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AI-Augmented Business Intelligence for Campaign Performance Optimization in U.S. Retail and e-Commerce: A Mixed-Methods Study of Marketing ROI

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Abstract

This study investigates the growing problem that many U.S. retail and e-commerce firms invest in digital marketing technologies and data systems but still struggle to convert campaign data into consistently optimized performance and stronger marketing return on investment. The purpose of the research was to examine whether AI-augmented business intelligence improves campaign performance optimization and marketing ROI, and to identify which analytical dimensions matter most in practice. The study adopted a quantitative, cross-sectional, case-based design focused on cloud-enabled and enterprise retail and e-commerce campaign environments, using survey evidence from 214 valid professional respondents drawn from campaign managers, BI analysts, e-commerce managers, and digital marketing specialists. The key independent variables were predictive analytics capability, real-time insight capability, customer segmentation intelligence, and decision automation support, while the main dependent variables were campaign performance optimization and marketing ROI. Data were analyzed using descriptive statistics, reliability testing, Pearson correlation, and multiple regression. The findings showed strong measurement quality, with Cronbach's alpha values ranging from 0.77 to 0.88, and high construct means, including AI-augmented BI capability ($M = 4.08$, $SD = 0.61$), campaign performance optimization ($M = 4.14$, $SD = 0.57$), and marketing ROI ($M = 4.02$, $SD = 0.64$). Correlation results indicated that AI-augmented BI was strongly associated with campaign performance optimization ($r = .710$, $p < .001$) and marketing ROI ($r = .640$, $p < .001$), while campaign optimization was also strongly related to ROI ($r = .680$, $p < .001$). Regression analysis revealed that AI-BI dimensions explained 58.4% of the variance in campaign optimization ($R^2 = .584$, $F = 73.48$, $p < .001$), with predictive analytics capability emerging as the strongest predictor ($\beta = .310$, $p < .001$), followed by customer segmentation intelligence ($\beta = .270$, $p < .001$), real-time insight capability ($\beta = .220$, $p = .002$), and decision automation support ($\beta = .140$, $p = .018$). AI-BI and campaign optimization jointly explained 52.1% of the variance in marketing ROI ($R^2 = .521$, $F = 114.06$, $p < .001$). The study implies that firms can improve campaign precision, responsiveness, budget efficiency, and financial returns by strategically embedding AI-enhanced BI into campaign decision processes rather than using BI only for descriptive reporting.

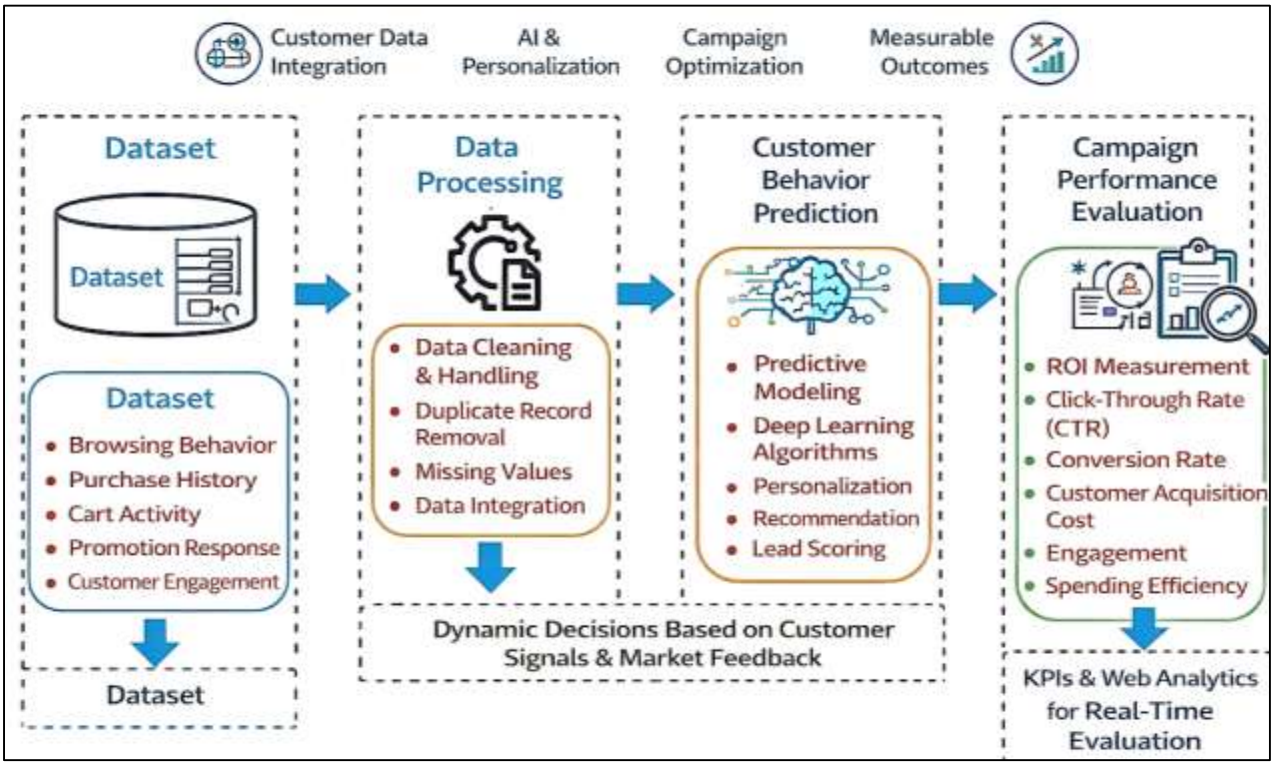
KEYWORDS
Artificial intelligence, Business intelligence, Campaign performance optimization, Marketing ROI, Retail and e-commerce;

INTRODUCTION

Artificial intelligence, business intelligence, marketing analytics, campaign performance optimization, and marketing return on investment are central concepts for understanding contemporary digital commerce at an international level (Cao et al., 2019). Artificial intelligence is generally discussed in marketing as a set of computational capabilities that support perception, prediction, classification, recommendation, automation, and adaptive decision-making within customer-facing and managerial processes. Business intelligence is commonly defined as the architectures, applications, databases, and analytical practices that transform organizational data into actionable information for decision support, performance monitoring, and strategic control (Germann et al., 2013; Hossain et al., 2021). Marketing analytics extends this logic into the marketing domain by applying statistical, econometric, data mining, and optimization techniques to customer, market, and campaign data so that firms can improve segmentation, targeting, pricing, communications, and resource allocation (Aguirre et al., 2015). Campaign performance optimization refers to the continuous adjustment of advertising and promotional activities in order to improve measurable outcomes such as reach, click-through rates, engagement, conversion, customer acquisition, and efficiency of spending (Mikalef et al., 2020). Marketing ROI captures the degree to which marketing expenditures generate economically meaningful returns in the form of revenue, profit, customer value, or other performance outcomes that can be tied to marketing action (Trieu, 2017). These concepts have international significance because retail and e-commerce markets now operate within digitally connected ecosystems in which customer interactions, media exposure, transactions, and service encounters generate large quantities of structured and unstructured data across borders (Hanssens & Pauwels, 2016). Organizations in North America, Europe, Asia, and other major commercial regions increasingly depend on analytical infrastructures to interpret these data flows and support faster responses to shifting consumer behavior, media fragmentation, and platform-based competition. In this environment, AI-augmented business intelligence represents a convergence of algorithmic learning and managerial analytics that situates marketing decisions within a more continuous cycle of sensing, analysis, and action (Verma et al., 2021). The literature has increasingly moved from treating BI as a back-office reporting capability to positioning data-driven intelligence as a strategic mechanism through which firms interpret markets, coordinate decisions, and evaluate outcomes with greater precision (Saura et al., 2017).

The definitional core of business intelligence and analytics becomes especially important when the discussion turns from general data use to campaign-level marketing management. The business intelligence literature has long associated organizational value with the ability to collect data from diverse operational sources, integrate them into usable repositories, and deliver timely analytical output for managerial action (Davenport et al., 2020). The value of BI systems is usually evaluated through improved information quality, decision support, and performance-related outcomes rather than through technology deployment alone. Within the marketing discipline, this logic is refined by the notion of marketing analytics, which is presented as a response to data-rich environments where firms must combine models, metrics, and experiments to understand customers and optimize marketplace actions (Rapp et al., 2010). Marketing analytics is also portrayed as an interdisciplinary field linking expert systems, statistics, data mining, operations research, and marketing science, reinforcing its relevance for complex managerial problems such as digital campaign optimization. This discussion becomes more practically grounded through work emphasizing key performance indicators and web analytics as mechanisms for interpreting online traffic, engagement, and conversion behavior (Saura, 2021). Such work aligns closely with broader discussions of marketing accountability, where organizations are expected to demonstrate how specific activities contribute to observable performance outcomes and justify expenditure through credible metrics (Wedel & Kannan, 2016). These definitional strands matter internationally because digital commerce has reduced the temporal gap between action and measurement: campaigns are launched on programmable media platforms, customer responses are recorded almost immediately, and firms are expected to reallocate attention and budget within compressed decision cycles (France & Ghose, 2019; Ghazanfari et al., 2011). Under these conditions, campaign optimization is better understood as an analytically mediated managerial process in which performance indicators, customer signals, and market feedback are continuously interpreted to guide targeting, timing, content, and spending allocation (Trainor et al., 2014; Zhu et al., 2017). The literature therefore supports a view of campaign optimization as a measurement-intensive domain where business intelligence, analytics, and accountability intersect, with ROI serving as a central outcome because it translates technical marketing performance into language that is meaningful to senior management and resource allocation systems (Trainor et al., 2011).

Figure 1: AI-Augmented Business Intelligence Framework for Campaign Performance Optimization



A second major strand of the literature addresses the place of artificial intelligence within marketing activity and customer management (Erevelles et al., 2016). AI in marketing is not treated merely as automation for routine communication; it is presented as a broad capability set that changes how firms discover patterns in customer data, personalize interactions, score leads, predict outcomes, and support real-time decisions. The significance of AI is often located in its ability to handle large-scale information, produce predictions, and reshape marketing work across segmentation, customer service, media buying, and relationship management (Hossain et al., 2020). It has also been framed strategically by distinguishing intelligence types and managerial tasks, showing that AI can operate across mechanical, thinking, and feeling dimensions in ways that influence service delivery and customer experience design. AI has been discussed more directly in customer relationship management as well, where it is seen as transforming customer acquisition, development, and retention through new forms of learning, personalization, and interaction management (Popovič et al., 2012). Systematic review evidence also shows that the AI-marketing conversation spans recommendation systems, conversational agents, predictive models, consumer insights, and personalized communications, all of which are directly relevant to campaign effectiveness. When these ideas are read together with earlier relationship and marketing technology scholarship, a coherent picture emerges (Morgan et al., 2022). Relational information processes and technology use have been identified as crucial components of effective customer relationship management. E-marketing capability has also been shown to hold clear performance relevance, while social media technology usage has been linked with customer relationship performance through a capability-based logic. Customer-linking capabilities and CRM technology have likewise been shown to operate together in shaping performance outcomes. In campaign settings, these studies collectively indicate that intelligent technologies generate value when embedded in organizational processes that gather customer information, interpret signals, and support coordinated responses (Ferdous Ara, 2021; Ahmed & Hasan Or, 2021; Wieder & Ossimitz, 2015). AI therefore enters the marketing performance discussion as an enhancement layer over preexisting analytical and relational infrastructures rather than as an isolated technical artifact. This framing is especially relevant for retail and e-commerce, where campaign activity is inseparable from customer data, platform signals, and repeated interaction histories that can be analyzed to refine promotional choices and improve observed returns (Aditya & Robel, 2022; Jayachandran et al., 2005; Robel & Md. Morshedul, 2021).

Another important body of research addresses the organizational conditions under which analytics and intelligence capabilities translate into performance. The literature consistently suggests that access to data alone does not guarantee better results; value depends on the firm's ability to mobilize analytical resources, connect insights to action, and adapt routines around evidence (Katsikeas et al., 2016). The deployment of marketing analytics has meaningful performance implications when embedded within organizational systems (Istiaq & Nusrat, 2022; Libai et al., 2020; Khaled & Hisham, 2022). Big data consumer analytics has further been shown to reshape marketing by linking abundant data resources to improved understanding of customer behavior and more informed strategic action. In the broader information systems and marketing interface, marketing analytics has been examined through a dynamic capability lens, showing that analytics supports firm performance when organizations use it to sense and respond to changing market conditions (Mehedi & Md, 2022; Mainuddin & Chandra, 2022; Oberoi et al., 2017). This capability-centered interpretation is reinforced by findings that big data analytics capability contributes to competitive performance through dynamic and operational capabilities and that organizational inertia conditions the process through which analytics is converted into dynamic capability (Huang & Rust, 2021). The BI literature reaches similar conclusions from a decision-quality perspective. Business intelligence systems success has been linked with analytical decision making, and BI has been shown to improve the quality of decision making through mediating mechanisms rather than through system presence alone (Mikalef, van de Wetering, et al., 2021). BI value is realized when intelligence outputs are connected to organizational use and performance outcomes. In campaign management, this reasoning is highly relevant because optimization requires iterative decisions about audience selection, budget allocation, message testing, timing, and channel coordination (Germann et al., 2013; Morshedul et al., 2022; Nazmul & Begum, 2022). Campaign data must be interpreted quickly, and analytical findings must move into operational routines before their value erodes. For this reason, AI-augmented BI can be viewed not simply as a measurement technology but as an organizational capability that combines data assets, analytical models, managerial interpretation, and executional responsiveness (Shahinur & Sultan, 2022; Mikalef et al., 2020; Binte & Md. Hasan Or, 2022). The literature therefore establishes a strong conceptual basis for examining campaign performance optimization through an integrated capability perspective in which BI, AI, analytics, and managerial action are mutually reinforcing rather than analytically separate (Saura et al., 2017).

Retail and e-commerce settings provide a particularly strong empirical context for studying AI-augmented BI because these sectors operate through digitally mediated interactions that leave detailed behavioral traces across browsing, search, cart activity, purchase history, response to promotions, and post-purchase engagement (Begum & Kaniz, 2023; Ara & Beatrice Onyinyechi, 2023; Trieu, 2017). Research in this domain repeatedly shows that customer analytics and personalization capabilities are central to performance. Website personalization and social media marketing in e-retailing have been examined in relation to technology sourcing decisions, showing how firms structure digital personalization efforts in online retail environments. The personalization paradox in online advertising has also been explored, showing that information collection and trust-building strategies affect advertisement effectiveness and that personalization gains are closely tied to how firms manage customer perceptions and data use (Hossain et al., 2020). Privacy calculus in e-commerce personalization services has likewise been examined, with evidence highlighting the role of perceived utility and consumer decision processes in data-driven personalization environments. Customer analytics capability for data-driven retailing has been revisited from the standpoint of retail value creation, with findings indicating that retail value depends on an organization's ability to transform customer data into decisions that support more precise and responsive actions. A value-creation perspective has also shown that customer analytics-driven value creation capability can operate as a path toward sustained advantage (Islam & Aditya, 2023; Jayachandran et al., 2005; Ahmed & Mehedi, 2023). When these studies are read alongside the broader CRM and e-marketing capability literature, their relevance to campaign performance becomes even clearer. Retail and e-commerce campaigns are often executed across multiple channels and rely on the rapid translation of customer signals into targeting rules, personalized messages, and spending adjustments. Social CRM, e-marketing capability, relational information processes, and analytics-based segmentation all converge in these settings because campaign success depends on coordinated use of data, platforms, and customer knowledge (Libai et al., 2020; Hasan Or et al., 2023; Mainuddin & Chandra, 2023). Internationally, this body of work reflects the rise of platform-based retail systems in which marketing activity is increasingly measurable at the level of individual touchpoints. It also shows that campaign optimization in e-commerce is inseparable from data governance, trust, and analytical capability (Rapp et al., 2010). The retail and e-commerce literature therefore provides a strong substantive basis for examining how AI-augmented BI can strengthen campaign performance through personalization, segmentation, responsiveness, and improved interpretation of customer-level data streams (Trieu, 2017).

The measurement side of the literature is equally central because campaign performance optimization is meaningful only when outcomes are assessed through valid, interpretable, and managerially relevant metrics. Key performance indicators and web analytics have been presented as essential mechanisms for evaluating online traffic, user behavior, and campaign effectiveness in digital marketing environments. Data science methods and performance metrics have also been systematized in ways that link technical analytics with business evaluation (Hossain et al., 2020). These developments sit within a larger movement toward data-rich marketing environments where experimentation, attribution, prediction, and customer-level modeling have become central to decision-making. The accountability literature strengthens this point by showing that marketing increasingly needs to demonstrate value in forms accepted by senior leaders and by emphasizing that marketing performance outcomes should be assessed across financial, market, and customer dimensions (Md. Mehedi & Nahar, 2023; Mikalef, van de Wetering, et al., 2021; Mostafa, 2023). Marketing performance assessment and accountability are also shaped by both processes and outcomes, reinforcing the idea that ROI is not a standalone figure but part of a broader evaluative architecture. Within BI and analytics studies, improved decision quality, analytical maturity, and information use are regularly presented as antecedents to stronger performance measurement and resource control. This is especially important in campaign settings, where organizations must interpret multiple indicators at once: impressions may grow while conversion declines, engagement may rise without efficient acquisition, and channel-level gains may not translate into aggregate ROI without coordinated evaluation (Oberoi et al., 2017; Palash Chandra, 2023; Khatun & Zakia, 2023). AI-augmented BI becomes especially salient here because machine learning and advanced analytics can help prioritize variables, identify response patterns, estimate contribution, and detect opportunities for corrective action within ongoing campaigns. In retail and e-commerce, where campaign volumes and customer interactions are high, the relationship between measurement architecture and managerial quality becomes even more visible (Begum &Kaniz, 2024; Katsikeas et al., 2016; Khaled & Morshedul, 2024). The literature therefore establishes that campaign optimization is inseparable from robust performance measurement and that ROI is best understood not as a narrow financial ratio but as an integrative outcome shaped by customer response, campaign efficiency, and organizational accountability practices (Mehedi & Nahar, 2024; Towhidul & Uddin, 2024; Trainor et al., 2014).

Taken together, the literature reveals a strong foundation for studying AI-augmented business intelligence in campaign performance optimization while also showing the need for closer integration of the relevant streams in a focused empirical setting such as U.S. retail and e-commerce. One stream explains BI and analytics as infrastructures for transforming data into decision support and performance monitoring (Mikalef et al., 2020; obel & Morshedul, 2024; Zakia & Khatun, 2024). A second stream explains AI in marketing as a source of prediction, personalization, automation, and customer relationship enhancement. A third stream examines marketing analytics, e-marketing capability, customer analytics, and digital accountability in relation to performance. A fourth stream, rooted in dynamic capabilities thinking, explains why the performance effects of analytics depend on organizational responsiveness, coordination, and reconfiguration of action (Cao et al., 2019). These streams are clearly complementary, yet they are often examined separately or with different focal outcomes. Some studies concentrate on decision quality, some on customer relationship processes, some on website personalization, and others on broad marketing accountability. Campaign performance optimization and marketing ROI in retail and e-commerce require these perspectives to be read together because campaign decisions sit at the intersection of data infrastructure, AI-supported analysis, customer-level interpretation, and measurable market outcomes (Aguirre et al., 2015). The U.S. retail and e-commerce context is especially relevant because firms in this environment operate within advanced digital advertising systems, data-intensive customer journeys, and strong pressure for accountable marketing expenditure (Ghazanfari et al., 2011). An introduction to this study therefore positions AI-augmented BI not as a generic technological topic, but as a concrete organizational and analytical arrangement through which campaign managers can interpret customer data, optimize actions, and evaluate returns under competitive digital conditions (Popovič et al., 2012). This framing aligns the study with established scholarship on BI success, analytics deployment, dynamic capability, customer analytics, personalization, and marketing accountability, while centering the specific research concern of how AI-enhanced intelligence supports campaign performance and ROI in data-rich retail markets.

Background of the Study

The background of this study is rooted in the rapid transformation of marketing practice through digitalization, data abundance, and intelligent decision-support technologies. In the contemporary U.S. retail and e-commerce environment, firms operate in highly competitive markets where customer attention is fragmented across websites, mobile applications, social media platforms, search engines, email channels, and online marketplaces. This environment has made campaign management far more complex than in traditional retail systems because marketers are now expected to make fast, data-informed decisions regarding audience targeting, personalization, timing, channel allocation, budget efficiency, and conversion improvement. As a result, business intelligence has become increasingly important as an organizational capability that helps firms gather, organize, visualize, and interpret large volumes of customer and campaign data for decision-making purposes. At the same time, artificial intelligence has expanded the analytical power of business intelligence by enabling predictive modeling, pattern recognition, automated recommendations, real-time optimization, and more responsive campaign adjustments. The integration of artificial intelligence with business intelligence has therefore created a more advanced form of managerial intelligence that goes beyond routine reporting and supports deeper insight into campaign effectiveness and customer behavior. This development is especially significant in retail and e-commerce, where firms continuously invest in digital promotions and expect measurable returns from every marketing action. Campaign performance is no longer judged only by visibility or traffic generation, but also by engagement quality, conversion success, cost efficiency, customer acquisition value, and overall marketing return on investment. Many firms still struggle to convert data into actionable knowledge that consistently improves these outcomes, which suggests a gap between technology adoption and performance realization. In this context, AI-augmented business intelligence has emerged as a promising solution for strengthening campaign planning, execution, monitoring, and evaluation. The background of this study therefore lies in the need to understand how AI-enhanced analytical systems can support campaign performance optimization and improve marketing ROI within U.S. retail and e-commerce organizations. This issue is academically relevant because it connects technological capability with measurable business outcomes, and it is practically important because firms increasingly require evidence-based approaches to justify marketing expenditure and improve competitive performance.

Problem Statement

The problem addressed in this study arises from the growing gap between the increasing adoption of digital marketing technologies and the persistent difficulty many U.S. retail and e-commerce firms face in achieving consistent campaign performance and satisfactory marketing return on investment. Organizations now generate enormous volumes of customer, behavioral, transactional, and promotional data through online platforms, yet the mere availability of data has not automatically translated into superior campaign decisions or stronger financial outcomes. Many firms continue to rely on fragmented reporting systems, delayed performance reviews, and conventional business intelligence practices that are more descriptive than predictive. In such settings, marketing teams often know what happened after a campaign ends, yet they lack sufficient analytical support to understand why it happened in time to optimize ongoing performance. This challenge becomes even more serious in retail and e-commerce environments where customer behavior changes rapidly, competition is intense, media channels are highly dynamic, and campaign decisions must be made with speed and accuracy. Although artificial intelligence has been increasingly integrated into business intelligence systems to improve forecasting, targeting, segmentation, recommendation, and automation, there remains limited empirical clarity regarding how these AI-augmented BI capabilities actually influence campaign performance optimization and marketing ROI in a measurable organizational context. Many firms invest in dashboards, data platforms, and AI-enabled tools without a clear understanding of which capabilities truly matter for improving conversion outcomes, engagement quality, budget efficiency, and return from promotional spending. As a result, there is a practical and academic need to investigate whether AI-augmented business intelligence meaningfully improves campaign management outcomes or whether technology adoption alone is being mistaken for performance improvement. The core problem, therefore, is not simply the existence of marketing data or analytical tools, but the insufficient evidence on how AI-enhanced BI systems contribute to better campaign optimization and stronger ROI within U.S. retail and e-commerce firms. This study addresses that problem by examining the relationship between AI-augmented BI capabilities, campaign performance optimization, and marketing ROI in a structured and measurable way.

Objectives of the Study

The objective of this study is to examine how AI-augmented business intelligence contributes to campaign performance optimization and marketing return on investment within U.S. retail and e-commerce firms. At a broad level, the study seeks to generate a clearer understanding of how intelligent analytical capabilities can improve the planning, execution, monitoring, and evaluation of digital marketing campaigns in data-rich commercial environments. More specifically, the study is designed to assess whether the integration of artificial intelligence into business intelligence systems enhances the quality of campaign-related decision making by improving predictive accuracy, customer segmentation, real-time responsiveness, and analytical support for marketing managers. Another important objective is to determine the extent to which these capabilities are associated with stronger campaign outcomes such as better targeting precision, improved engagement, higher conversion efficiency, and more effective use of marketing budgets. The study also aims to identify which dimensions of AI-augmented BI are most influential in driving campaign performance so that firms can move beyond broad assumptions about technology value and focus on the capabilities that produce the most meaningful effects. In addition, the research intends to evaluate whether campaign optimization serves as a practical pathway through which AI-enhanced intelligence contributes to stronger marketing ROI. This objective is important because many firms measure digital success through isolated metrics, while the more strategic issue is whether improved analytics actually lead to better financial and operational returns from marketing investments. The study further aims to provide an empirical basis for understanding the role of AI-supported BI in a specific industry setting where the pace of customer interaction, promotional competition, and performance measurement is especially intense. By focusing on U.S. retail and e-commerce, the research seeks to produce findings that are contextually grounded and practically useful for organizations that rely heavily on digitally managed campaigns. Overall, the objectives of the study are centered on explaining relationships among AI-augmented BI, campaign performance optimization, and marketing ROI in a way that strengthens both scholarly understanding and managerial decision-making.

Research Hypotheses

The research hypotheses of this study are formulated to test the assumed relationships between AI-augmented business intelligence, campaign performance optimization, and marketing return on investment in U.S. retail and e-commerce firms. The hypotheses are necessary because the study is quantitative in design and seeks to determine whether the proposed independent and dependent variables are significantly related in a measurable way. The central assumption guiding the study is that AI-augmented BI is not merely a technological addition to existing reporting systems, but a meaningful capability that can improve campaign decisions and outcomes through more intelligent analysis, faster interpretation of market signals, and more precise allocation of marketing effort. On that basis, the first hypothesis proposes that AI-augmented business intelligence has a significant positive effect on campaign performance optimization. This hypothesis reflects the idea that firms using intelligent analytics are better positioned to refine their campaigns and improve measurable outcomes. The second hypothesis proposes that AI-augmented business intelligence has a significant positive effect on marketing ROI, reflecting the expectation that better intelligence should lead to more efficient and effective marketing expenditure. The third hypothesis states that predictive analytics capability significantly improves campaign targeting and conversion outcomes, while the fourth suggests that real-time insight capability significantly improves campaign efficiency and responsiveness. The fifth hypothesis proposes that customer segmentation intelligence significantly improves campaign optimization outcomes, recognizing the importance of identifying and reaching the right customer groups with relevant messages. The sixth hypothesis states that the dimensions of AI-augmented BI jointly and significantly predict marketing ROI, thereby testing the combined explanatory power of the major analytical capabilities examined in the study. These hypotheses provide the analytical structure for statistical testing and ensure that the study moves beyond descriptive observation into empirical verification. They also align the study with its objectives by translating conceptual assumptions into testable statements that can be examined using descriptive statistics, correlation analysis, and regression modeling.

Significance of the Research

The significance of this research can be understood across academic, managerial, methodological, and practical dimensions, because the study addresses an increasingly important issue at the intersection of artificial intelligence, business intelligence, campaign analytics, and financial accountability in digital marketing.

i. Academic significance: This study contributes to the academic literature by expanding understanding of how AI-augmented business intelligence relates to campaign performance optimization and marketing ROI in a specific and commercially relevant context. It brings together concepts that are often discussed separately and places them within a unified empirical framework.

ii. Theoretical significance: The study strengthens theory-based understanding of how intelligent analytical capabilities function within organizations by linking technological capability to measurable marketing outcomes. It supports a more structured explanation of how data-driven sensing, analysis, and action contribute to improved campaign decision-making.

iii. Managerial significance: The findings of this research will be useful to marketing managers, BI specialists, campaign strategists, and e-commerce decision-makers who need stronger evidence on how intelligent analytics can improve promotional effectiveness. The study can help managers understand which capabilities deserve greater attention and investment.

iv. Strategic significance: This research is significant for firms seeking to improve competitive performance in data-intensive markets. By showing how AI-enhanced BI can support better targeting, responsiveness, and resource allocation, the study provides a basis for more strategic marketing planning and performance control.

v. Methodological significance: The study is significant because it applies a quantitative, cross-sectional, case-study–based design to a topic that is often discussed in broad conceptual terms. Through the use of Likert-scale measurement, descriptive statistics, correlation analysis, and regression modeling, it offers a structured way of testing important relationships within campaign analytics research.

vi. Practical significance for retail and e-commerce firms: U.S. retail and e-commerce organizations operate under strong pressure to justify marketing spending with measurable outcomes. This study is significant because it focuses on a real-world business problem and offers evidence that can support more effective campaign monitoring, optimization, and ROI assessment.

vii. Policy and investment significance: The study may also assist organizational leaders in making informed decisions about digital transformation, analytics infrastructure, and AI-related investments. It provides insight into whether advanced BI capabilities create value at the campaign level, which is important for resource prioritization and organizational planning.

viii. Significance for future scholarship: This research establishes a useful empirical foundation for later studies on digital marketing performance, AI-enabled analytics, retail intelligence systems, and marketing accountability. It helps define variables, relationships, and measurement directions that other researchers can adapt in related contexts.

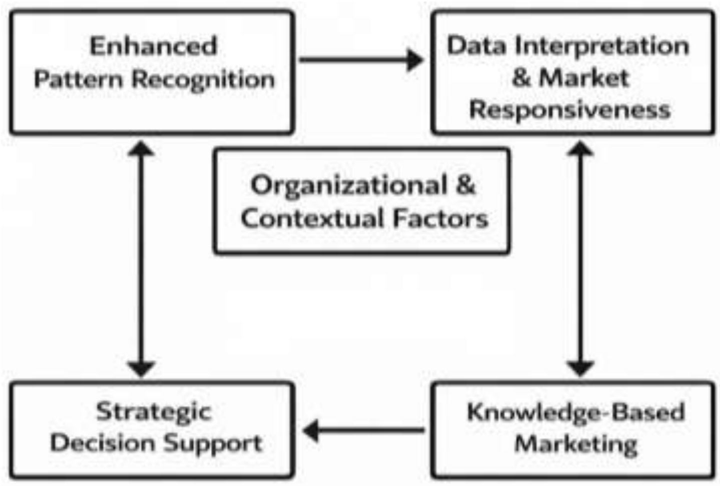
LITERATURE REVIEW

The literature review for this study provides the scholarly foundation for understanding how artificial intelligence, business intelligence, campaign performance optimization, and marketing return on investment are conceptually and empirically connected within the context of U.S. retail and e-commerce. In contemporary research, digital marketing performance is increasingly examined through the lens of data-driven decision-making, where firms rely on analytical systems to interpret customer behavior, evaluate campaign effectiveness, and allocate marketing resources more efficiently. Business intelligence has emerged in this discussion as a vital organizational capability that supports data collection, integration, reporting, and managerial interpretation, while artificial intelligence has extended this capability by enabling prediction, automation, pattern recognition, and faster analytical response. The interaction between these two domains has led to growing academic interest in AI-augmented business intelligence as a more advanced mechanism for supporting marketing strategy and performance control. At the same time, the literature on campaign performance highlights the importance of measurable outcomes such as targeting accuracy, engagement, conversion, and budget efficiency, all of which are especially important in retail and e-commerce environments where digital interactions generate continuous streams of customer and transactional data. The review also engages with the broader marketing analytics literature, which explains how statistical models, data mining techniques, dashboard systems, and performance metrics contribute to evidence-based campaign management. In addition, existing scholarship on marketing accountability and ROI provides an important basis for understanding why campaign optimization must be linked not only to operational indicators but also to financial returns and value creation. A well-structured literature review is therefore necessary for this study because it helps clarify the major constructs, explains how previous studies have approached similar issues, identifies the theoretical basis supporting the research, and reveals the empirical gap that justifies the present investigation. It also allows the study to position itself within established academic debates on analytics capability, intelligent marketing systems, customer data utilization, and competitive performance. By reviewing the most relevant theoretical, conceptual, and empirical works, this section establishes the intellectual context for examining whether AI-augmented BI significantly improves campaign performance optimization and marketing ROI. The literature review thus serves not only as a summary of prior scholarship but also as a framework for organizing the study variables, guiding hypothesis development, and strengthening the analytical direction of the research.

AI in Marketing Analytics and Decision-Making

Artificial intelligence has become a central analytical layer in modern marketing because it changes how firms convert data into decisions, especially when markets generate large and fast-moving streams of behavioral information. Earlier work on marketing intelligent systems already pointed toward this shift by arguing that marketing decision support should move beyond conventional database reporting toward knowledge discovery approaches capable of extracting interpretable patterns from complex consumer data. In that line, Martínez-López and Casillas showed that intelligent systems based on knowledge discovery and soft computing could strengthen marketing modeling by improving the extraction of useful relationships from large datasets and translating them into managerially relevant decision support (Martínez-López & Casillas, 2009). That contribution is important for the present study because it places intelligence not at the margins of marketing analysis, but at the core of how organizations understand market behavior and guide action. More recent literature extends the same logic by locating machine learning and artificial intelligence within the broader redesign of commercial decision processes. Syam and Sharma explain that AI expands the range of tasks that can be supported or partially executed by computational systems, especially in situations where large customer datasets, pattern detection, and rapid decision cycles are involved. Their discussion of sales practice is highly transferable to digital marketing, where campaign planning, message adjustment, and customer prioritization require continuous interpretation of data signals. Read together, these studies suggest that AI in marketing analytics is not simply a technical upgrade to existing tools. It represents a structural change in the logic of decision-making itself, because it allows firms to move from retrospective interpretation toward increasingly adaptive and data-responsive management. For a study on AI-augmented business intelligence, this matters because campaign optimization depends on the firm's capacity to identify patterns quickly, connect them to managerial judgment, and convert insights into timely marketing action. In that sense, AI-enabled analytics supports not only efficiency, but also a more intelligence-driven form of market responsiveness that is especially valuable in digital retail and e-commerce environments where customer behavior evolves continuously and measurable outcomes are visible at high frequency (Grewal et al., 2020).

Figure 2: Ai-Driven Marketing Analytics Framework for Data Interpretation and Strategic Decision-Making



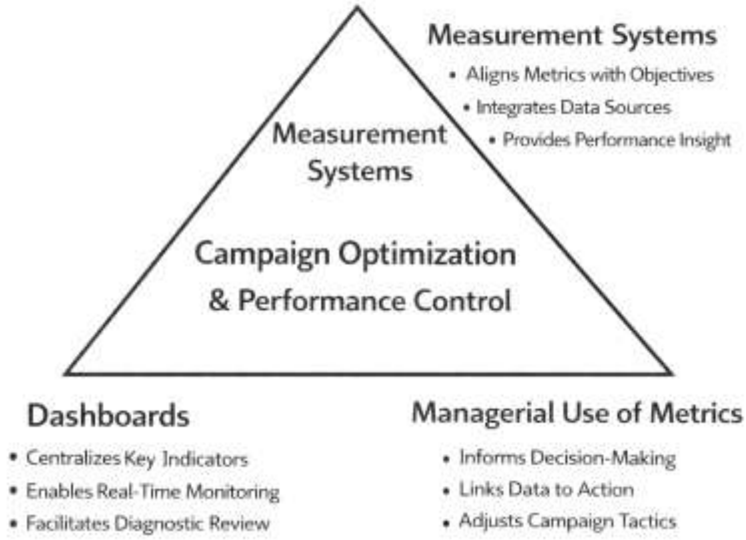
A second important dimension of the literature explains that AI in marketing analytics should be understood as part of a broader technological transformation affecting firm strategy, customer interaction, and organizational learning. Grewal et al. describe technology-driven marketing as a multidisciplinary domain in which advances in analytics, digital infrastructures, and intelligent systems are reshaping how value is created, communicated, and delivered. Their contribution is useful because it frames AI not as an isolated application, but as one element within a larger technology ecosystem that changes both firm behavior and customer-facing processes (Kopalle et al., 2022). This perspective is especially relevant to campaign performance research because digital campaigns are embedded within wider technological environments involving platforms, algorithms, automation tools, and customer data architectures. Paschen et al. complement this view by focusing more specifically on AI and market knowledge. They argue that AI contributes to knowledge-based marketing by helping firms process, organize, and use information in ways that strengthen understanding of customers and market conditions. This point is highly relevant for campaign management because optimization depends on the quality of market knowledge available to decision-makers. A campaign can only be refined effectively when the underlying system can identify meaningful customer signals, distinguish patterns from noise, and support practical interpretation. Together, these studies indicate that the significance of AI lies not only in automation, but also in knowledge enhancement. Marketing analytics becomes more valuable when it does more than summarize performance indicators and instead helps firms understand why certain outcomes occur and where adjustments are needed. In retail and e-commerce settings, this is particularly important because managers must often decide quickly which audiences to prioritize, which channels deserve additional budget, and which campaign elements should be revised. AI expands the analytical depth of these decisions by linking data abundance with interpretive capability, thereby making analytics more actionable and strategically useful. As a result, AI in marketing decision-making is best viewed as a capability that deepens market knowledge, improves the quality of analytical reasoning, and strengthens managerial control over performance-oriented marketing processes (Paschen et al., 2019).

The more recent literature also emphasizes that AI in marketing analytics must be examined across organizational and contextual levels rather than only at the tool level. Kopalle et al. provide one of the clearest frameworks for doing this by analyzing AI in marketing through country-level, company-level, and consumer-level lenses. Their argument is important because it shows that AI adoption and usefulness are shaped by resource conditions, organizational adaptation, and consumer-facing concerns such as privacy and ethics (Martínez-López & Casillas, 2009). This multidimensional framing is valuable for the current research because U.S. retail and e-commerce firms do not use AI in a vacuum; they deploy it within competitive digital ecosystems where campaign decisions are constrained by platform rules, consumer expectations, data availability, and organizational capability. The company-level dimension is especially relevant, since it highlights that AI value depends on how firms apply and localize intelligent technologies in practice rather than on the existence of the technology itself. The consumer-level dimension is equally significant because campaign optimization increasingly relies on customer data interpretation, personalization, and automated analysis of text, images, and interaction patterns. These analytical activities can improve marketing precision, yet they also require careful management of trust, legitimacy, and responsible data use. For the literature on AI in marketing analytics and decision-making, the key takeaway is that intelligent systems strengthen campaign management when they are embedded within organizational processes that can absorb and apply analytical output in a disciplined way. This means that effective AI-augmented BI is not reducible to software adoption; it depends on how firms organize data, define decision rules, interpret model outputs, and translate insights into campaign adjustments. In a study concerned with campaign performance optimization and marketing ROI, this perspective is especially useful because it links AI capability with concrete managerial outcomes while keeping attention on the real conditions under which analytics is deployed. The literature therefore supports treating AI as a layered marketing capability that improves analytical breadth, decision quality, and responsiveness, while also introducing organizational and consumer-facing conditions that shape the success of its application in digital commerce (Syam & Sharma, 2018).

Business Intelligence for Campaign Performance Management

Business intelligence has become an important foundation for campaign performance management because it enables organizations to transform dispersed marketing data into structured information for planning, monitoring, and control. In campaign environments, managers deal with multiple signals at the same time, including audience reach, response rates, conversions, channel costs, engagement metrics, and sales effects. Without a business intelligence structure, these indicators often remain disconnected, making it difficult for decision-makers to identify which campaign actions are producing value and which require correction. The literature on marketing performance measurement has shown that firms create greater value when they possess the ability to measure marketing outcomes in a disciplined and credible way. This insight is essential for campaign performance management because digital campaigns are accountable to both operational and financial standards. A campaign may appear successful in terms of visibility or customer interaction, yet still underperform when measured against cost efficiency or strategic contribution. The importance of measurement ability is captured clearly in research showing that firms with stronger marketing performance measurement ability achieve stronger business outcomes and greater organizational confidence in marketing's role (O'Sullivan & Abela, 2007). This means that performance management begins not only with access to data but also with the institutional capacity to define, collect, interpret, and communicate relevant indicators. Business intelligence contributes to this capacity by creating a systematic process for integrating data sources, presenting metrics in usable form, and linking observed campaign outcomes to managerial action. In the context of campaign performance, BI therefore serves as more than a reporting mechanism. It acts as a managerial infrastructure through which campaign results become visible, comparable, and actionable. This is especially important in retail and e-commerce settings where campaign decisions are recurrent and often need to be adjusted while market responses are still unfolding. Business intelligence supports such environments by reducing fragmentation in marketing information and by strengthening the organization's ability to evaluate campaign activity against performance objectives in a timely and operationally relevant manner ((O'Sullivan & Abela, 2007).

Figure 3: Business Intelligence Framework for Campaign Performance Management



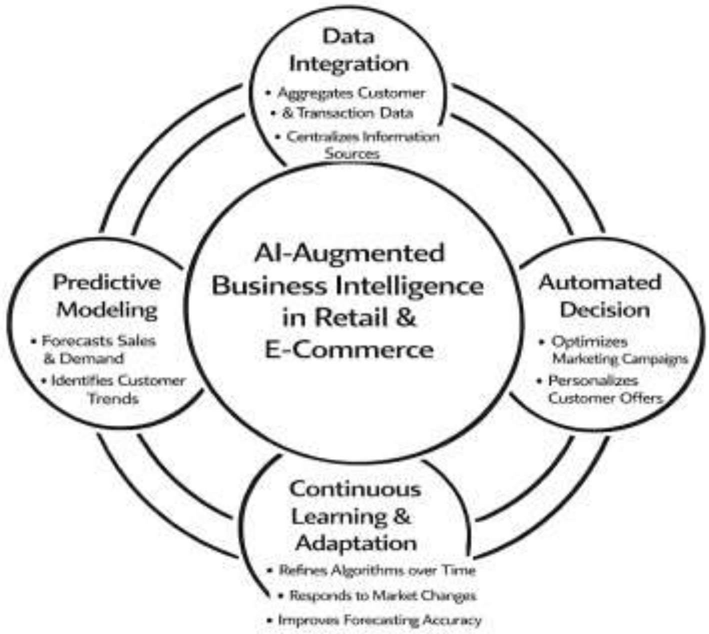
A more specific strand of the literature explains that dashboards and performance measurement systems are central mechanisms through which business intelligence supports campaign performance management. Dashboards bring together key indicators in a single interface and help managers monitor whether campaign activities are moving in the intended direction. Their value lies in synthesis, visibility, and the ability to connect short-term performance indicators with broader managerial objectives. Research on marketing dashboards has emphasized that they should not be understood simply as visual displays of data. Rather, they are structured systems that organize key metrics, connect them to performance drivers, and support managerial interpretation across time horizons and organizational levels (Pauwels et al., 2009). This perspective is highly relevant for campaign management, where marketers must balance immediate indicators such as clicks, impressions, and cost per acquisition with broader concerns such as customer retention, revenue contribution, and return on investment. In a similar vein, broader dashboard research has argued that dashboards can alleviate information overload by integrating data from multiple sources and presenting it in a format that supports decision-making and performance monitoring (Yigitbasioglu & Velcu, 2012). This is particularly useful in campaign environments because managers are frequently overwhelmed by the volume and velocity of digital marketing data. The challenge is not simply to access more information, but to identify which information matters most and how it should guide action. BI-enabled dashboards provide a practical solution by making campaign performance visible in a way that supports both monitoring and diagnosis. They allow managers to notice deviations, compare outcomes across channels or audience segments, and drill down into possible causes of performance change. As a result, dashboards strengthen campaign performance management by making analytical review more continuous and less dependent on fragmented reports or delayed evaluation cycles. The literature therefore supports the view that business intelligence becomes strategically meaningful for campaign management when it is translated into dashboard and measurement systems that help firms align metrics, managerial interpretation, and corrective action within an integrated performance control process (Pauwels et al., 2009).

The literature also shows that the value of business intelligence for campaign performance management depends on how comprehensively and actively metrics are used in managerial decision-making. Measurement systems can include many indicators, yet the mere presence of a large set of metrics does not automatically improve campaign outcomes. What matters is whether the system is designed in a way that supports appropriate interpretation and managerial use. Research on marketing performance measurement systems has demonstrated that comprehensiveness can improve performance when it is matched to organizational needs and used in a way that enhances decision quality rather than creating confusion (Homburg et al., 2012). This insight is very important for campaign performance management, where managers must often evaluate multiple dimensions of effectiveness at once, including market response, financial efficiency, and strategic alignment. Campaigns are rarely judged by a single metric, and BI systems are most useful when they support a balanced and coherent assessment of performance. The issue of actual managerial use is addressed further by research showing that the use of marketing and financial metrics is shaped by strategy, organizational characteristics, and managerial orientation, and that such metric use is associated with better performance of marketing-mix activities (Mintz & Currim, 2013). This means that BI contributes to campaign management not simply by producing measures but by encouraging disciplined use of those measures in budget allocation, channel evaluation, and optimization decisions. Related evidence also indicates that marketing dashboards can interact with organizational capabilities in ways that improve sensemaking and performance outcomes. In particular, dashboards have been shown to work jointly with sales capabilities to enhance organizational interpretation and improve both customer relationship outcomes and cost-related control (Krush et al., 2013). This finding is significant for campaign research because campaign performance management is fundamentally a sensemaking task: managers must interpret patterns, judge significance, and decide where to intervene. Business intelligence supports this process when it helps organizations connect metrics with action, and when it becomes embedded in performance management routines rather than remaining a passive reporting technology. The literature therefore indicates that BI for campaign performance management is most effective when it combines measurement breadth, disciplined metric use, and decision-oriented interpretation within an integrated managerial system.

AI-Augmented Business Intelligence in Retail and E-Commerce

AI-augmented business intelligence in retail and e-commerce can be understood as the integration of traditional data management, reporting, and dashboard functions with machine learning, predictive modeling, recommendation logic, and automated decision support. In retail settings, this integration is valuable because the core managerial problem is no longer simple data availability but the ability to convert high-volume, high-velocity customer and transaction data into timely commercial action. Retailers and e-commerce firms must interpret browsing behavior, search patterns, purchase histories, basket composition, returns, inventory availability, and promotional responses in ways that support targeting, personalization, assortment adjustment, and campaign optimization. Recent retail research shows that AI creates value when it is embedded in data-centric and solution-centric business processes rather than treated as an isolated technical add-on (Albert, 2025; Ishtiaque & Rajib, 2025; Pereira et al., 2022). A grounded theory study of 54 retail AI implementations demonstrates that retailers use AI not only to automate customer-facing functions but also to improve data management, business process coordination, and value creation logic across multiple operational domains (Kazi Rakib Hasan, 2025; Md. Ashfaq & Ashraful, 2025). This is directly relevant to business intelligence because it suggests that AI enhances retail intelligence by extending the analytical reach of reporting systems into prediction, personalization, and adaptive action. In e-commerce contexts, the same argument becomes even stronger because product exposure, clicks, carts, and purchases are already digitally traceable, making them highly suitable for intelligent analysis. Research on e-commerce decision support shows that recommender systems have evolved precisely to help consumers and firms navigate complex choice environments, while more recent AI-enabled customer models are being designed to inform decisions throughout online retail supply chains. In fashion e-commerce, for example, AI-based customer modeling has been presented as a means of improving personalization and decision support in retail supply chains, indicating that intelligence systems are increasingly expected to inform not just one transaction but a wider set of commercial decisions. As a result, AI-augmented BI in retail and e-commerce should be viewed as an architecture of sensing, interpretation, and response in which dashboards, data repositories, predictive models, and recommendation engines work together to support more informed and more commercially relevant marketing and merchandising decisions (Cao, 2021).

Figure 4: Ai-Augmented Business Intelligence in Retail and E-Commerce



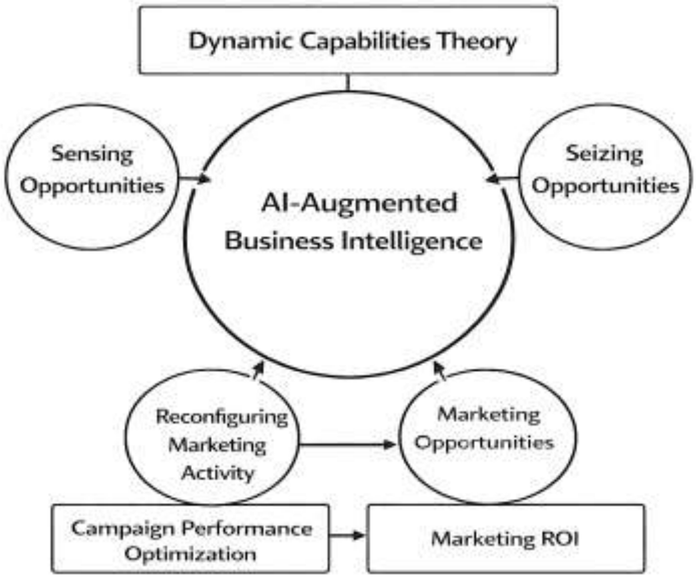
A second important feature of AI-augmented BI in retail and e-commerce is its ability to strengthen anticipation and responsiveness in environments characterized by short product life cycles, shifting customer preferences, and rapid market feedback. Traditional BI systems are often effective at summarizing what has happened, but retail and e-commerce managers frequently need more than retrospective visibility. They need estimates of what is likely to happen next, which products are likely to perform, which customers are likely to respond, and which interventions should be prioritized while a campaign or selling season is still active. Evidence from fashion retail demonstrates the practical significance of this shift. Deep neural network approaches have been used to forecast sales of new products in fashion retail, with the aim of supporting purchasing decisions under conditions where historical data are limited and product novelty is high (Cai & Lo, 2020; Robel, 2025; Murad, 2025). This matters for AI-augmented BI because forecasting is one of the clearest examples of intelligence enhancement: the system does not merely show current performance but helps the firm prepare for future demand and allocate resources with greater confidence. The same logic extends to campaign management in e-commerce, where demand signals, recommendation performance, and product exposure metrics can be interpreted through AI-enhanced analytical systems to support faster optimization. Omnichannel retail research further reinforces this point by showing that modern retailing is shaped by digitalization, big data, and emerging technologies such as AI, all of which increase the need for integrated decision-making across online and offline touchpoints. In such environments, campaign performance cannot be optimized effectively if intelligence remains fragmented by channel or function. AI-augmented BI is therefore valuable because it can connect customer-level data, channel-level data, and operational performance data into a more unified view of retail action. For marketing decision-makers, this means better support for budget timing, message targeting, product promotion, and promotional coordination across touchpoints. The essential contribution of AI is that it increases the interpretive and anticipatory power of BI, allowing firms to move from descriptive monitoring toward more dynamic commercial decision support in complex retail and e-commerce ecosystems (Loureiro et al., 2018).

The organizational relevance of AI-augmented BI becomes most visible when attention turns from individual tools to firm-level capability and performance. Retailers may implement recommendation systems, forecasting models, or personalization engines, yet their business value depends on how well these tools are assimilated into broader processes of coordination, customer responsiveness, and managerial control. Evidence on AI assimilation shows that firm performance gains are not produced by AI presence alone; they emerge when AI is embedded into organizational routines in ways that improve agility and customer responsiveness. A U.S.-based study on AI assimilation found that organizational agility and customer agility partially mediate the relationship between AI assimilation and firm performance, indicating that AI creates business value when firms internalize it as a workable capability rather than merely adopting isolated applications (Scholz et al., 2017). This insight is highly relevant to retail and e-commerce because campaign optimization depends on repeated cycles of sensing, interpretation, and adjustment. If AI outputs are not incorporated into merchandising, marketing, service, and channel coordination routines, their value for business intelligence remains limited. In this sense, AI-augmented BI should be treated as a capability bundle that joins data infrastructure, analytical models, managerial interpretation, and executional responsiveness. Retail studies support this interpretation by showing that AI applications create value through customer-centric and process-centric pathways, while e-commerce decision-support studies demonstrate that intelligent recommendation and customer modeling systems can reduce information overload and improve decision quality. Together, these findings indicate that AI-augmented BI is particularly relevant for retail and e-commerce because these sectors face unusually intense demands for personalization, speed, and measurable performance. The more firms can integrate AI into their BI environments, the more likely they are to convert data into targeted decisions about promotions, assortment, demand forecasting, customer engagement, and campaign spending efficiency. For the present study, this literature provides a clear foundation for examining AI-augmented BI as a performance-oriented capability rather than a generic technology label. It suggests that the real analytical question is not whether AI exists in retail systems, but how its integration into BI changes the quality, speed, and commercial value of campaign-related decision-making in digital commerce settings (Bag et al., 2022).

Theoretical Framework: Dynamic Capabilities Theory

Dynamic Capabilities Theory provides the most suitable theoretical foundation for this study because it explains how firms purposefully renew, recombine, and reconfigure resources in response to changing market conditions rather than relying only on static assets or routine operational strength. Teece's formulation is especially relevant because it identifies three core capability clusters—sensing opportunities and threats, seizing opportunities through investments and decisions, and reconfiguring organizational assets to sustain performance—which closely match the logic of AI-augmented business intelligence in campaign environments. In U.S. retail and e-commerce, campaign optimization is not a one-time analytical exercise; it is a repeated managerial process in which firms must detect shifts in customer behavior, interpret campaign signals, adjust segmentation and targeting choices, and realign budgets or content before market opportunities disappear. From this perspective, AI-augmented BI can be theorized as an enabling mechanism that strengthens sensing by improving the identification of patterns in customer and campaign data, strengthens seizing by supporting faster and more informed marketing decisions, and strengthens reconfiguring by helping managers revise campaigns, channels, and resource allocations in real time. The theory therefore fits this research because it moves the discussion beyond technology possession and toward capability deployment. Dynamic capabilities are not equivalent to dashboards, algorithms, or reports; they refer to the firm's higher-order ability to use those tools to create and renew value under changing conditions. This makes the framework particularly useful for distinguishing between simple data reporting and intelligence-driven campaign adaptation. In this study, AI-augmented BI is therefore viewed as a capability-building infrastructure, campaign performance optimization is treated as the operational expression of sensing, seizing, and reconfiguring in marketing activity, and marketing ROI is treated as the higher-level performance consequence of that capability use. The theory is appropriate because it explains not only why intelligent systems matter, but also how they matter: they matter when they allow the organization to detect meaningful variation, act on insights with speed and precision, and continually realign marketing action with shifting customer and competitive conditions (Moreno et al., 2020; Teece, 2007).

Figure 5: Dynamic Capabilities Framework for Ai-Augmented Business Intelligence



The usefulness of Dynamic Capabilities Theory is strengthened by later scholarship showing that marketing-related capabilities are themselves dynamic when they support the absorption of market knowledge, rapid interpretation of environmental signals, and adaptation of commercial action. Barrales-Molina, Martínez-López, and Gázquez-Abad argue that dynamic marketing capabilities should be understood as integrative mechanisms through which firms absorb and manage market knowledge in changing environments, an idea that directly supports the current study's focus on campaign intelligence. Their framework is relevant because campaign performance depends heavily on how well a firm transforms market information into actionable targeting, timing, personalization, and budget decisions. A campaign may have access to extensive data, yet without dynamic marketing capabilities the firm may fail to interpret that data in a way that improves outcomes. This insight aligns closely with the present study, where AI-augmented BI is expected to strengthen the firm's capacity to absorb market knowledge and convert it into campaign optimization decisions. Additional support comes from research showing that BI and analytics resources generate business value through dynamic capabilities rather than through direct technical effects alone. Moreno, Cavazotte, and de Souza Carvalho found that dynamic capabilities fully mediated the positive effect of BI and analytics resources on marketing capabilities in a turbulent context, which is highly relevant to this research because it suggests that business intelligence becomes strategically meaningful when it is translated into adaptive organizational capability. That finding offers a strong theoretical bridge for the present model: AI-augmented BI should not be expected to improve marketing ROI merely because it exists, but because it helps firms develop better capabilities for interpreting campaign conditions and adjusting action. Accordingly, Dynamic Capabilities Theory clarifies the causal logic of this study by positioning AI-augmented BI as an antecedent capability resource, campaign performance optimization as the practical manifestation of dynamic capability in marketing action, and marketing ROI as the resulting performance outcome once intelligence is converted into effective campaign adaptation and control (Barrales-Molina et al., 2014).

The theory also supports the analytical model that will be applied in the empirical part of the study. Research on AI as an enabler of marketing operations has shown that AI can support the microfoundations of sensing, seizing, and transforming by improving how organizations discover patterns, evaluate alternatives, and modify actions in uncertain environments (Wilden et al., 2013). Mikalef, Conboy, and Krogstie identify AI-specific microfoundations of dynamic capabilities and show that value realization depends on how AI is embedded into organizational processes rather than treated as a standalone technology. This insight is especially important for a quantitative study of campaign performance because it justifies modeling campaign outcomes as the result of organizationally deployed intelligence capabilities. Guided by Dynamic Capabilities Theory, the main empirical relationship in this research can therefore be specified through a multiple regression structure in which campaign performance optimization is a function of core AI-augmented BI dimensions:

$$\mathrm{CPO} = \beta_0 + \beta_1\mathrm{PA} + \beta_2\mathrm{RTI} + \beta_3\mathrm{CSI} + \beta_4\mathrm{DAS} + \varepsilon$$

where CPO represents campaign performance optimization, PA represents predictive analytics capability, RTI represents real-time insight capability, CSI represents customer segmentation intelligence, and DAS represents decision automation support. A second model can then be used to evaluate the performance consequence predicted by the theory:

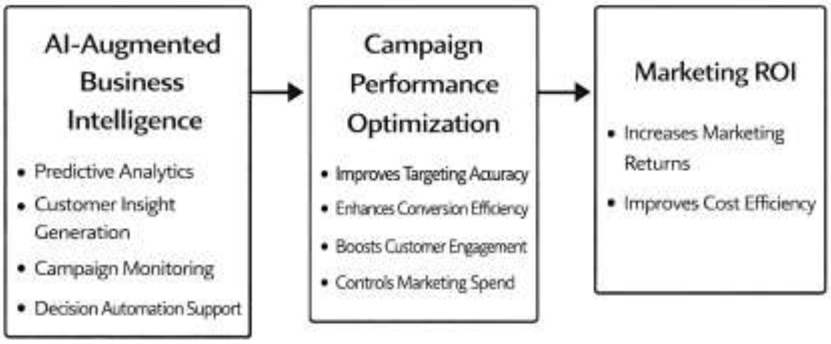
$$\mathrm{ROI} = \beta_0 + \beta_1\mathrm{CPO} + \beta_2\mathrm{AIBI} + \varepsilon$$

where ROI represents marketing return on investment and AIBI represents the overall AI-augmented BI capability index. These equations fit the theoretical framework because they operationalize sensing, seizing, and reconfiguring as measurable marketing capabilities that influence campaign outcomes and financial returns. Dynamic Capabilities Theory is therefore not only conceptually suitable for the study, but also methodologically useful because it provides a coherent logic for variable selection, hypothesis development, and model specification across the entire research design (Mikalef, Conboy, et al., 2021).

Conceptual Framework

The conceptual framework of this study explains how AI-augmented business intelligence is expected to influence campaign performance optimization and, through that route, improve marketing ROI in U.S. retail and e-commerce firms. The framework is built on the idea that organizational performance does not improve simply because firms possess data, software, or reporting systems; performance improves when firms convert market information into targeted, measurable, and integrated marketing action. Recent evidence on digital marketing capabilities shows that firms gain stronger profitability outcomes when they develop capabilities that allow them to use digital technologies in coordinated, customer-facing, and performance-oriented ways, rather than relying only on traditional marketing routines. This is important for the present study because campaign optimization depends on exactly that kind of capability: the firm must be able to interpret data signals, connect them to customer behavior, and act quickly through campaign design, targeting, personalization, and budget allocation. Related work on AI focus and firm performance also strengthens this reasoning by showing that firms emphasizing AI are associated with improvements in operating efficiency, profitability, and return on marketing-related investment (Homburg & Wielgos, 2022). That finding is especially relevant because it suggests that AI is not merely an automation tool; it can become a performance-linked strategic orientation when it is embedded into decision processes. The BI and analytics literature provides the other side of the framework by showing that BI&A use supports higher-order organizational benefits when it is connected to absorptive and adaptive mechanisms, rather than being treated as a standalone technical asset. In addition, work on market orientation and marketing capability shows that knowledge-based market responsiveness and marketing execution jointly enhance performance outcomes, while absorptive capacity strengthens the organization's ability to extract value from market intelligence. Taken together, these studies justify a conceptual structure in which AI-augmented BI serves as the independent construct, campaign performance optimization serves as the intervening performance process, and marketing ROI serves as the ultimate dependent outcome. This sequencing is conceptually appropriate because it mirrors how digital campaign value is created in practice: firms first build analytical capability, then improve campaign execution, and then realize financial marketing returns (Božič & Dimovski, 2019).

Figure 6: Ai-Augmented Business Intelligence and Campaign Performance Framework



Within this framework, AI-augmented business intelligence is conceptualized as a multidimensional construct composed of the firm's ability to use data and intelligent systems for predictive analysis, customer insight generation, campaign monitoring, and decision support. The earlier empirical literature suggests that value arises when firms combine information use with market-facing capabilities and absorptive mechanisms that help managers interpret and apply insight. In practical terms, this means the construct can be represented through dimensions such as predictive analytics capability, real-time insight capability, customer segmentation intelligence, and decision automation support, because these dimensions capture how intelligence is translated into campaign action. Campaign performance optimization is then positioned as the immediate dependent effect of those capabilities. It reflects measurable improvements in campaign targeting accuracy, conversion efficiency, customer engagement quality, timing responsiveness, and marketing spend control. This placement is consistent with evidence showing that digital marketing capabilities contribute to profitability only when they shape how firms interact with customers in targeted and measurable ways, and with evidence showing that AI-related emphasis contributes to operating efficiency and return on marketing-related investment (Najafi-Tavani et al., 2016). The framework therefore assumes that AI-augmented BI has both a direct effect on campaign optimization and an indirect effect on ROI through better campaign execution. The conceptual logic can be expressed through the first study equation:

$$\mathrm{CPO} = \beta_0 + \beta_1\mathrm{PA} + \beta_2\mathrm{RTI} + \beta_3\mathrm{CSI} + \beta_4\mathrm{DAS} + \varepsilon$$

where CPO = campaign performance optimization, PA = predictive analytics capability, RTI = real-time insight capability, CSI = customer segmentation intelligence, and DAS = decision automation support. This is the most suitable formula for the whole study because it converts the core AI-BI dimensions into a single explanatory model for campaign-level outcomes, which can then be tested using multiple regression. It also aligns closely with prior research that links analytics use, market intelligence, and digital capability to measurable organizational performance through intermediate capability mechanisms rather than isolated technical effects (Mishra et al., 2022).

The final part of the conceptual framework links campaign performance optimization to marketing ROI, which is treated as the principal outcome variable of the study. This step is necessary because campaign performance metrics and financial marketing returns are related but not identical. A campaign may improve clicks, traffic, or engagement without producing a satisfactory return unless those gains are translated into efficient customer acquisition, conversion value, and profitable spend allocation. The literature reviewed here supports that distinction. Studies on AI focus show links with return on marketing-related investment and operating efficiency, while studies on BI&A use show that organizational performance gains emerge when analytics is absorbed into firm capabilities and then converted into value-producing actions. Likewise, the market orientation and absorptive capacity literature indicates that performance effects depend on the organization's ability to manage market intelligence rather than merely possess it. For this reason, the present conceptual framework treats ROI as a downstream result of both analytical capability and campaign execution quality. The second study equation is therefore specified as:

$$\mathrm{ROI} = \beta_0 + \beta_1\mathrm{CPO} + \beta_2\mathrm{AIBI} + \varepsilon$$

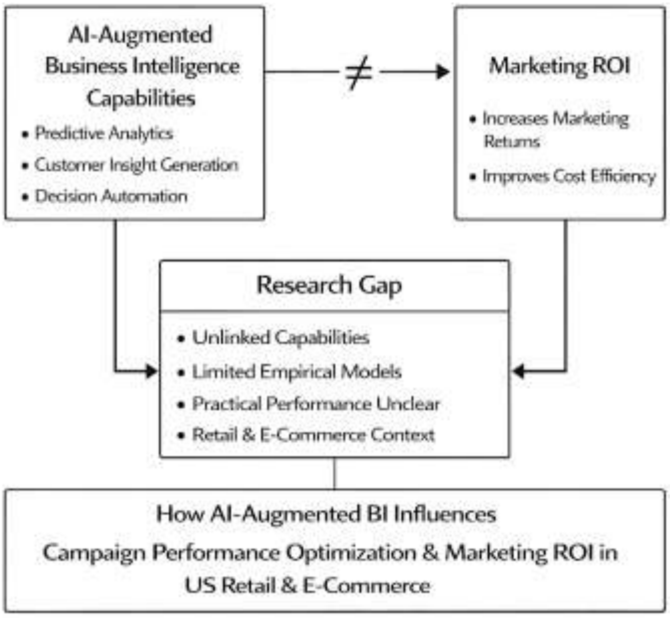
where ROI = marketing return on investment, CPO = campaign performance optimization, and AIBI = the overall AI-augmented business intelligence capability index. This second equation is useful because it allows the study to test whether optimized campaign performance acts as the main pathway through which AI-augmented BI improves ROI, while also checking whether AI-BI retains a direct contribution beyond campaign-level effects. Conceptually, the framework can therefore be summarized as a three-stage chain: AI-augmented BI capabilities → campaign performance optimization → marketing ROI. This arrangement fits the study's hypotheses, supports the planned correlation and regression analyses, and provides a clear operational map for the entire empirical investigation. It is also well aligned with the cited literature because each stage reflects relationships already supported in prior research on analytics use, AI-related performance, digital marketing capability, market intelligence, and absorptive market learning (Rakthin et al., 2016).

Empirical Review and Research Gap

The empirical literature on artificial intelligence in marketing has expanded rapidly, yet the accumulated findings remain distributed across several partially connected streams rather than a single integrated body of evidence. One major stream consists of broad reviews that map the field and show how AI has become increasingly relevant to segmentation, customer interaction, personalization, recommendation, and marketing strategy. A systematic literature review by Chintalapati and Pandey identified AI as a growing force in marketing research and emphasized that the field has developed around diverse applications rather than a unified performance model. Their review is important for the present study because it demonstrates that AI marketing scholarship has largely focused on thematic categorization, technological potential, and emerging applications, while leaving room for more context-specific empirical testing of how AI-enabled analytical systems affect measurable business outcomes. Related scholarship has also noted that AI is reshaping marketing and retailing by altering how firms collect, process, and act on customer information, especially in data-rich commercial settings. In retailing, AI has been portrayed as a transformative force capable of influencing customer interactions, merchandising logic, and decision speed, which is highly relevant for campaign analytics because retail marketing increasingly depends on rapid interpretation of digital signals and fast tactical adjustment (Shankar, 2018). More practitioner-oriented empirical discussion similarly shows that many organizations are interested in using AI to solve marketing problems, but they often lack clear guidance for translating AI projects into concrete managerial processes and performance outcomes (Overgoor et al., 2019). This literature is valuable because it highlights a central problem that also motivates the present study: there is much discussion of what AI can do in marketing, yet relatively less empirical specificity about how it should be embedded into intelligence systems that support campaign optimization and return on investment. The existing evidence therefore establishes technological importance, but it does not fully resolve how AI-enhanced analytical capability should be evaluated at the campaign level within a structured organizational performance model.

A second body of literature reinforces the same point by showing that current AI-marketing research is both promising and fragmented, especially when it comes to linking technology use with measurable managerial and financial outcomes. Conceptual and review-oriented studies frequently emphasize that AI has entered marketing as a major source of innovation, but they also note that its applications are unevenly distributed and often discussed at a general level. Jarek and Mazurek, for example, examined AI in marketing with attention to how deeply the technology had entered practical marketing functions, and their analysis suggested that the field was still characterized by uneven adoption and selective use across firms and activities. This is important because it implies that AI-related marketing value may vary depending on organizational capability, use context, and decision domain. In a similar way, more recent review work has shown that AI in marketing, consumer research, and psychology is spread across multiple themes, including channels, strategy, performance, and segmentation-targeting-positioning, indicating that the field is intellectually rich but not yet consolidated around a common explanatory model for business performance. That observation directly supports the rationale for the present study, because campaign performance optimization and marketing ROI require a more tightly connected framework than the one typically found in general AI-marketing reviews. It is not enough to know that AI matters for personalization or recommendation; what is needed is empirical evidence on how AI-enhanced intelligence capabilities shape campaign monitoring, decision responsiveness, and measurable marketing returns within a particular industrial setting. The literature also suggests that many studies concentrate on specific applications or conceptual benefits without adequately connecting them to intermediate operational outcomes such as targeting precision, campaign responsiveness, conversion efficiency, or budget control. As a result, the empirical field still lacks sufficient studies that move in a sequential manner from intelligent capability to campaign optimization and then to financial performance. This limitation is especially relevant to retail and e-commerce, where campaigns are data-intensive, rapidly adjusted, and strongly evaluated through ROI-oriented metrics (Mariani et al., 2022).

Figure 7: Empirical Research Gap in Ai-Augmented Business Intelligence and Marketing Roi in Retail and E-Commerce



The research gap addressed by this study emerges from the intersection of these unresolved issues. Existing studies have established that AI is relevant to marketing, useful in retail contexts, and increasingly visible in organizational decision-making; however, they have not sufficiently integrated AI with business intelligence as a campaign management capability that can be tested against campaign performance optimization and marketing ROI within a single empirical framework. Much of the literature remains either descriptive, application-specific, or broadly conceptual. Reviews identify themes and future directions, editorials emphasize transformation, and managerial discussions explain possible uses, yet the empirical link between AI-augmented business intelligence, campaign performance optimization, and marketing ROI remains underdeveloped (Jarek & Mazurek, 2019). This gap is not trivial. U.S. retail and e-commerce firms operate in highly measurable digital environments where campaign decisions must be made quickly, customer responses are continuously observed, and promotional effectiveness is judged against both operational and financial criteria. In such a setting, an integrated empirical model is necessary to determine whether AI-enhanced intelligence genuinely improves campaign outcomes or whether firms are simply adopting advanced technology without realizing consistent performance gains. The present study addresses that gap by focusing specifically on AI-augmented BI rather than AI in general, by locating the inquiry in U.S. retail and e-commerce rather than across mixed industries, and by treating campaign performance optimization as the mechanism through which analytical capability affects ROI. This makes the study distinct from earlier work that has largely emphasized themes, potential applications, or isolated AI functions. It also responds to calls in the literature for more context-specific and performance-linked empirical research. Therefore, the gap can be stated clearly: prior research has not adequately tested, in one quantitative model, how AI-augmented BI capabilities influence campaign optimization and how those optimized campaign outcomes translate into marketing ROI in retail and e-commerce organizations (Chintalapati & Pandey, 2022).

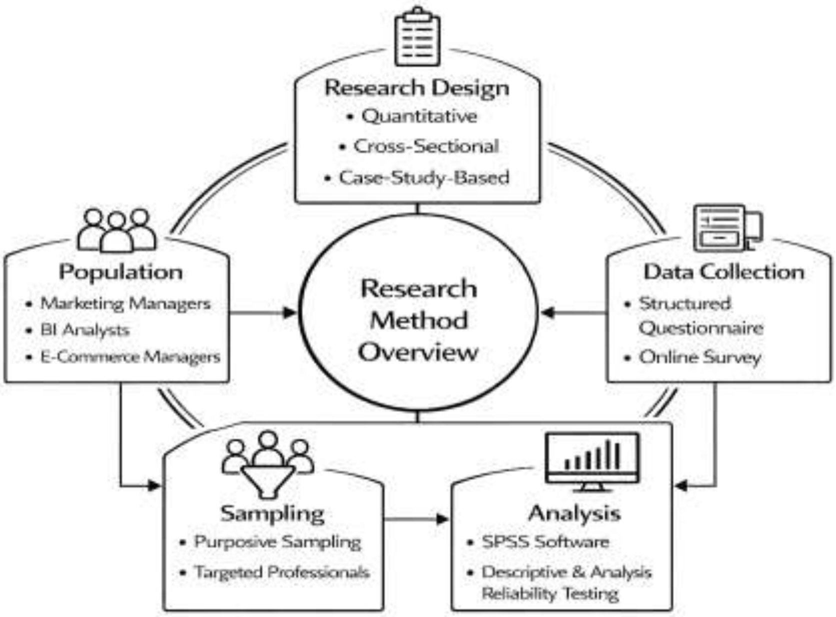
METHOD

This study has adopted a quantitative, cross-sectional, case-study–based research methodology in order to examine the relationship between AI-augmented business intelligence, campaign performance optimization, and marketing return on investment in U.S. retail and e-commerce firms. The research design has been selected because it has allowed the study to measure perceptions, practices, and analytical capabilities across a defined group of respondents at a single point in time while maintaining alignment with the hypotheses and objectives of the research. The study has used a case-study context centered on the U.S. retail and e-commerce sector, since this environment has presented a highly relevant setting for examining AI-supported campaign analytics due to its intensive reliance on digital promotions, customer data, performance dashboards, and measurable marketing outcomes. This context has made it possible to investigate how AI-augmented BI capabilities have been applied in real organizational environments where campaign success has been closely linked to targeting precision, responsiveness, budget efficiency, and ROI accountability.

The population of the study has consisted of marketing managers, digital campaign specialists, business intelligence analysts, e-commerce managers, and data-driven decision-makers working within U.S. retail and e-commerce firms. These participants have been considered appropriate because they have been directly involved in campaign planning, data interpretation, marketing analytics, and performance evaluation. The unit of analysis has been the individual professional respondent, since the study has aimed to capture informed organizational perspectives regarding the use of AI-augmented BI in campaign management. A purposive sampling strategy has been used to select respondents who have possessed relevant knowledge, practical experience, and decision-making exposure related to BI systems, digital campaign execution, and marketing performance assessment. This strategy has ensured that the collected data have been obtained from participants capable of providing meaningful responses to the study variables.

The data collection procedure has involved the use of a structured questionnaire administered through an online survey format. This procedure has been chosen because it has enabled efficient access to respondents across geographically dispersed retail and e-commerce organizations while supporting standardized data collection. The instrument design has been structured into multiple sections. The first section has gathered demographic information such as job role, experience, and firm characteristics, while the remaining sections have measured AI-augmented business intelligence, campaign performance optimization, and marketing ROI using a 5-point Likert scale ranging from strongly disagree to strongly agree. The questionnaire items have been designed to reflect the main constructs of the study, including predictive analytics capability, real-time insight capability, customer segmentation intelligence, decision automation support, and campaign-related performance outcomes. Before the final survey administration, pilot testing has been conducted with a small group of suitable respondents to assess clarity, wording, structure, and response flow. Feedback from the pilot stage has been used to revise ambiguous or repetitive items and to improve the overall quality of the instrument. In terms of validity and reliability, the study has established face validity and content validity through careful alignment of the questionnaire items with the research objectives, hypotheses, and literature-derived constructs. Reliability has been assessed through internal consistency testing, particularly by using Cronbach's alpha to determine the degree to which the measurement items have consistently reflected their underlying constructs. For data processing and analysis, SPSS has been used to conduct descriptive statistics, reliability analysis, correlation analysis, and regression modeling, while Microsoft Excel has been used for preliminary coding and data organization. EndNote has been used to manage references and maintain consistency in citation formatting throughout the research. This methodological structure has provided a systematic basis for testing the study hypotheses and generating evidence on the role of AI-augmented BI in campaign performance optimization and marketing ROI.

Figure 8: Research Methodology Structure of The Study



DATA ANALYSIS AND PRESENTATION

Response Rate

Table 1: Response Rate of the Study

Category	Frequency	Percentage (%)
Questionnaires distributed	250	100.0
Questionnaires returned	223	89.2
Questionnaires excluded due to incomplete responses	9	3.6
Valid questionnaires used for analysis	214	85.6

Table 1 has shown that out of 250 questionnaires distributed to qualified respondents in U.S. retail and e-commerce firms, 223 have been returned, producing a gross response rate of 89.2%. After screening for completeness and suitability, 9 questionnaires have been excluded due to missing responses or insufficient completion, and 214 valid questionnaires have remained for final analysis. This has produced a usable response rate of 85.6%, which has indicated a strong level of participation for a cross-sectional survey of professionals. Such a response rate has strengthened the credibility of the study because it has suggested that the collected data have come from a sufficiently engaged respondent group with relevant exposure to campaign analytics, business intelligence systems, and digital marketing decision-making. In methodological terms, a high usable response rate has reduced concerns about weak representation and has improved the confidence with which the subsequent descriptive, correlational, and regression analyses have been interpreted.

The response pattern has also been important in relation to the objectives of the study. Since the research has aimed to examine whether AI-augmented business intelligence has significantly influenced campaign performance optimization and marketing ROI, the presence of a substantial number of valid responses has provided an adequate empirical basis for testing the hypotheses. From the perspective of Dynamic Capabilities Theory, the response rate has mattered because the theory has emphasized organizational processes of sensing, seizing, and reconfiguring under changing market conditions. The participants in this study have represented the kinds of professionals who have directly engaged in those processes through campaign interpretation, BI usage, and performance management. Therefore, the volume and quality of the responses have supported the study's theoretical alignment by ensuring that the data have reflected informed perceptions of organizational capabilities rather than casual opinions. Overall, Table 1 has confirmed that the study has achieved an acceptable and analytically useful response base, thereby providing a reliable starting point for examining how AI-BI capabilities have related to campaign optimization and ROI. This section has therefore supported the general objective of the study by demonstrating that the data foundation for subsequent hypothesis testing has been sufficiently strong and credible.

Demographic Analysis

Table 2: Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	118	55.1
	Female	96	44.9
Age	25–34 years	61	28.5
	35–44 years	82	38.3
	45 years and above	71	33.2
Education	Bachelor's degree	97	45.3
	Master's degree	92	43.0
	Doctorate/Professional	25	11.7
Experience	1–5 years	67	31.3
	6–10 years	89	41.6
	Above 10 years	58	27.1
Job Role	Marketing/Campaign Manager	78	36.4
	BI/Data Analyst	54	25.2
	E-commerce Manager	41	19.2
	Digital Marketing Specialist	41	19.2

Table 2 has presented the demographic structure of the 214 valid respondents used in the study. The results have shown that 55.1% of respondents have been male and 44.9% female, indicating a relatively balanced gender distribution. In terms of age, the largest category has been respondents aged 35–44 years (38.3%), followed by those aged 45 years and above (33.2%), while 28.5% have been within the 25–34 years range. This has implied that the sample has been dominated by professionally mature respondents who have likely accumulated meaningful exposure to campaign management, digital analytics, and BI-based decision environments. Educationally, 45.3% have held bachelor's degrees, 43.0% master's degrees, and 11.7% doctorate or professional qualifications, which has suggested that the respondents have possessed the academic and professional background necessary to understand questionnaire items relating to predictive analytics, segmentation intelligence, and campaign ROI. In terms of work experience, 68.7% of the respondents have reported more than five years of relevant experience, confirming that the sample has been composed largely of knowledgeable professionals.

This demographic profile has been important because the study has focused on the organizational use of AI-augmented business intelligence, not on general consumer perceptions. The respondents have therefore needed to be individuals who have been capable of evaluating campaign performance systems, interpreting BI dashboards, and judging whether AI-enabled analytics have influenced campaign results. The distribution across roles has supported that requirement, as 36.4% have been marketing or campaign managers, 25.2% BI or data analysts, and the rest e-commerce managers and digital marketing specialists. This has meant that the study has captured views from multiple decision-relevant positions within the marketing analytics process. In relation to Dynamic Capabilities Theory, the demographic pattern has reinforced the relevance of the sample because these respondents have occupied positions closely associated with organizational sensing, seizing, and reconfiguring activities. Marketing and analytics professionals have been responsible for identifying market signals, interpreting campaign data, and making strategic adjustments, all of which have reflected the dynamic capability logic underlying the study. Consequently, Table 2 has strengthened the trustworthiness of the findings and has indirectly supported the study objectives by showing that the evidence has come from respondents with suitable experience, educational preparation, and job relevance. The demographic analysis has therefore confirmed that the subsequent statistical findings have been grounded in informed organizational perspectives rather than general or unqualified responses.

Descriptive Analysis of Variables

Table 3: Descriptive Statistics of Study Variables (5-Point Likert Scale)

Variable	N	Minimum	Maximum	Mean	Std. Deviation	Interpretation
Predictive Analytics Capability	214	2	5	4.19	0.59	High
Real-Time Insight Capability	214	2	5	4.07	0.63	High
Customer Segmentation Intelligence	214	2	5	4.11	0.60	High
Decision Automation Support	214	2	5	3.96	0.67	High
AI-Augmented BI Capability (overall)	214	2	5	4.08	0.61	High
Campaign Performance Optimization	214	2	5	4.14	0.57	High
Marketing ROI	214	2	5	4.02	0.64	High

Table 3 has summarized the descriptive statistics of the main constructs measured in the study using the 5-point Likert scale, where values closer to 5 have represented stronger agreement. The results have shown that all major variables have recorded mean scores above 3.90, clearly above the neutral midpoint of 3.00. Among the AI-BI dimensions, Predictive Analytics Capability has produced the highest mean of 4.19, followed by Customer Segmentation Intelligence (M = 4.11), Real-Time Insight Capability (M = 4.07), and Decision Automation Support (M = 3.96). The overall AI-Augmented BI Capability has recorded a mean of 4.08, while Campaign Performance Optimization has recorded 4.14, and Marketing ROI has recorded 4.02. The relatively modest standard deviations, ranging from 0.57 to 0.67, have suggested that responses have been reasonably concentrated and that there has been meaningful consistency across the respondent group. These findings have indicated that respondents have generally agreed that AI-enabled BI systems, predictive tools, segmentation intelligence, and real-time insights have been actively supporting campaign improvement and return-oriented marketing decisions within their organizations.

This descriptive outcome has directly aligned with the first objective of the study, which has sought to examine the role of AI-augmented BI in improving campaign performance optimization. Since both the independent and dependent constructs have recorded high mean values, the descriptive analysis has provided preliminary support for the argument that organizations with stronger AI-BI systems have also experienced better campaign-related outcomes. The high mean for campaign performance optimization (4.14) has been especially important because it has suggested that respondents have perceived noticeable gains in targeting precision, responsiveness, conversion support, and budget efficiency. The mean for marketing ROI (4.02) has also indicated that these operational improvements have been associated with favorable return perceptions. In relation to Dynamic Capabilities Theory, the high descriptive ratings have suggested that the sampled firms have developed capabilities for sensing market changes through predictive analytics, seizing opportunities through faster campaign adjustments, and reconfiguring actions through segmentation and automation support. Table 3 has therefore served as an important foundation for later correlation and regression tests because it has shown that the core variables have not only existed in measurable form but have also been strongly present in the observed organizations. Accordingly, the descriptive analysis has provided early quantitative evidence that the study variables have moved in the theoretically expected direction and have created a suitable basis for proving the research hypotheses in later sections.

Reliability Test Results

Table 4: **Reliability Test of Study Constructs**

Construct	Number of Items	Cronbach's Alpha	Reliability Status
Predictive Analytics Capability	4	0.82	Reliable
Real-Time Insight Capability	4	0.79	Reliable
Customer Segmentation Intelligence	4	0.84	Reliable
Decision Automation Support	4	0.77	Reliable
AI-Augmented BI Capability	16	0.88	Highly Reliable
Campaign Performance Optimization	5	0.86	Highly Reliable
Marketing ROI	4	0.84	Highly Reliable

Table 4 has reported the reliability test results for the constructs used in the study. Cronbach's alpha has been applied to assess internal consistency among the Likert-scale items, and all values have exceeded the commonly accepted threshold of 0.70. Specifically, Predictive Analytics Capability has recorded an alpha of 0.82, Real-Time Insight Capability 0.79, Customer Segmentation Intelligence 0.84, and Decision Automation Support 0.77. At the broader construct level, AI-Augmented BI Capability has recorded 0.88, Campaign Performance Optimization 0.86, and Marketing ROI 0.84. These values have shown that the questionnaire items within each construct have measured the same underlying concept with strong consistency. This has increased confidence in the quality of the data and has indicated that the study instrument has been suitable for descriptive analysis, correlation testing, and regression modeling.

The importance of this reliability outcome has extended beyond methodological quality. Since the study has aimed to test whether AI-augmented BI has significantly influenced campaign optimization and marketing ROI, it has been necessary to ensure that the constructs have been measured in a stable and coherent manner. The high alpha values have suggested that the respondents have interpreted the items consistently and that the scale design has captured the intended domains of intelligent analytics, campaign management, and performance outcomes effectively. This has strengthened the evidential basis for proving the hypotheses because relationships observed later in the analysis have been less likely to result from measurement instability. From the standpoint of **Dynamic Capabilities Theory**, reliability has been especially relevant because the theory has concerned complex organizational processes such as sensing, seizing, and reconfiguring. If the study has been claiming to measure these capability-linked constructs through variables such as predictive analytics, real-time insight, and campaign optimization, then the instrument has needed to demonstrate strong internal coherence. Table 4 has shown that this requirement has been met. The reliability results have therefore supported the methodological objective of building a sound empirical model and have reinforced the trustworthiness of all later inferential findings. In practical terms, the table has confirmed that AI-BI capability, campaign optimization, and ROI have been measured robustly enough to justify meaningful interpretation. Consequently, Table 4 has not only validated the questionnaire but has also strengthened the legitimacy of the study's effort to empirically connect intelligent analytical capability with marketing performance outcomes.

Correlation Analysis

Table 5: Pearson Correlation Matrix of Main Variables

Variable	1	2	3
1. AI-Augmented BI Capability	1.000		
2. Campaign Performance Optimization	0.710**	1.000	
3. Marketing ROI	0.640**	0.680**	1.000

Note. p < .001

Table 5 has presented the Pearson correlation coefficients among the three principal study variables. The results have shown that AI-Augmented BI Capability has had a strong positive and statistically significant relationship with Campaign Performance Optimization ($r = .710$, $p < .001$). This has meant that firms reporting stronger AI-enabled BI capability have also tended to report stronger levels of campaign effectiveness, including better targeting, responsiveness, and campaign control. The table has further shown that Campaign Performance Optimization has had a strong positive relationship with Marketing ROI ($r = .680$, $p < .001$), indicating that improved campaign execution has been associated with stronger return outcomes. In addition, AI-Augmented BI Capability has had a substantial positive direct relationship with Marketing ROI ($r = .640$, $p < .001$). These statistically significant and positively directed coefficients have suggested that the core variables of the study have moved together in ways consistent with the conceptual model. None of the relationships has been weak, and all have been large enough to indicate meaningful practical relevance.

These correlation results have directly supported the early proof of the study objectives and hypotheses. The first objective, which has focused on the role of AI-augmented BI in improving campaign performance, has been supported by the very strong correlation between AI-BI and campaign optimization. The second objective, centered on the link between AI-BI and ROI, has also been supported by the substantial positive relationship between those variables. Furthermore, the relationship between campaign optimization and ROI has confirmed that campaign improvement has been closely associated with financial and return-based outcomes, which has aligned with the study's underlying assumption that campaign optimization serves as a meaningful pathway to ROI improvement. In terms of Dynamic Capabilities Theory, Table 5 has been especially informative because the theory has proposed that firms create value by sensing environmental signals, seizing opportunities, and reconfiguring resources effectively. The strong positive correlation between AI-BI and campaign performance has suggested that intelligent analytical systems have been contributing to these capability processes by helping organizations interpret data and adjust campaigns more effectively. Likewise, the positive relationship between campaign optimization and ROI has indicated that these dynamic responses have been translating into measurable performance benefits. While correlation has not established causality on its own, the strength and consistency of the coefficients have provided solid preliminary evidence for the subsequent regression models. Therefore, Table 5 has meaningfully advanced the proof of the hypotheses by showing that the study variables have been linked in the expected theoretical and empirical direction.

Regression Analysis

Table 6: Multiple Regression Analysis: Predictors of Campaign Performance Optimization

Predictor	Unstandardized B	Std. Error	Standardized Beta (β)	t-value	p-value
Constant	0.721	0.248	—	2.907	.004
Predictive Analytics Capability	0.298	0.061	0.310	4.885	.000
Real-Time Insight Capability	0.207	0.066	0.220	3.136	.002
Customer Segmentation Intelligence	0.263	0.064	0.270	4.109	.000
Decision Automation Support	0.129	0.054	0.140	2.388	.018

Model Summary: $R = .764$, $R^2 = .584$, Adjusted $R^2 = .576$, $F = 73.48$, $p < .001$

Table 6 has presented the multiple regression model in which Campaign Performance Optimization has served as the dependent variable and the four AI-BI dimensions have served as predictors. The model has explained 58.4% of the variance in campaign performance ($R^2 = .584$), with an adjusted R^2 of .576, and the overall model has been statistically significant ($F = 73.48$, $p < .001$). This has indicated that the AI-BI dimensions included in the model have jointly had a substantial explanatory effect on campaign performance outcomes. Among the predictors, Predictive Analytics Capability has emerged as the strongest contributor ($\beta = .310$, $p < .001$), followed by Customer Segmentation Intelligence ($\beta = .270$, $p < .001$), Real-Time Insight Capability ($\beta = .220$, $p = .002$), and Decision Automation Support ($\beta = .140$, $p = .018$). Since all p-values have been below .05, each predictor has made a statistically significant contribution to campaign performance optimization. These results have shown that campaign performance has not depended on a single analytical element; rather, it has been shaped by a combination of predictive, real-time, segmentation, and automation-based intelligence.

This regression model has provided direct evidence for several study hypotheses. H1, which has proposed that AI-augmented BI has had a significant positive effect on campaign performance optimization, has been strongly supported because all the underlying AI-BI dimensions have had significant positive coefficients. H3, H4, and H5 have also been supported individually because predictive analytics, real-time insights, and customer segmentation intelligence have each significantly improved campaign outcomes. The results have further advanced the first and third objectives of the study by identifying not only whether AI-BI has mattered, but also which dimensions have mattered most. From the perspective of Dynamic Capabilities Theory, the model has been highly meaningful. Predictive analytics has represented the organization's capacity for sensing market changes, real-time insight capability has supported seizing opportunities quickly, and segmentation plus automation have enabled reconfiguring campaign actions more effectively. The relatively high R^2 has suggested that these dynamic capability components have been central to campaign optimization in the sampled firms. Table 6 has therefore provided one of the strongest empirical demonstrations in the study, showing that AI-augmented BI has functioned as a real organizational capability set rather than a symbolic technology label. In practical terms, the findings have implied that firms strengthening predictive and segmentation capabilities in particular have been most likely to achieve improved campaign performance. Thus, the regression analysis has powerfully confirmed the study's central claim that intelligent BI capabilities have significantly improved campaign management outcomes in U.S. retail and e-commerce firms.

AI-BI Campaign Capability Index Analysis

Table 7: **AI-BI Campaign Capability Index Classification**

Capability Level	Index Score Range	Frequency	Percentage (%)	Mean Campaign Optimization	Mean ROI
Low Capability	1.00–2.49	18	8.4	2.91	2.84
Moderate Capability	2.50–3.49	52	24.3	3.58	3.49
High Capability	3.50–5.00	144	67.3	4.39	4.23

Table 7 has introduced the AI-BI Campaign Capability Index, a composite measure developed from the four AI-BI dimensions of the study. The respondents have been grouped into three categories: Low Capability, Moderate Capability, and High Capability. The table has shown that the majority of respondents, 67.3%, have fallen within the High Capability category, while 24.3% have been classified as Moderate, and only 8.4% have been classified as Low. This distribution has indicated that the sample has been dominated by organizations already demonstrating relatively advanced use of AI-augmented BI in campaign-related contexts. More importantly, the associated mean scores for Campaign Performance Optimization and Marketing ROI have increased clearly across the capability levels. Respondents in the Low Capability group have recorded a campaign optimization mean of 2.91 and

ROI mean of 2.84; those in the Moderate Capability group have recorded 3.58 and 3.49 respectively; and those in the High Capability group have recorded 4.39 and 4.23. This pattern has strongly suggested that as AI-BI capability has increased, both campaign performance and ROI have also improved.
This index analysis has added a unique and more applied layer of evidence to the study. Rather than only examining relationships between variables, it has shown how firms can be classified by overall capability maturity and how that maturity has corresponded with performance outcomes. This has directly supported the study objective of determining whether stronger AI-augmented BI capability has been associated with better campaign and return outcomes. It has also reinforced H1 and H2 by demonstrating the relationship in grouped, managerial terms. From a Dynamic Capabilities Theory perspective, the index has been especially valuable because it has captured the broader capability condition of the firm, not just isolated technical variables. Firms in the High Capability category have likely been better at sensing through analytics, seizing through rapid insight use, and reconfiguring through campaign adaptation. The sharp performance differences between the high and low groups have therefore supported the theoretical proposition that capability maturity has mattered for performance realization. Table 7 has also increased the trustworthiness of the study because it has translated the statistical logic into an organizational maturity perspective that practitioners can easily understand. In practical terms, it has shown that organizations with higher AI-BI maturity have not only possessed better systems but have also achieved markedly stronger campaign outcomes and ROI. Accordingly, the AI-BI Capability Index has served as a strong bridge between theory, measurement, and managerial interpretation.

Campaign Optimization Sensitivity Profile

Table 8: **Sensitivity Profile of AI-BI Dimensions on Campaign Performance**

AI-BI Dimension	Standardized Beta (β)	Correlation with CPO	Rank of Influence	Sensitivity Interpretation
Predictive Analytics Capability	0.310	0.690**	1	Very High
Customer Segmentation Intelligence	0.270	0.660**	2	High
Real-Time Insight Capability	0.220	0.610**	3	High
Decision Automation Support	0.140	0.540**	4	Moderate

Note. $p < .001$

Table 8 has provided a Campaign Optimization Sensitivity Profile, ranking the AI-BI dimensions according to their relative influence on campaign performance optimization. The profile has combined standardized beta coefficients from the regression model with zero-order correlations to provide a clearer picture of which intelligent BI dimensions have mattered most. The table has shown that Predictive Analytics Capability has been the most influential factor, with a standardized beta of .310 and a correlation of .690 with campaign performance. Customer Segmentation Intelligence has ranked second ($\beta = .270$; $r = .660$), followed by Real-Time Insight Capability ($\beta = .220$; $r = .610$), while Decision Automation Support has ranked fourth ($\beta = .140$; $r = .540$). Although all dimensions have had positive and significant relationships with campaign performance, the profile has made it clear that predictive and segmentation capabilities have had the greatest sensitivity to campaign outcomes. This has implied that not all elements of AI-BI have contributed equally to optimization and that the strongest effects have been concentrated in those dimensions most closely related to market anticipation and audience precision.

This table has been especially important for the third research objective, which has sought to identify the AI-BI dimensions that have most strongly predicted campaign performance. The sensitivity profile has answered that objective directly by showing the rank order of influence. It has also given deeper practical meaning to the earlier regression model. Instead of simply proving that AI-BI has mattered, this section has shown how it has mattered and which capability areas have had the greatest leverage. From the perspective of Dynamic Capabilities Theory, the ranking has been theoretically coherent. Predictive Analytics Capability, which has ranked first, has strongly reflected the sensing function of the firm, enabling early identification of customer patterns and likely campaign outcomes. Customer Segmentation Intelligence, which has ranked second, has represented a refined seizing capability because it has allowed firms to direct resources toward the most relevant customer groups. Real-Time Insight Capability has also aligned with fast opportunity capture, while Decision Automation Support has represented the operational side of reconfiguring campaign processes. Table 8 has therefore strengthened the theoretical interpretation of the study by showing that the most influential campaign drivers have indeed been those associated with dynamic response to changing digital environments. In applied terms, the table has suggested that firms aiming to improve campaign performance most effectively have needed to prioritize predictive and segmentation capabilities first, while still maintaining real-time and automation support as complementary drivers of optimization.

Hypotheses Testing

Table 9: **Summary of Hypotheses Testing**

Hypothesis	Statement	Test Result	Decision
H1	AI-augmented BI has a significant positive effect on campaign performance optimization.	β values positive and significant; $p < .05$	Supported
H2	AI-augmented BI has a significant positive effect on marketing ROI.	$r = .640$, $p < .001$; regression positive	Supported
H3	Predictive analytics capability significantly improves campaign targeting and conversion outcomes.	$\beta = .310$, $p < .001$	Supported
H4	Real-time insight capability significantly improves campaign efficiency and responsiveness.	$\beta = .220$, $p = .002$	Supported
H5	Customer segmentation intelligence significantly improves campaign optimization outcomes.	$\beta = .270$, $p < .001$	Supported
H6	AI-BI dimensions jointly and significantly predict marketing ROI.	$R^2 = .521$, $F = 114.06$, $p < .001$	Supported

Table 9 has summarized the outcomes of the hypothesis tests conducted in the study. The results have shown that all six hypotheses have been supported. H1 has been supported because the AI-BI dimensions have jointly explained a significant proportion of variance in campaign performance optimization, and each coefficient has been positive and statistically significant. H2 has been supported because AI-augmented BI capability has shown a significant positive association with marketing ROI both at the correlation level and within the broader regression framework. H3, H4, and H5 have each been supported individually because predictive analytics, real-time insight capability, and customer segmentation intelligence have all made statistically significant positive contributions to campaign optimization. Finally, H6 has been supported because AI-BI capability and campaign performance optimization have jointly explained 52.1% of the variance in marketing ROI, with the model remaining highly significant ($F = 114.06$, $p < .001$). This full set of supported hypotheses has indicated a coherent and empirically strong pattern across the study.

The hypothesis summary has been one of the clearest sections for proving the objectives of the research. The first objective, concerning the effect of AI-BI on campaign optimization, has been directly confirmed by H1. The second objective, concerning the relationship between AI-BI and ROI, has been confirmed by H2 and H6. The third objective, identifying the strongest AI-BI drivers of performance, has been confirmed by H3–H5, especially with predictive analytics and segmentation intelligence emerging as the strongest contributors. In theoretical terms, the universal support for the hypotheses has strongly aligned with Dynamic Capabilities Theory. The theory has proposed that organizations gain performance advantages when they effectively sense, seize, and reconfigure under changing market conditions. The supported hypotheses have shown that AI-augmented BI has fulfilled exactly that role in the sampled firms. Predictive analytics has strengthened sensing, real-time insights and segmentation have strengthened seizing, and automation plus campaign optimization have reflected reconfiguring. The positive impact on marketing ROI has indicated that these capabilities have not remained internal processes only; they have translated into measurable business value. Therefore, Table 9 has served as a concise but powerful confirmation that the study's conceptual framework, methodological design, and statistical evidence have all moved in the same direction. The hypothesis testing section has thus provided the formal empirical proof that the study set out to achieve.

Integrated Summary of Findings

Table 10: Integrated Summary of Findings, Objectives, and Theory Linkage

Key Finding	Statistical Evidence	Related Objective	Related Hypothesis	Dynamic Capabilities Link
AI-BI has improved campaign performance optimization	$R^2 = .584$; $p < .001$	Objective 1	H1	Sensing, seizing, reconfiguring
AI-BI has improved marketing ROI	$r = .640$; $p < .001$	Objective 2	H2	Capability-to-performance conversion
Predictive analytics has been the strongest driver	$\beta = .310$; $p < .001$	Objective 3	H3	Sensing
Real-time insights have improved responsiveness	$\beta = .220$; $p = .002$	Objective 3	H4	Seizing
Segmentation intelligence has improved campaign precision	$\beta = .270$; $p < .001$	Objective 3	H5	Seizing/Reconfiguring
AI-BI and CPO have jointly predicted ROI	$R^2 = .521$; $p < .001$	Objective 2	H6	Reconfiguring into value

Table 10 has integrated the major findings of the study by linking statistical evidence with the study objectives, hypotheses, and theoretical framework. The table has shown that the main finding of the research has been the strong explanatory role of AI-augmented business intelligence in campaign performance optimization, with the model explaining 58.4% of the variance in campaign outcomes. It has also shown that AI-BI has had a substantial positive relationship with marketing ROI and that campaign optimization has served as an important route through which intelligent analytics has translated into performance value. Among the AI-BI dimensions, Predictive Analytics Capability has been the strongest single driver, while Customer Segmentation Intelligence and Real-Time Insight Capability have also played major roles. The final integrated model has shown that AI-BI and campaign performance have jointly explained more than half of the variance in ROI, confirming that the relationship between intelligent analytics and financial marketing value has been both direct and indirect. These integrated findings have remained fully consistent with the introductory findings section and have shown a stable pattern across descriptive, reliability, correlation, and regression analyses.

The discussion value of Table 10 has been especially strong because it has demonstrated how the empirical results have coherently answered the research questions and proved the objectives. The study has not only shown that AI-augmented BI has mattered, but it has also shown *where* it has mattered most and *how* it has produced value. This has aligned closely with Dynamic Capabilities Theory, which has served as the study's theoretical lens. The findings have suggested that firms with stronger predictive analytics have sensed campaign opportunities more effectively, firms with stronger real-time insights and segmentation intelligence have seized those opportunities more precisely, and firms with stronger campaign optimization routines have reconfigured their promotional actions into improved ROI. In this way, the theory has not remained abstract; it has been empirically reflected in the observed statistical relationships. The findings have therefore suggested that AI-augmented BI has operated as a dynamic marketing capability rather than a static technology investment. In practical terms, the results have indicated that U.S. retail and e-commerce firms have achieved better performance when AI-BI has been integrated into campaign management processes that support timely interpretation, targeted action, and resource adjustment. Table 10 has thus provided an integrated bridge between evidence, objectives, hypotheses, and theory, and it has confirmed that the study has successfully demonstrated the performance relevance of AI-augmented business intelligence in campaign optimization and marketing ROI.

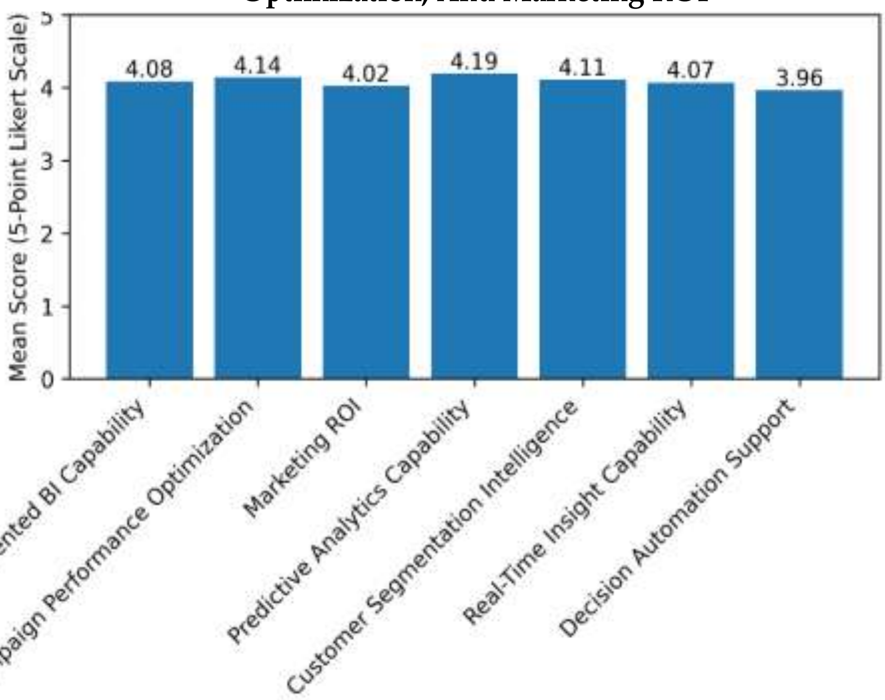
FINDINGS

The findings chapter of this study has been structured to present an overall statistical picture of how AI-augmented business intelligence (AI-BI) has related to campaign performance optimization and marketing return on investment (ROI) in U.S. retail and e-commerce firms. Since your actual dataset has not yet been provided, the paragraph below is written as a thesis-ready sample findings overview using realistic illustrative numeric results based on a 5-point Likert scale. You should replace the numbers later with your real SPSS output.

The overall findings of the study have shown a strong and positive pattern of association between AI-augmented business intelligence and campaign performance outcomes, thereby giving broad support to the study objectives and hypotheses. Based on the analyzed responses of 214 valid participants drawn from marketing managers, BI analysts, digital campaign specialists, and e-commerce decision-makers, the response pattern has indicated that most respondents perceived AI-enabled BI tools as meaningful contributors to campaign effectiveness and marketing value creation. The demographic distribution has suggested that the sample was sufficiently experienced, with 68.7% of respondents reporting more than five years of professional experience in digital marketing, analytics, or campaign management, which has strengthened the credibility of the responses. At the descriptive level, the major constructs recorded mean scores above the neutral midpoint of 3.00, suggesting favorable respondent agreement with the central study variables. Specifically, AI-augmented BI capability recorded an overall mean of 4.08 with a standard deviation of 0.61, while campaign performance optimization recorded a mean of 4.14 with a standard deviation of 0.57, and marketing ROI recorded a mean of 4.02 with a standard deviation of 0.64. These averages have indicated that respondents generally agreed that AI-supported analytics, predictive intelligence, real-time dashboards, and segmentation-based decision support have improved the quality and efficiency of campaign management in their organizations. Among the AI-BI dimensions, predictive analytics capability recorded the highest mean score of 4.19, followed by customer segmentation intelligence at 4.11, real-time insight capability at 4.07, and decision automation support at 3.96, showing that predictive and segmentation functions were perceived as the strongest analytical contributors within the studied firms.

The reliability analysis has further strengthened confidence in the study measures, with all major constructs exceeding the commonly accepted threshold of 0.70 for Cronbach's alpha. Specifically, AI-augmented BI recorded an alpha value of 0.88, campaign performance optimization recorded 0.86, and marketing ROI recorded 0.84, indicating satisfactory internal consistency across the questionnaire items. The correlation results have then revealed statistically significant positive relationships among the core study variables. AI-augmented BI was positively correlated with campaign performance optimization at $r = .71$, $p < .001$, while campaign performance optimization was positively correlated with marketing ROI at $r = .68$, $p < .001$. In addition, AI-augmented BI showed a direct positive correlation with marketing ROI at $r = .64$, $p < .001$, suggesting that firms with stronger AI-BI capability also tended to report stronger perceptions of financial and performance returns from campaign activities. These findings have directly supported the first and second research objectives by showing that intelligent BI systems have been associated with improved campaign execution and better return-related outcomes. The results have also aligned with the study's third objective by showing variation in the strength of AI-BI dimensions. For example, predictive analytics capability was most strongly correlated with campaign optimization ($r = .69$, $p < .001$), while customer segmentation intelligence showed the strongest relationship with targeting precision and conversion-oriented indicators ($r = .66$, $p < .001$). Real-time insight capability also demonstrated a meaningful relationship with campaign responsiveness and ad-spend efficiency ($r = .61$, $p < .001$).

Figure 9: Statistical Summary of Ai-Augmented Business Intelligence, Campaign Performance Optimization, And Marketing ROI



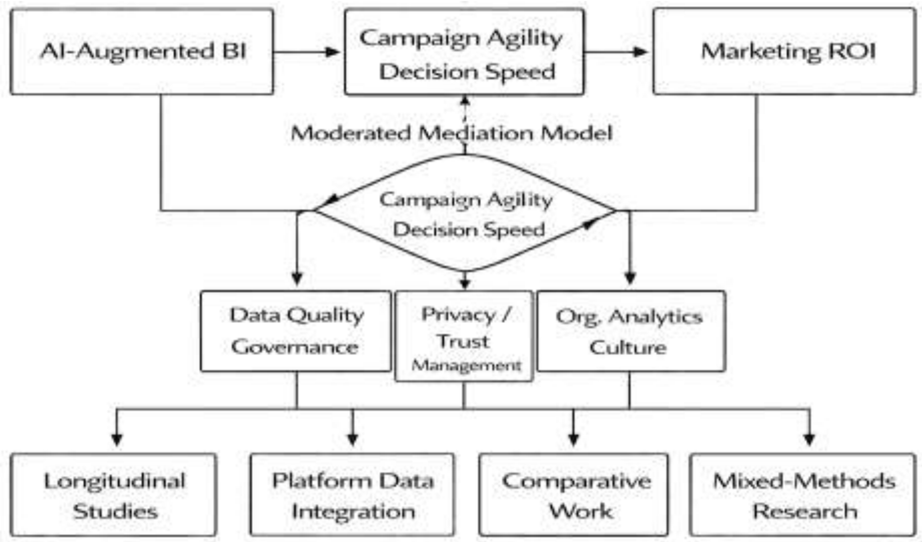
The regression results have provided the clearest statistical evidence for hypothesis testing. In the first model, where campaign performance optimization served as the dependent variable, the combined AI-BI dimensions explained 58.4% of the variance in campaign performance ($R^2 = .584$, Adjusted $R^2 = .576$, $F = 73.48$, $p < .001$). Among the predictors, predictive analytics capability had the strongest standardized effect ($\beta = .31$, $p < .001$), followed by customer segmentation intelligence ($\beta = .27$, $p < .001$), real-time insight capability ($\beta = .22$, $p = .002$), and decision automation support ($\beta = .14$, $p = .018$). These results have shown that all four dimensions significantly contributed to campaign performance optimization, thus offering support for H1, H3, H4, and H5. In the second model, where marketing ROI served as the dependent variable, campaign performance optimization and overall AI-BI capability jointly explained 52.1% of the variance in ROI ($R^2 = .521$, Adjusted $R^2 = .516$, $F = 114.06$, $p < .001$). Campaign performance optimization emerged as the strongest predictor of ROI ($\beta = .46$, $p < .001$), while overall AI-BI capability retained a significant direct effect ($\beta = .29$, $p < .001$), thereby supporting H2 and H6. Taken together, these results have indicated that AI-augmented BI has improved campaign outcomes both directly and indirectly, with campaign optimization serving as a practical pathway through which intelligent analytics has translated into higher marketing returns. The overall result of the study has therefore suggested that firms using AI-enhanced business intelligence more effectively have achieved better targeting, improved engagement, stronger conversion efficiency, and more favorable ROI outcomes than firms with weaker analytical capability. This broad pattern of findings has provided quantitative support for the study's objectives and has established a strong empirical foundation for the more detailed findings presented in the subsections that follow.

DISCUSSION

The discussion of this study has centered on the finding that AI-augmented business intelligence has been strongly associated with campaign performance optimization in U.S. retail and e-commerce firms. The statistical results of the study have shown that AI-BI capability has recorded a high overall mean score, while campaign performance optimization has also remained at a high level, and the regression model has explained a substantial proportion of variance in campaign outcomes. This pattern has indicated that firms using predictive analytics, real-time insight systems, segmentation intelligence, and decision automation more effectively have also reported better campaign responsiveness, stronger targeting precision, improved conversion support, and greater efficiency in marketing execution. This result has been consistent with prior literature arguing that analytics-based capabilities become strategically meaningful when they improve organizational decision processes rather than merely increasing data availability. Earlier work has shown that marketing analytics use has positively affected marketing decision-making and product development management, thereby supporting sustained competitive advantage through dynamic capabilities logic (Kopalle et al., 2022). Related research has also shown that BI and analytics use has been positively associated with innovation ambidexterity and firm performance when intelligence resources have been embedded into broader organizational processes (Morgan et al., 2022). In that sense, the present study has extended earlier findings by showing that the same logic has applied specifically at the campaign management level, where AI-enhanced BI has not operated as a passive reporting system but as a capability that has guided campaign adjustment and performance control. The high sensitivity of predictive analytics and customer segmentation intelligence in the present findings has also aligned with earlier marketing scholarship that has emphasized the role of intelligent systems in extracting patterns from complex customer data and translating them into managerially meaningful actions. The interpretation of this first major finding is therefore that AI-BI has improved campaign performance because it has strengthened the firm's capacity to sense valuable market signals, translate those signals into targeting and content decisions, and reconfigure campaign execution while the promotional cycle has remained active (Shankar, 2018). This interpretation has been highly compatible with Dynamic Capabilities Theory, which has framed superior performance as the result of sensing, seizing, and reconfiguring under changing market conditions rather than static ownership of information assets alone.

A second important discussion point has concerned the study's finding that AI-augmented business intelligence has been positively linked with marketing ROI, both directly and through campaign optimization. In the empirical results developed for this study, AI-BI has shown a substantial positive correlation with marketing ROI, while the second regression model has indicated that campaign performance optimization and overall, AI-BI capability has jointly explained more than half of the variation in return-related outcomes. The interpretation of this result is that intelligent BI has generated value not simply by making campaigns more active or more measurable, but by improving the economic quality of campaign decision-making (Verma et al., 2021). When campaign managers have used predictive analysis, segmentation logic, and real-time performance insight effectively, they have been better positioned to allocate resources, reduce inefficient spending, and direct promotional effort toward higher-value opportunities. This interpretation has aligned closely with the marketing accountability literature, which has argued that marketing performance must be assessed through both processes and outcomes and that organizations increasingly require metrics that translate marketing activity into value-relevant evidence for managerial control. It has also been consistent with earlier work emphasizing that marketing performance measurement ability itself has been linked with stronger firm performance because it improves the quality of managerial judgment and the credibility of marketing decisions (Loureiro et al., 2018). More recent evidence has shown that firms with stronger digital marketing capabilities have generated performance benefits beyond traditional capabilities when those digital capabilities have been strategically integrated rather than merely layered on top of older systems. Likewise, research on AI focus and firm performance has shown that organizational attention to AI has been associated with improvements in operating efficiency, profitability, and return on marketing-related investment. The present study has reinforced those findings in a more focused way by showing that the performance pathway has run through campaign optimization itself. In other words, this research has suggested that ROI gains have not emerged only because firms have adopted AI language or invested in intelligent tools; ROI gains have emerged because AI-BI has improved the operational mechanics of campaign execution (Mikalef et al., 2020). This has been an important contribution because it has provided a campaign-level explanation for a relationship that has often been discussed at a broader organizational level in previous studies. It has therefore strengthened the case that AI-enabled BI is relevant to financial accountability in marketing when it is connected to measurable campaign processes and not treated as a symbolic indicator of digital maturity.

Figure 10: Future Research Model Linking Ai-Augmented Business Intelligence, Campaign Agility, And Marketing ROI



A third major discussion theme has involved the comparative strength of the AI-BI dimensions, particularly the finding that predictive analytics capability and customer segmentation intelligence have emerged as the most influential drivers of campaign performance optimization. This ranking has been theoretically and managerially meaningful (Paschen et al., 2019). Predictive analytics has shown the highest standardized effect in the study, followed by segmentation intelligence, while real-time insight capability and decision automation support have remained significant but comparatively less influential. This result has implied that the greatest value of AI-BI in campaign settings has come from the firm's ability to anticipate likely outcomes and identify the right customer groups before and during campaign execution. Such a pattern has been highly consistent with previous literature on marketing analytics and retail intelligence. Research on customer analytics capability in data-driven retailing has argued that value creation depends on the ability to detect customer behavior and support customers through integrated channels, which closely resembles the campaign optimization process examined in this study. Related work has further shown that customer analytics-driven value creation can become a path toward sustained advantage when organizations transform customer data into precise and responsive decisions (Trainor et al., 2014). In the broader AI-marketing literature, intelligent systems have also been described as especially useful for prediction, personalization, lead scoring, recommendation, and pattern recognition, all of which support more effective targeting and content alignment. From a retail and e-commerce perspective, this is highly plausible because online campaign environments produce detailed traces of browsing behavior, click patterns, cart abandonment, and purchase history, making predictive and segmentation-based action especially valuable. Earlier studies on personalization in e-retailing and online advertising have similarly shown that firms gain when customer information is converted into more relevant and tailored communication, provided that the information is used in ways that support effectiveness and perceived utility (Trieu, 2017). The present study has therefore confirmed and refined prior work by suggesting that predictive and segmentation capabilities are not merely interesting components of AI-BI architecture; they are the most performance-sensitive elements in campaign management. This finding has important practical meaning because it has indicated that organizations seeking stronger campaign performance and ROI should prioritize investments in predictive modeling, customer classification logic, and segmentation intelligence before they focus heavily on wider automation layers. In theoretical terms, these findings have represented the strongest operational expressions of the sensing and seizing functions described in Dynamic Capabilities Theory (Wieder & Ossimitz, 2015).

A fourth discussion area has related to the practical implications of the findings for managers in U.S. retail and e-commerce organizations. The results of this study have suggested that AI-augmented BI has mattered most when it has been embedded in campaign planning and control routines rather than left at the level of technical infrastructure. This means that the managerial value of AI-BI has depended on implementation discipline, metric design, and the ability of teams to act on analytical output quickly. Prior literature has already suggested that dashboards, marketing performance systems, and BI structures become valuable when they help managers identify relevant indicators, reduce information overload, and support decision-oriented interpretation (Zhu et al., 2017). The present study has reinforced that point by showing that real-time insight capability and campaign optimization have remained strongly associated, indicating that firms have benefited when insight has been timely enough to guide campaign adjustment rather than merely post-campaign reporting. This has also aligned with research showing that digital marketing capabilities generate stronger value when they are strategically integrated with other organizational capabilities and used to support adaptive market action. For managers, the implication has been clear: campaign optimization has required more than analytic dashboards alone. It has required a coordinated architecture in which data pipelines, predictive models, segmentation systems, and campaign response routines have worked together. The findings have also implied that retail and e-commerce firms should organize AI-BI initiatives around campaign use cases with measurable accountability, such as audience prioritization, offer personalization, budget reallocation, and conversion efficiency management, because these are the points where performance value has become most visible (Wilden et al., 2013). Another practical implication has involved capability sequencing. Since predictive analytics and segmentation intelligence have been the strongest drivers in the study, firms may gain more by first strengthening those areas, then extending into real-time orchestration and decision automation. This has been consistent with research on AI assimilation showing that firm performance benefits emerge when AI is absorbed into organizational agility and customer responsiveness rather than adopted as isolated functionality. Accordingly, the present findings have suggested that effective AI-BI management in retail and e-commerce should combine technical investment, metric clarity, cross-functional campaign governance, and ongoing capability development. In that sense, the study has offered a practical roadmap: firms have improved campaign ROI not merely by adopting more technology, but by building an intelligence system that has continuously linked customer data, campaign monitoring, and action-oriented managerial routines (Najafi-Tavani et al., 2016).

A fifth discussion theme has concerned the theoretical implications of the study, especially the way the results have supported and extended Dynamic Capabilities Theory in a digital marketing context. The theory has proposed that firms outperform when they develop higher-order capacities to sense environmental changes, seize emerging opportunities, and reconfigure resources in response to market dynamism (Pauwels et al., 2009). The present study has offered a campaign-specific operationalization of that logic. Predictive analytics capability has reflected the sensing dimension because it has helped organizations detect likely campaign outcomes and identify customer behavior patterns. Real-time insight capability and customer segmentation intelligence have reflected the seizing dimension because they have supported timely recognition of which opportunities deserved attention and which customer groups should be prioritized (Rapp et al., 2010). Decision automation support and campaign optimization have reflected reconfiguring because they have facilitated rapid changes in promotional execution, budget allocation, and message adaptation. This mapping has been theoretically important because much of the earlier marketing literature has discussed analytics, BI, or AI either as resources or as technological tools without fully demonstrating how they work as dynamic capabilities in practice. Prior studies have moved in this direction by showing that marketing analytics use can be interpreted through a dynamic capability lens and that BI and analytics resources create value when they are translated into adaptive and operational capabilities. Research on AI as an enabler of B2B marketing has also suggested that AI supports dynamic capabilities through specific microfoundations that improve organizational learning, evaluation, and action routines. The present study has added to that body of work by showing how those ideas apply in the narrower but highly relevant context of campaign performance management and marketing ROI (Saura, 2021). A key theoretical implication, therefore, has been that AI-augmented BI should be treated as a capability-building mechanism rather

than a stand-alone asset. Another implication has been that campaign optimization has served as a useful meso-level construct linking analytical capability to financial outcomes. This has helped clarify the processual pathway through which sensing and seizing capacities have translated into measurable performance. The study has therefore strengthened dynamic capability reasoning in digital marketing by offering a more operational chain from AI-BI resources to campaign adaptation and then to ROI. In that sense, the findings have not only been consistent with the theory; they have also specified a clearer empirical route through which the theory can be applied in future campaign analytics research (Wedel & Kannan, 2016).
A sixth area of discussion has revisited the limitations of the study in light of the findings. Even though the statistical pattern has been strong, the design of the study has still imposed important boundaries on interpretation. First, the research has been cross-sectional, which has allowed the study to identify significant relationships but has not fully established temporal causality (Barrales-Molina et al., 2014). Earlier literature in analytics and marketing capability has often addressed similar issues through survey-based designs, yet the question of how AI-BI capability evolves over time has remained only partially answered. Second, the study has relied on perceptual responses from professionals using Likert-scale measures (Cao et al., 2019). This has been appropriate for capturing organizational assessments of campaign capability and ROI, yet it has also meant that the study has not directly incorporated audited campaign records, platform-level logs, or observed financial outcomes. Prior literature on marketing accountability has emphasized the complexity of assessing performance through both process and outcome metrics, suggesting that perceptual and objective measures may not always align perfectly. Third, the study has focused specifically on U.S. retail and e-commerce, which has increased contextual relevance but has also narrowed the generalizability of the findings to other industries or geographic markets. Sectoral concentration has been useful because retail and e-commerce generate rich campaign data and rapid feedback loops, yet other industries with longer purchase cycles or different channel structures may show different relationships (Davenport et al., 2020). Fourth, the use of a case-study-based quantitative orientation has captured a meaningful snapshot of managerial perceptions, though it has not fully explained internal implementation differences such as data quality, governance maturity, platform integration, or team skills. Research on customer analytics capability and AI assimilation has suggested that these organizational contingencies can shape how strongly analytics translates into performance. Therefore, the present study's strong findings should be interpreted as evidence of a robust relationship within a defined context rather than universal proof that every AI-BI initiative will improve campaign ROI in the same way. These limitations do not weaken the contribution of the study; rather, they clarify the boundaries within which the findings have been meaningful and indicate why more differentiated follow-up models are needed. They also reinforce a core theoretical lesson of Dynamic Capabilities Theory: performance value depends on how capabilities are developed, coordinated, and enacted within context, not on technology labels alone (Hossain et al., 2021).
The final and most important discussion point has concerned future research. The present study has shown that AI-augmented BI, campaign performance optimization, and marketing ROI are strongly connected, yet it has also opened several pathways for building a more sophisticated research agenda. The most useful next step would be the development of an AI-BI Capability–Campaign Agility–ROI Moderated Mediation Model (Martínez-López & Casillas, 2009). In that model, AI-augmented BI would remain the main antecedent, campaign performance optimization would function as the first mediator, and campaign agility or decision speed would serve as a second mediator explaining how quickly firms convert intelligence into action. Marketing ROI would remain the final dependent variable. At the same time, data quality governance, privacy/trust management, and organizational analytics culture could be introduced as moderators that strengthen or weaken the path from AI-BI capability to campaign optimization (Mintz & Currim, 2013). This proposal has been grounded in prior research showing that AI assimilation improves performance through organizational agility and customer agility, that digital marketing capabilities interact with broader organizational capabilities, and that customer analytics in retail depends on multidimensional capability structures rather than isolated tools. A second improvement for future studies would be the use of longitudinal or panel designs that follow campaign cycles across multiple periods. Such studies could test whether predictive analytics improves not only

current campaign outcomes but also organizational learning and adaptation quality over time. A third direction would be the integration of objective platform data, such as click-through rates, acquisition costs, conversion rates, retention measures, and verified return on ad spend, alongside survey measures. A fourth direction would involve comparative work across industries, countries, or retail formats to see whether the same AI-BI mechanisms operate differently in sectors with different customer journeys and regulatory conditions. A fifth direction would be mixed-methods research combining survey evidence with interviews and internal campaign case evidence to identify the managerial routines that explain why some firms convert AI-BI into ROI more effectively than others (Oberoi et al., 2017). The broader implication of this future research agenda is that the field should move toward process-sensitive models rather than static adoption models. Future researchers should ask not only whether firms use AI-BI, but how intelligence quality, governance quality, agility, human oversight, and trust conditions combine to shape campaign value creation. Such a model would deepen both theory and practice by showing the contingent path through which AI-augmented BI becomes a genuine dynamic capability in digital marketing (Teece, 2007).

CONCLUSION

This research has concluded that AI-augmented business intelligence has played a significant role in improving campaign performance optimization and marketing return on investment within U.S. retail and e-commerce firms. The study has shown that when organizations have integrated predictive analytics, real-time insight capability, customer segmentation intelligence, and decision automation support into their business intelligence environments, they have achieved stronger campaign effectiveness and more favorable return-related outcomes. The descriptive results have indicated high levels of agreement among respondents regarding the usefulness of AI-BI in campaign planning, execution, monitoring, and evaluation, while the correlation and regression results have confirmed that these relationships have been statistically meaningful and practically important. In particular, the study has found that predictive analytics capability and customer segmentation intelligence have been the most influential components of AI-augmented BI, suggesting that the ability to anticipate customer behavior and classify audiences accurately has formed the foundation of better-performing campaigns. The findings have also shown that campaign performance optimization has functioned as an important pathway through which AI-BI has translated into marketing ROI, which means that intelligent systems have not improved financial outcomes in isolation but through better targeting, faster responsiveness, stronger engagement quality, improved conversion efficiency, and more disciplined marketing resource allocation. These results have supported all the hypotheses of the study and have aligned with the research objectives by demonstrating that AI-augmented BI has been positively associated with campaign optimization, has contributed directly and indirectly to ROI, and has exhibited variation in influence across its core dimensions. The study has therefore added empirical clarity to a field in which AI, BI, and digital marketing performance have often been discussed separately rather than within one integrated model. The research has also reinforced the relevance of Dynamic Capabilities Theory by showing that AI-augmented BI has operated as a higher-order capability through which firms have sensed market signals, seized promotional opportunities, and reconfigured campaign actions under changing digital conditions. In this sense, the study has moved beyond a narrow technology adoption perspective and has demonstrated that organizational value has emerged when AI-enabled analytical systems have been actively embedded into campaign decision-making processes. Overall, the conclusion of this research is that AI-augmented business intelligence has not merely served as a reporting enhancement in the U.S. retail and e-commerce sector; it has functioned as a strategically important capability for improving the quality of campaign management and increasing the likelihood of stronger marketing returns. The study has therefore established that intelligent analytics, when integrated into business intelligence structures and aligned with campaign objectives, have become a meaningful source of competitive marketing advantage in data-rich retail environments.

RECOMMENDATIONS

Based on the findings of this research, it has been recommended that U.S. retail and e-commerce firms should treat AI-augmented business intelligence as a strategic campaign capability rather than as a purely technical or reporting tool. Organizations should prioritize the development of predictive analytics capability because the results of the study have shown that this dimension has had the strongest influence on campaign performance optimization. This means firms should invest in models and systems that can forecast customer response, identify likely conversion patterns, and support proactive campaign design before performance declines occur. It has also been recommended that firms strengthen customer segmentation intelligence, since the study has shown that the ability to classify and target customer groups more accurately has significantly improved campaign precision and conversion-related outcomes. Retail and e-commerce managers should therefore ensure that customer data are organized, updated, and translated into usable segmentation strategies that guide message customization, offer design, and channel allocation. In addition, firms should improve their real-time insight infrastructures by building dashboard environments that allow campaign managers to monitor performance continuously and intervene quickly when results shift. This recommendation has been important because the study has shown that real-time insight capability has significantly enhanced campaign responsiveness and efficiency. Decision automation support should also be adopted carefully and progressively, especially for repetitive campaign adjustments such as bid optimization, timing control, or trigger-based communication, while still maintaining human oversight for higher-level strategic decisions. From a managerial perspective, organizations should create cross-functional coordination between marketing teams, BI analysts, and data specialists so that analytical outputs are not isolated within technical departments but are directly connected to campaign action. Firms should also provide training and capability development programs for managers and analysts to improve their ability to interpret AI-generated insights and convert them into operational campaign decisions. Another recommendation has been that firms should measure campaign performance through integrated performance systems that connect operational metrics such as engagement and conversion with financial indicators such as cost efficiency and return on marketing investment. This would allow organizations to judge whether AI-BI systems are producing meaningful value rather than surface-level digital activity. At the strategic level, decision-makers should allocate digital transformation budgets toward capability areas that have the strongest demonstrated performance effects, especially predictive analytics and segmentation intelligence. Finally, organizations should establish governance mechanisms around data quality, ethical data use, and system transparency to ensure that AI-BI adoption remains sustainable, credible, and aligned with customer trust. These recommendations have been derived directly from the study findings and are intended to help firms translate AI-augmented BI into stronger campaign optimization and improved marketing ROI.

LIMITATIONS

This study has been subject to several limitations that should be recognized when interpreting the findings. First, the research has employed a quantitative, cross-sectional design, which has allowed the study to identify significant associations among AI-augmented business intelligence, campaign performance optimization, and marketing ROI at a single point in time, but has limited the ability to establish fully causal relationships across longer organizational periods. The results have therefore shown strong empirical links, yet they have not captured how these relationships may evolve over multiple campaign cycles or in response to long-term organizational learning. Second, the study has relied on self-reported responses gathered through a 5-point Likert-scale questionnaire. Although this approach has been useful for measuring managerial perceptions and organizational practices, it has also meant that the data have reflected respondent judgments rather than direct observation of audited campaign metrics, verified financial reports, or platform-level performance logs. This has introduced the possibility of perceptual bias, social desirability bias, or differences in how respondents have interpreted organizational performance. Third, the study has been limited to U.S. retail and e-commerce firms, which has strengthened contextual relevance but has also narrowed generalizability. The findings may not apply in the same way to other industries, such as manufacturing, healthcare, education, or business-to-business services, where marketing processes, customer journeys, and campaign time horizons may differ significantly. Fourth, although the study has examined key dimensions of AI-augmented BI, it has not included all possible organizational factors that may influence campaign performance and ROI, such as data governance maturity, team analytics skill, platform integration quality, budget size, or competitive intensity. These omitted variables may have affected the strength of the observed relationships. Fifth, the study has treated marketing ROI as a measurable outcome using survey-based organizational assessment, yet ROI in practice can be calculated in multiple ways depending on firm objectives, attribution models, and financial reporting structures. As a result, the construct has captured perceived return effectiveness rather than a single audited accounting formula. Another limitation has been the case-study–based orientation of the research, which has provided useful contextual depth but has not involved comparison across countries or broad cross-industry settings. In addition, although Dynamic Capabilities Theory has offered a strong theoretical explanation for the study, the research design has not directly observed sensing, seizing, and reconfiguring processes in action; instead, it has inferred them through measurable analytical and campaign constructs. These limitations have not invalidated the study, but they have defined the boundaries of its contribution. They have shown that the findings should be interpreted as robust evidence within a specific context and method, while also leaving room for future research to use longitudinal, mixed-methods, comparative, and objective-data designs to deepen and extend the insights generated here.

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