified because the search relied on a single database. Title-and-abstract screening excluded 38 records, leaving 68 reports for full-text retrieval and eligibility assessment. All 68 reports were retrieved. Full-text assessment excluded 42 reports, resulting in a final analytical set of 26 studies. The archived screening record grouped exclusions into three broad reasons: absence of a clear digital-marketing context, non-comparable conceptual or opinion content, and insufficient methodological information. Because reason-specific frequencies were not retained, only the aggregate full-text exclusion count is reported.

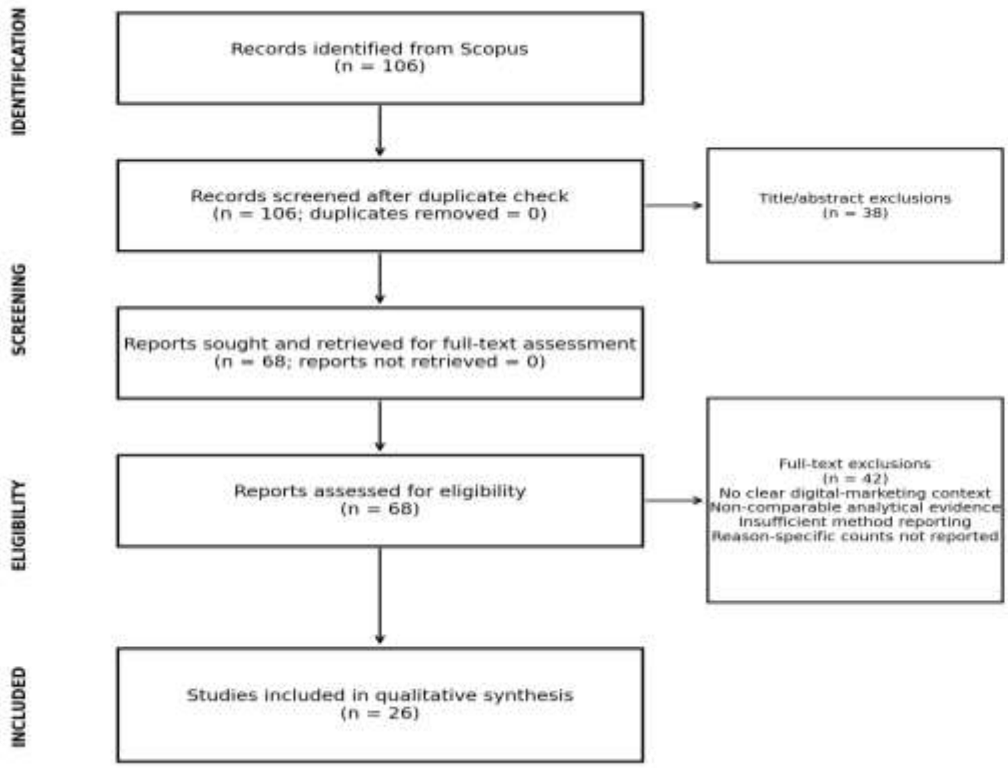

Figure 1. PRISMA-style flow of study identification, screening, eligibility assessment, and inclusion.

3.5 Data extraction and synthesis

The unit of analysis was the individual article. Data extraction focused on bibliographic characteristics, research context, methodological design, focal technologies, organizational or customer mechanisms, performance outcomes, and principal findings. The synthesis organized the evidence into five analytical domains: (1) BDA and data capability; (2) AI-enabled marketing mechanisms; (3) capability-conversion and organizational enablers; (4) digital marketing performance outcomes; and (5) governance, privacy, and ethical boundary conditions. Thematic analysis followed the established sequence of familiarization, coding, theme development, review, and interpretation (Braun & Clarke, 2006). Statistical pooling was not undertaken because of substantial heterogeneity in constructs, measures, research designs, and outcome definitions.

3.6 Methodological rigor and limits of the review process

Methodological rigor was pursued through explicit reporting of screening counts, predefined inclusion logic, separation of empirical evidence from theoretical inference, and avoidance of untraceable numerical claims. However, the retained review documentation does not contain a formal study-level quality score, an inter-coder agreement statistic, or a registered protocol. These omissions restrict reproducibility and the strength of certainty statements. Consequently, the review interprets recurring patterns as convergent evidence rather than as pooled causal effects and treats methodological transparency as a central limitation.

4. Results

4.1 Study-selection results

The review retained 26 of the 106 identified records (24.5%). The largest reduction occurred during full-text assessment, when 42 of 68 reports were excluded. This pattern indicates that broad searches around BDA and AI retrieve a substantial body of literature outside the narrower digital-marketing intersection, making eligibility decisions consequential for the final synthesis. Because the evidence base is restricted to Scopus and the publication window was not preserved in the archived search documentation, the final sample should be interpreted as a bounded systematic evidence set rather than an exhaustive census of global research.

4.2 Descriptive profile of the included literature

Descriptive profiling indicates that the topic became substantially more visible after 2020 and spans marketing, management, information systems, and consumer research. Quantitative survey designs, structural-equation approaches, and multivariate models are prominent, while longitudinal, experimental, qualitative, and mixed-method designs are less common. The evidence base also displays uneven geographic and sectoral coverage, with comparatively limited representation of SMEs, B2B markets, and traditional industries. These patterns are consistent with broader bibliometric evidence showing rapid growth and thematic diversification in digital marketing research (Ortegón-Cortázar et al., 2025).

The theoretical landscape is similarly heterogeneous. The most defensible integrative lenses for the present research question are the RBV and Dynamic Capabilities Theory because they explain why technological resources require complementary routines and organizational reconfiguration before they affect performance (Barney, 1991; Teece et al., 1997). This choice also aligns with empirical BDA research showing that analytics capabilities create greater value when coupled with strategic alignment, agility, and innovation routines (Akter et al., 2016; Mikalef et al., 2019; Shuradze et al., 2018; Wamba et al., 2017).

4.3 Thematic synthesis

Theme	Representative constructs	Synthesized interpretation	Illustrative literature
1. BDA and data capability	Data integration, quality, analytical infrastructure, analytical talent, strategic alignment	BDA creates the decision-information foundation; performance depends on the organizational ability to convert data into usable market knowledge.	(Akter et al., 2016; Akter et al., 2021; Bajrami et al., 2025; Gupta & George, 2016; Brewis et al., 2023)
2. AI-enabled marketing mechanisms	Prediction, automation, recommendation, NLP/sentiment analysis, personalization	AI extends the data foundation by scaling prediction and action; it complements rather than substitutes for data quality, strategy, and human judgment.	(Davenport et al., 2020; Huang & Rust, 2018; Huang & Rust, 2021)
3. Capability conversion and agility	Customer insight, dynamic capabilities, organizational agility, innovation routines	Value is realized through routines that translate analytical outputs into timely market responses and customer-relevant actions.	(Mikalef et al., 2019; Shuradze et al., 2018; Sultana et al., 2022; Zhang et al., 2025)
4. Digital marketing performance	Engagement, conversion, retention/customer value, market performance, operational efficiency	Outcomes are multidimensional; evidence generally supports positive associations between analytical capability and performance, but magnitudes are context dependent.	(Olabode et al., 2022; Wedel & Kannan, 2016; Kannan & Li, 2017; Zhang et al., 2025)
5. Governance and responsible use	Privacy, transparency, data governance, trust, human oversight	Governance is a boundary condition: data-intensive personalization may create value, while opaque or intrusive practices can undermine trust and performance.	(Martin et al., 2017; Martin & Murphy, 2017; Quach et al., 2022)

Table 2. Main themes identified in the revised synthesis.

4.4 BDA-AI complementarity and digital marketing performance

Across the reviewed literature, BDA and AI are best understood as complementary components of a data-to-action architecture. BDA enables firms to collect, integrate, and analyze heterogeneous data, whereas AI supports pattern recognition, prediction, recommendation, language processing, automation, and adaptive response. In digital marketing, this combination can increase the speed and granularity with which firms understand audiences, allocate resources, personalize interactions, and adjust campaigns (Davenport et al., 2020; Erevelles et al., 2016; Huang & Rust, 2021; Wedel & Kannan, 2016). Recent evidence also links BDA use to improved targeting, customer engagement, and digital-marketing decision quality, although effect sizes remain context dependent (Bajrami et al., 2025).

The pathway from technological capability to performance appears to be indirect rather than automatic. Customer insight and personalization translate analytical outputs into more relevant customer experiences, while organizational agility determines whether firms can act on those insights before market conditions change. Empirical research links analytics capabilities to dynamic capabilities, innovation, and market performance (Mikalef et al., 2019; Olabode et al., 2022; Shuradze et al., 2018; Wamba et al., 2017). Recent evidence on digital marketing and corporate performance similarly highlights an information-capability mechanism between digital activity and firm outcomes (Zhang et al., 2025). It is therefore more rigorous to model customer- and organization-level processes as capability-conversion mechanisms than to assume a direct technology-to-performance effect.

The evidence supports complementarity but does not yet establish a universal super-additive effect. A super-additive claim requires direct evidence that the joint effect of BDA and AI exceeds the effect expected from their separate contributions. Systems-theoretic research demonstrates that digital resources can exhibit interaction effects (Dong & Yang, 2020), but this does not constitute direct proof of a general BDA-by-AI interaction across digital-marketing contexts. The defensible conclusion is therefore narrower: BDA and AI are expected to create greater strategic value when mutually reinforcing and embedded in complementary organizational capabilities, while the magnitude and statistical form of that complementarity remain empirical questions.

Data governance is central to this interpretation. Better data quality and governance improve the reliability and legitimacy of analytics, while privacy failures can offset the benefits of personalization. Research on data privacy demonstrates that customer responses depend not only on data use but also on transparency, control, fairness, and contextual expectations (Martin et al., 2017; Martin & Murphy, 2017; Quach et al., 2022). Thus, responsible governance should be modeled as a boundary condition rather than treated as a peripheral implementation issue.

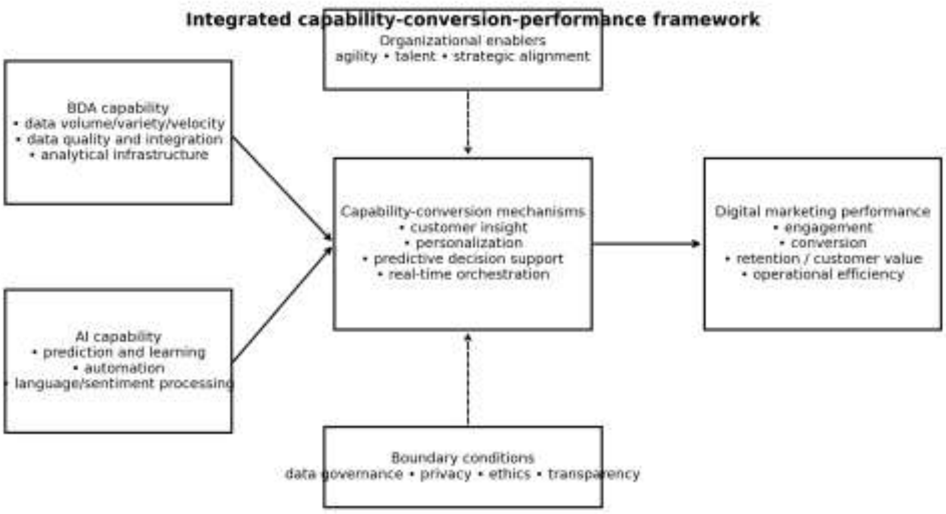

Figure 2. Integrated capability-conversion-performance framework derived from the thematic synthesis.

4.5 Research gaps

First, causal evidence remains weaker than the conceptual confidence often expressed in the literature. Cross-sectional survey designs can establish associations but are poorly suited to identifying how analytics capabilities accumulate, interact, and affect performance over time. Longitudinal, quasi-experimental, field-experimental, and panel designs are therefore important for testing the temporal ordering implied by Dynamic Capabilities Theory.

Second, direct tests of BDA-AI complementarity are scarce. Future studies should operationalize BDA capability and AI capability separately and estimate interaction, complementarity, or configurational effects rather than inferring synergy from the independent significance of each capability. Such designs would allow the super-additive proposition to be evaluated rather than assumed.

Third, many studies rely on perceptual survey outcomes instead of behavioral or platform-level data. Integrating real-time campaign data, customer journeys, clickstream measures, conversion records, and experimental outcomes could reduce common-method bias and strengthen the connection between digital capabilities and observable marketing performance.

Fourth, generalizability remains constrained by uneven sectoral and geographic coverage. SMEs, B2B firms, traditional industries, and underrepresented country contexts require greater attention because resource constraints, data maturity, institutional environments, and customer expectations may alter the value of BDA and AI.

Fifth, responsible AI and data governance require deeper theorization. Privacy, transparency, explainability, fairness, and human-AI collaboration should be integrated into performance models because they can influence trust, adoption, perceived value, and regulatory exposure (Martin & Murphy, 2017; Quach et al., 2022).

5. Discussion

5.1 Theoretical contribution

The primary theoretical contribution is to recast BDA-AI integration as a capability-conversion system. The RBV explains why data assets, analytical infrastructure, AI tools, and human expertise can form a valuable resource bundle, while Dynamic Capabilities Theory explains how that bundle is mobilized through sensing, seizing, and transforming activities (Barney, 1991; Teece et al., 1997). The reviewed evidence implies that the strategic value of BDA and AI resides not in possession of technology but in the organization's ability to integrate data, produce reliable insights, reconfigure marketing actions, and learn from customer responses. This interpretation is consistent with contemporary work on data-driven capabilities and digital transformation (Brewis et al., 2023; Vial, 2019; Verhoef et al., 2021).

The synthesis also clarifies the relationship between technology and customer outcomes. BDA and AI do not generate engagement or conversion by themselves. They alter the quality, speed, and granularity of market knowledge and enable more adaptive personalization or decision support. Customer insight, relevance, perceived value, and engagement are therefore plausible conversion mechanisms between digital capability and performance. This avoids a common conceptual error in technology research: treating adoption or analytical sophistication as equivalent to realized value.

A second theoretical contribution is greater conceptual discipline around synergy. BDA and AI are plausibly complementary because AI depends on reliable, accessible data, while BDA becomes more actionable when advanced algorithms convert data into predictions and decisions. Nevertheless, complementarity, moderation, interaction, and super-additivity are distinct propositions. Demonstrating super-additivity requires explicit comparison of joint and separate effects. Because the reviewed evidence rarely performs such a test, the present synthesis treats super-additivity as a future empirical proposition rather than a settled conclusion.

5.2 Managerial implications

For managers, the review suggests that investment decisions should be organized around an integrated capability stack rather than isolated technology purchases. Data architecture, quality control, analytical talent, AI models, business-process integration, and managerial accountability must reinforce one another. Firms that purchase AI applications without reliable data or decision routines may automate poor-quality information rather than improve marketing performance.

Second, organizations should evaluate BDA-AI initiatives against explicit marketing outcomes. Engagement, conversion, retention, customer value, and operational efficiency represent different objectives and may require different data, models, and governance. A disciplined measurement architecture helps prevent technology adoption from becoming an end in itself (Kannan & Li, 2017; Wedel & Kannan, 2016).

Third, organizational agility matters because the value of prediction deteriorates when firms cannot act. Cross-functional processes connecting analytics, marketing, IT, sales, customer service, and senior management are therefore central to value realization. This implication follows directly from research linking analytics capabilities with agility and dynamic capabilities (Mikalef et al., 2019; Shuradze et al., 2018).

Fourth, privacy and responsible data use should be designed into the system. Governance mechanisms covering consent, access, quality, provenance, retention, transparency, and human oversight can protect customer trust and reduce the risk that personalization becomes intrusive or discriminatory (Martin et al., 2017; Quach et al., 2022).

5.3 Limitations and future research

This review has five main limitations. First, the evidence base is restricted to Scopus. Second, the archived search documentation does not retain the exact search date, complete search string, or publication window, which constrains full reproducibility. Third, a formal study-level quality appraisal and inter-coder reliability statistic were not available. Fourth, the studies are heterogeneous in design, construct operationalization, and performance measurement, precluding defensible statistical pooling. Fifth, direct empirical tests of integrated BDA-AI capability are less common than studies examining BDA or AI separately, so some conclusions rely on theoretically informed triangulation across adjacent streams of literature. These limitations narrow the strength of causal inference but do not negate the value of the systematic thematic synthesis.

Future research should therefore prioritize longitudinal and experimental designs, direct interaction or configurational tests of BDA-AI complementarity, real-time behavioral data, multi-country and cross-industry comparisons, and research on SMEs and B2B settings. Human-AI collaboration is especially important: effective marketing decisions are likely to depend on allocation of tasks between algorithms and human judgment rather than unrestricted automation. Research should also examine how privacy, algorithmic transparency, fairness, and governance interact with customer trust and performance outcomes.

6. Conclusion

This systematic literature review synthesizes a bounded evidence set of 26 Scopus-indexed studies concerning BDA, AI, and digital marketing performance. The findings support a complementary capability perspective: BDA provides the data, integration, and analytical foundation, whereas AI expands organizational capacity for prediction, automation, personalization, and adaptive decision support. Marketing value is realized through conversion mechanisms such as customer insight, relevance, engagement, and organizational agility rather than through technology ownership alone. Data governance, privacy, and responsible use shape the conditions under which this value can be sustained. The review therefore advances an integrated capability-conversion-performance framework grounded in the RBV and Dynamic Capabilities Theory. It also clarifies an important boundary in the evidence: BDA-AI complementarity is theoretically and empirically plausible, but a universal super-additive interaction has not yet been established. Direct tests of complementarity, longitudinal and real-time designs, broader sectoral and geographic coverage, and explicit modeling of human-AI collaboration and responsible governance constitute the most important priorities for future research.

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