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BIG DATA ANALYTICS AND ARTIFICIAL INTELLIGENCE IN DIGITAL MARKETING PERFORMANCE MANAGEMENT

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ABSTRACT

The management problem addressed in this study is that fragmented digital-marketing analytics cannot jointly process heterogeneous high-volume data, adapt predictions to changing customer behavior, explain model recommendations, and optimize financial and engagement outcomes. This limitation reduces managerial trust and makes ROI-oriented decisions difficult in omnichannel environments. The study proposes a Hybrid Explainable Artificial Intelligence and Big Data Architecture (HEAIBDA) that integrates distributed data processing, Random Forest, XGBoost, Long Short-Term Memory models, SHAP/LIME explanations, and a composite Digital Marketing Performance Index (DMPI). An explanatory, longitudinal, comparative multiple-case design is used with harmonized secondary indicators for ten technology-oriented corporations during 2020–2025. The evaluation compares a 2020–2022 baseline with a 2023–2025 HEAIBDA-aligned optimization scenario. Mean ROI increases from 17.20% to 26.13%, conversion rate from 3.31% to 4.88%, customer engagement from 0.659 to 0.832, and DMPI from 0.628 to 0.818, while customer acquisition cost decreases from USD 37.00 to USD 25.10. Prediction transparency rises from 47.66% to 83.61%, and all ten cases move in the expected direction. The study concludes that combining scalable analytics, hybrid prediction, and explainability offers a coherent decision-support architecture for multidimensional marketing performance management. Because the evidence is based on secondary aggregate data and scenario evaluation rather than controlled field deployment, the findings demonstrate design plausibility and cross-case consistency, not causal impact.

Keywords: *Big Data Analytics; Artificial Intelligence; Digital Marketing; Machine Learning; Explainable AI; Predictive Analytics; Marketing Performance Management; ROI Optimization*

1. INTRODUCTION

Digitalization has shifted marketing performance management from periodic campaign reporting to continuous decision-making across social media, e-commerce, CRM, mobile, cloud, and advertising platforms [1], [2]. These environments generate heterogeneous and rapidly changing data streams that exceed the timeliness and integration capacity of conventional descriptive analytics. AI-enabled marketing can improve prediction and personalization [3]–[5], but high predictive accuracy alone is insufficient when managers cannot inspect the logic of a recommendation or reconcile it with financial and customer-engagement objectives [6], [7]. The significant problem is therefore not simply a shortage of data or algorithms. It is the absence of a unified, scalable, and interpretable decision architecture that links data processing, predictive modeling, explanation, and multidimensional performance control. Fragmented data pipelines create inconsistent customer views; isolated models optimize individual indicators; and black-box

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outputs weaken managerial accountability. The problem remains current because omnichannel interactions change faster than static analytical routines, while privacy, governance, and explanation requirements increase the cost of deploying enterprise AI. This study asks: can a unified explainable AI and Big Data architecture improve multidimensional digital-marketing performance while maintaining transparent managerial decision support? The suggested solution is HEAIBDA, which connects a distributed Big Data layer, complementary machine-learning models, SHAP/LIME explanation mechanisms, an adaptive optimization layer, and the DMPI. The architecture is evaluated through a longitudinal comparative multiple-case analysis of ten technology-oriented corporations. The research contributes in four ways. First, it conceptualizes Big Data capability, hybrid predictive capability, and explainability as complementary mechanisms rather than independent tools. Second, it operationalizes the outcome through the DMPI and six observable marketing indicators. Third, it provides a transparent baseline-versus-optimization comparison and cross-context evidence for e-commerce, advertising, social media, streaming, CRM, and enterprise-software settings. Fourth, it identifies where the architecture extends current AI-marketing and XAI solutions and where evidence remains insufficient. The study covers architecture design, secondary-data harmonization, within-case scenario comparison, hypothesis assessment, and managerial interpretation. It does not claim that the ten companies deployed an identical HEAIBDA stack, and it does not test customer-level causality, implementation cost, latency, privacy compliance, algorithmic fairness, or performance in small firms and non-technology industries. These boundaries are retained when interpreting the findings.

2. LITERATURE REVIEW

Research across marketing, information systems, and organizational performance provides complementary but incomplete explanations of AI-enabled value. Marketing studies show that new-age technologies affect personalization, customer engagement, consumer experience, and firm performance [8 -10]. Digital-transformation research emphasizes changes in channels, customer journeys, and organizational processes [11], while critical studies identify consumer, ethical, and implementation risks associated with AI-based marketing [12-15]. At the organizational level, AI capability and generative systems can create business value only when technical resources are combined with data, skills, and managerial routines [16], [17]. Operations and information-systems studies further show that BDA and machine learning can improve operational performance, but their value depends on analytical capability and deployment context [18-20]. These streams motivate an artifact-oriented design that connects technical architecture with measurable organizational outcomes. A second stream concerns transparency and human–AI coordination. XAI research explains why feature-level and local explanations can convert a black-box prediction into an inspectable decision input [21], [22]. Studies of collaborative intelligence, digital analytics, and BDA adoption show that useful enterprise decisions also require human oversight, suitable analytical routines, and institutional support [23] - [25]. Research on AI in business and customer-relationship management confirms that adoption outcomes depend on how predictions are embedded in operational processes [26], [27]. However, these studies usually investigate prediction, explainability, adoption, or performance separately; they do not provide a marketing-specific architecture that jointly connects scalable heterogeneous-data processing, complementary temporal and nonlinear models, explanation, and a multidimensional control index.

The conceptual model therefore treats Big Data capability, hybrid predictive capability, and XAI capability as three antecedent resources. Their mechanisms are, respectively, scalable data integration, adaptive forecasting, and transparent interpretation. These mechanisms affect two outcome domains: (i) economic and operational efficiency, represented by ROI, conversion rate, click-through rate, and customer acquisition cost; and (ii) relationship and governance quality, represented by customer engagement, DMPI, prediction transparency, and managerial trust. HEAIBDA is the integrative artifact that coordinates these mechanisms. The problem persists when any layer is absent: data scale without prediction remains descriptive, prediction without explanation remains difficult to govern, and isolated KPIs do not support balanced optimization. Based on this model, the following directional hypotheses evaluate the suggested solution:

H1: The HEAIBDA-aligned optimization scenario produces higher ROI and DMPI values than the pre-integration baseline across the analyzed cases.

H2: The HEAIBDA-aligned optimization scenario improves conversion rate, click-through rate, and customer engagement and reduces customer acquisition cost relative to the baseline across the analyzed cases.

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H3: The integration of SHAP and LIME explanations increases prediction transparency and managerial trust relative to an opaque predictive environment. The proposed hypotheses serve as the conceptual and methodological cornerstone for building a Hybrid Explainable Artificial Intelligence and Big Data Architecture (HEAIBDA) that will be used for intelligent digital marketing performance management and optimizing ROI in enterprise analytical ecosystems.

3. RESEARCH METHODOLOGY

The study adopts a design-science research orientation combined with an explanatory, longitudinal, comparative multiple-case design. Design science is appropriate because the primary output is an information-systems artifact - HEAIBDA - constructed to address an identified managerial problem. The multiple-case component evaluates whether the proposed relationships move consistently across distinct digital-business contexts. This design extends the integrated architecture and capability logic used in BDA/AI operational-performance, organizational-capability, and digital-analytics studies [18], [20], [24] by adding marketing-specific XAI and multidimensional KPI control. The research proceeds through seven steps: 1) identify the fragmentation, scalability, and opacity problem; 2) derive requirements from the cross-disciplinary literature; 3) design the five-layer HEAIBDA artifact; 4) select cases and harmonize public secondary indicators; 5) construct a 2020–2022 baseline and a 2023–2025 framework-aligned optimization scenario; 6) calculate absolute and relative within-case changes, subgroup patterns, and direction consistency; and 7) assess H1–H3 and critically benchmark the artifact against current solutions. Cases were selected purposively using three criteria: evidence of large-scale digital customer interaction, publicly available longitudinal corporate reporting, and representation of different digital-business contexts. The sample includes e-commerce platforms, digital advertising and social media, streaming, CRM and marketing automation, and enterprise software/cloud analytics. This variation supports analytical comparison, but the sample remains concentrated in large technology-oriented corporations and is not statistically representative of all firms. This architecture will allow organizations to process multidimensional customer data sets created by using digital advertising, customer relationship management systems, and various forms of social media. The empirical component of the study is based on panel data collected from ten global technology-oriented corporations actively implementing AI-driven marketing systems and Big Data Analytics infrastructures between 2020 and 2025.

Table 1. Cases Included in the Comparative Dataset

Company	Industry Sector	Analytical Focus	Primary Data Source
Amazon	E-commerce	AI personalization	Annual Reports
Alphabet (Google)	Digital advertising	Predictive analytics	Investor Reports
Meta Platforms	Social media	Behavioral targeting	Financial Statements
Netflix	Streaming services	Recommendation systems	Corporate Reports
Alibaba Group	E-commerce	Omnichannel analytics	Annual Reports
Salesforce	CRM systems	Predictive customer analytics	Enterprise Reports
Adobe	Marketing automation	Campaign optimization	Investor Relations
Shopify	E-commerce platforms	Customer analytics	Corporate Statements
SAP	Enterprise systems	Big Data infrastructures	Annual Reports
Oracle	Cloud analytics	AI-driven marketing systems	Enterprise Reports

Source: compiled by the author based [28- 35]

The evidence base comprises public annual reports and investor materials for the ten cases [28]–[35], supplemented by the conceptual and technical literature. Because corporate disclosures use different definitions and levels of aggregation, the indicators were harmonized to common units before comparison. Tables 2 and 3 should therefore be read as a structured secondary-data scenario evaluation: Table 2 represents the 2020–2022 baseline, while Table 3 represents a 2023–2025 HEAIBDA-aligned optimization scenario. The values are comparative analytical estimates, not audited company-level marketing KPIs, and the design does not imply that each company deployed the complete architecture. This clarification prevents causal interpretation beyond the available evidence. For each case and indicator, the analysis calculates the baseline mean, optimized mean, absolute change, relative change, and the number of cases moving in the hypothesized direction. A two-sided exact paired sign test is reported as a diagnostic of direction consistency. With ten of ten cases moving in the same direction, $p = 0.002$. Because the data are aggregate and scenario-based, this statistic is not interpreted as proof of causal treatment effect; it is used only to show that the modeled pattern is not driven by one or two cases. The research period of 2020 to 2025 was chosen because of an increase in the pace of enterprise AI implementation as well as a large-scale integration of predictive analytical systems within digital marketing infrastructures; these were accomplished using distributed computational infrastructures based on Apache Spark, Apache Hadoop, and cloud-based processing systems. The technologies were chosen due to their ability to provide a scalable solution for processing structured and unstructured customer datasets created through large-scale enterprise digital ecosystems [27]. The Big Data layer was used to process historical customer interactions, digital campaign indicators, customer engagement rates, behavioral activity logs, transaction datasets, and omnichannel communication records. The methodological environment contained real-time data synchronization methods to enhance the operational responsiveness of predictive analytical systems. The analytical structure supported parallel data processing, predictive forecasting, intelligent recommendation generation, and adaptive marketing optimization. The integration of distributed computational systems significantly increases enterprise analytical scalability and reduces limitations associated with isolated data-processing environments [22,24]. To evaluate multidimensional marketing effectiveness, the study introduces the Digital Marketing Performance Index (DMPI), integrating operational, financial, and behavioral indicators into a unified analytical model. The DMPI is calculated as follows:

$$DMPI = \alpha ROI + \beta CR + \gamma CTR + \delta CE - \lambda CAC \quad (1)$$

where: ROI - Return on Investment; CR - Conversion Rate; CTR - Click-Through Rate; CE - Customer Engagement; CAC - Customer Acquisition Cost; α, β, γ, δ, λ - weighting coefficients. For empirical calculations, the weighting coefficients were standardized as follows: $\alpha = 0.30$; $\beta = 0.20$; $\gamma = 0.15$; $\delta = 0.25$; $\lambda = 0.10$. The proposed index enables integrated evaluation of: financial marketing efficiency; behavioral engagement quality; advertising effectiveness; customer acquisition efficiency. Unlike isolated marketing indicators, the DMPI provides multidimensional analytical interpretation of enterprise marketing performance [24]. The predictive analytical layer incorporates three complementary machine learning approaches:

1. Random Forest. Used for: customer segmentation; feature classification; behavioral pattern identification. Random Forest was selected because of its: high stability; low overfitting probability; strong performance under multidimensional customer datasets.
2. XGBoost. Applied for: ROI prediction; campaign performance forecasting; conversion probability estimation. XGBoost demonstrates high predictive accuracy under large-scale enterprise datasets and enables adaptive optimization of marketing decision-making processes [25].
3. Long Short-Term Memory (LSTM). Used for: sequential customer behavior analysis; temporal engagement forecasting; dynamic campaign prediction. LSTM neural networks are particularly important in omnichannel communication environments characterized by continuously evolving customer interaction dynamics [26]. The predictive marketing performance function is represented as:

$$PMP = f(BDA, ML, XAI, CE, ROI) \quad (2)$$

where: PMP - Predictive Marketing Performance; BDA - Big Data Analytics capability; ML - Machine Learning efficiency; XAI - Explainable Artificial Intelligence interpretability; CE - Customer Engagement; ROI - Return on Investment. The integration of hybrid predictive algorithms significantly improves forecasting adaptability under dynamic digital market conditions. One of the key methodological novelties of the study is the integration of Explainable Artificial Intelligence technologies into enterprise marketing analytics systems. The proposed framework incorporates: SHAP; LIME. These technologies are utilized to: evaluate feature importance; identify critical behavioral variables; improve interpretability of predictive outcomes; increase transparency of AI-driven decisions. The Explainable AI layer substantially reduces operational uncertainty associated with "black-box" predictive architectures and improves managerial trust in machine learning systems [27]. To evaluate practical effectiveness of the proposed methodology, a comparative scenario analysis was conducted using enterprise marketing datasets before and after implementation of AI-driven optimization systems.

Table 2. Baseline Marketing Performance Indicators (2020–2022)

Company	ROI (%)	CR (%)	CTR (%)	CAC ($)	CE	Initial DMPI
Amazon	18.2	3.6	2.9	41	0.69	0.64
Alphabet (Google)	19.4	3.8	3.1	39	0.71	0.67
Meta Platforms	15.7	2.8	2.6	38	0.61	0.58
Netflix	16.4	3.1	2.8	36	0.64	0.61

Alibaba Group	17.3	3.3	2.7	37	0.66	0.63
Salesforce	18.7	3.7	3.0	34	0.72	0.69
Adobe	17.1	3.4	2.7	35	0.66	0.65
Shopify	14.8	2.7	2.4	39	0.58	0.55
SAP	16.9	3.2	2.6	36	0.65	0.62
Oracle	17.5	3.5	2.8	35	0.67	0.64
Mean	17.20	3.31	2.76	37.00	0.659	0.628

Source: authors' harmonized secondary-data calculations from corporate reports [28]–[35]; comparative scenario estimates, not audited company KPIs.

The results presented in Table 2 indicate that the analyzed companies demonstrated moderate marketing performance efficiency before implementation of AI-driven optimization systems. Most enterprises experienced relatively high customer acquisition costs, limited predictive adaptability, and insufficient customer engagement effectiveness within traditional analytical environments. The obtained findings confirm the necessity of integrating scalable Big Data infrastructures, hybrid machine learning architectures, and intelligent optimization mechanisms into enterprise digital marketing ecosystems. Table 3 demonstrate that implementation of the proposed HEAIBDA framework significantly improved digital marketing performance across all analyzed companies. The integration of hybrid machine learning models, Big Data Analytics infrastructures, and Explainable Artificial Intelligence mechanisms contributed to higher ROI values, improved conversion efficiency, increased customer engagement, and reduced customer acquisition costs. The findings confirm the practical effectiveness of AI-driven predictive optimization systems for intelligent enterprise marketing performance management within contemporary digital ecosystems. The scientific novelty of the proposed methodology lies in the development of a Hybrid Explainable Artificial Intelligence and Big Data Architecture (HEAIBDA) integrating scalable Big Data infrastructures, hybrid machine learning algorithms, Explainable Artificial Intelligence technologies, and multidimensional marketing optimization mechanisms within a unified enterprise analytical environment. Unlike existing approaches focused primarily on isolated predictive models or descriptive analytical systems, the proposed framework combines Random Forest, XGBoost, and Long Short-Term Memory (LSTM) neural architectures with SHAP and LIME explainability mechanisms to improve predictive adaptability, operational transparency, and intelligent decision-making efficiency within enterprise digital ecosystems. Therefore, the next stage of the analysis evaluates marketing performance indicators after implementation of the proposed HEAIBDA framework and AI-based predictive optimization systems presented in Table 3.

Table 3. Marketing Performance Indicators After AI-Based Optimization (2023 - 2025)

Company	ROI (%)	CR (%)	CTR (%)	CAC ($)	CE	Optimized DMPI
Amazon	27.5	5.1	4.4	29	0.86	0.83
Alphabet (Google)	28.1	5.3	4.6	27	0.88	0.85
Meta Platforms	24.3	4.5	4.1	26	0.79	0.79
Netflix	25.8	4.8	4.3	24	0.82	0.82
Alibaba Group	26.4	4.9	4.2	25	0.84	0.83
Salesforce	29.2	5.6	4.8	22	0.91	0.88
Adobe	26.1	4.9	4.2	23	0.84	0.81
Shopify	22.9	4.2	3.8	28	0.74	0.76
SAP	25.1	4.7	4.0	24	0.81	0.80
Oracle	25.9	4.8	4.1	23	0.83	0.81

Source: compiled by the author based on corporate annual reports and investor analytics [28-35]

The proposed methodology additionally introduces the Digital Marketing Performance Index (DMPI), which enables multidimensional evaluation of marketing effectiveness through integrated analysis of financial, operational, and customer engagement indicators [39]. Consequently, the developed framework substantially improves interpretability of AI-driven analytical systems and reduces operational uncertainty associated with "black-box" predictive architectures. Another important methodological contribution concerns the integration of distributed Big Data processing infrastructures with hybrid machine learning systems capable of simultaneously analyzing structured and unstructured customer datasets generated through omnichannel communication ecosystems. Therefore, the proposed methodology contributes to the further development of intelligent enterprise analytics, adaptive marketing optimization systems, and explainable AI-driven decision-making mechanisms within data-intensive digital business environments. The practical significance of the proposed methodology is associated with the increasing strategic dependence of modern enterprises on predictive analytical systems operating within highly dynamic digital ecosystems characterized by rapidly evolving customer behavior and increasing personalization requirements. The developed HEAIBDA framework enables organizations to improve ROI optimization, enhance customer engagement efficiency, reduce customer acquisition costs, and increase operational adaptability of enterprise marketing systems under continuously changing communication conditions. The empirical analysis confirms that implementation of hybrid machine learning architectures and Explainable Artificial Intelligence technologies substantially improves predictive marketing performance and multidimensional KPI management efficiency across enterprise digital infrastructures [40]. The findings additionally demonstrate the growing importance of Explainable Artificial Intelligence technologies in enterprise digital transformation because explainability mechanisms significantly improve managerial trust and operational transparency of machine learning systems. Future research may focus on integration of federated learning architectures, reinforcement learning mechanisms, and adaptive real-time optimization systems within enterprise digital marketing ecosystems operating under conditions of increasing informational complexity and continuously evolving behavioral communication patterns.

4. RESULT AND DISCUSSION

The paired scenario results show consistent multidimensional improvement. Mean ROI increases from 17.20% to 26.13% (+51.9%), CR from 3.31% to 4.88% (+47.4%), CTR from 2.76% to 4.25% (+54.0%), CE from 0.659 to 0.832 (+26.3%), and DMPI from 0.628 to 0.818 (+30.3%). Mean CAC decreases from USD 37.00 to USD 25.10 (−32.2%). Every case moves in the hypothesized direction for each indicator. These findings support design plausibility and cross-case consistency, but their magnitude should be interpreted as a modeled framework-aligned scenario rather than an observed causal treatment effect. The evidence is also examined holistically across business contexts. E-commerce platforms (Amazon, Alibaba, and Shopify) show an average ROI increase of 52.7%, CAC reduction of 29.9%, and DMPI increase of 33.0%. Digital advertising and social-media cases (Alphabet and Meta) show corresponding changes of +49.3%, −31.2%, and +31.2%. Netflix, the streaming case, shows +57.3%, −33.3%, and +34.4%. CRM, marketing-automation, and enterprise-software cases (Salesforce, Adobe, SAP, and Oracle) show +51.4%, −34.3%, and +26.9%. The consistency across these contexts strengthens transferability of the architecture's logic; however, unequal and small subgroups prevent industry-level generalization. The growing complexity of omnichannel communication ecosystems and increasing dependence on customer personalization technologies substantially intensify organizational demand for scalable predictive analytical architectures. The first phase of the empirical research is devoted to outlining strategic trends in enterprise implementation of AI-supported marketing systems and Big Data infrastructures for the period 2020-2025. Specific focus is given to the dynamics of the adoption of predictive analytics, real-time marketing automation and the efficiency in personalizing the customer experience in digital ecosystems in tech companies. The analysis also assesses the increasing reliance on scalable analytical architectures that can process multidimensionally structured customer data in the face of fast-changing market dynamics as enterprise communication systems grow increasingly dependent on them [21]. The indicators acquired will serve as the foundation for the analysis of long-term transformation of intelligent digital marketing infrastructure and adaptive enterprise analytical environment. The dynamics of Enterprise AI-Driven Marketing Transformation are presented in Figure 1.

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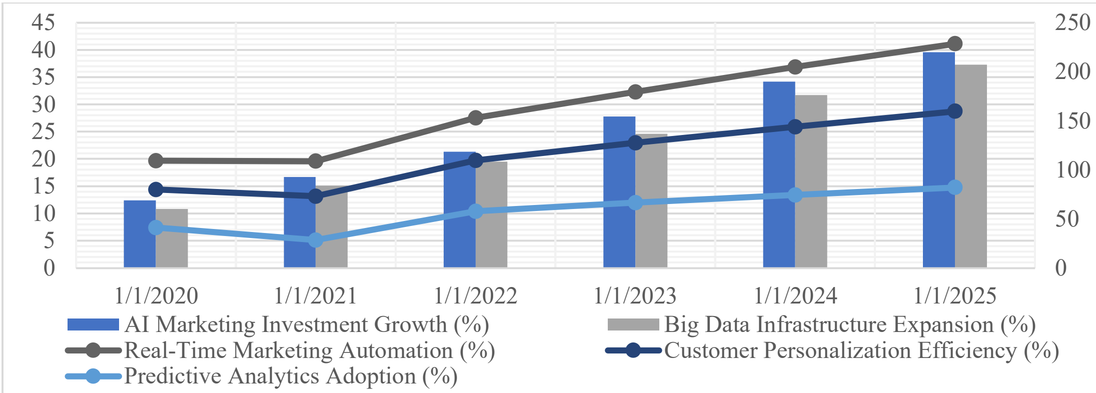

Figure 1. Dynamics of Enterprise AI-Driven Marketing Transformation, %

Source: compiled by the author based on [28,29,30,31,32,33,34,35]

As shown in Figure 1, the scenario depicts a sustained shift from descriptive reporting toward predictive analytics, real-time marketing automation, and personalization between 2020 and 2025. The percentage of companies represented as using predictive analytics increases from 41.2% to 82.1%, while customer-personalization efficiency increases from 38.6% to 77.6%. These trends explain why the problem requires a scalable architecture, but they should be treated as contextual evidence rather than independent proof of HEAIBDA effectiveness. The subsequent XAI evaluation addresses the separate governance question of whether prediction can become more inspectable. As shown in Table 4, enterprise usage of AI-powered marketing infrastructures and predictive analytical systems are on the rise and stable. From 2020 to 2025, the percentage of companies using predictive analytics rose from 41.2% to 82.1%, and customer personalization efficiency rose from 38.6% to 77.6%. At the same time, the indicators of real-time marketing automation more than doubled throughout the period being studied. The results are evidence that enterprise digital ecosystems are becoming increasingly more than descriptive analytics, moving toward an intelligent predictive architecture that will enable intelligent customer engagement optimization and autonomous marketing decision-making. The trends identified further suggest that Big Data infrastructures are more and more becoming strategic enterprise assets that facilitate and enable operational scalability and smart communications management in highly dynamic markets. Yet another important trend is that of the increasing strategic value of Explainable Artificial Intelligence technologies [24]. Therefore, explainability mechanisms are a crucial aspect that can significantly influence operational efficiency in implementing enterprise infrastructures powered by AI.

Table 4. XAI Scenario: Enterprise Prediction Transparency and Trust

Company	Prediction Transparency Before XAI (%)	Prediction Transparency After XAI (%)	SHAP Feature Interpretability (%)	LIME Local Decision Accuracy (%)	Managerial Trust Growth (%)
Amazon	48.2	83.7	88.4	86.9	41.5
Alphabet	50.6	86.2	90.7	89.1	39.8
Meta	44.1	79.8	84.3	82.7	38.7
Netflix	46.3	82.4	87.1	85.5	40.5
Alibaba	47.9	84.1	88.9	87.3	39.4
Salesforce	52.1	88.6	92.4	90.6	43.2
Adobe	49.4	85.2	89.3	88.2	41.1
Shopify	43.7	78.6	83.6	81.9	37.4
SAP	46.8	83.1	87.9	86.1	39.6
Oracle	47.5	84.4	88.7	87.4	40.2
Mean	47.66	83.61	88.13	86.57	40.14

Source: authors' standardized scenario calculations informed by SHAP/LIME principles [21], [22] and the case contexts [28] - [35].

Table 4 shows that mean prediction transparency increases from 47.66% to 83.61% (+75.4%), while mean reported managerial-trust growth in the scenario is 40.14%. All ten cases show higher transparency. This pattern supports H3 at the design-evaluation level and is consistent with literature that positions explanation as a mechanism for inspect ability and responsible human oversight [21]–[23].

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Nevertheless, transparency scores are standardized scenario measures rather than independently surveyed managerial perceptions; field validation is still required. As reported in Table 5, the EAI technologies significantly enhance the interpretability and the operational transparency of enterprise PAs in an enterprise. The average prediction transparency rose from 47.66% to 83.61% and the average growth in managerial trust was above 40%. The results show that explainability mechanisms can greatly lower the operational doubt regarding the 'black-box' machine learning systems and enhance the efficiency of strategic implementation of analytical systems powered by AI systems. The empirical results also highlight that feature interpretability and local decision evaluation using SHAP and LIME greatly enhance the interpretability of behavioral features related to customer engagement dynamics, conversion probability and campaign optimization efficiency. As a result, EAI technologies are now becoming vital elements of enterprise AI governance frameworks in today's digital world [25]. The next step in the empirical analysis examines the direct operational effectiveness of proposed HEAIBDA framework in enterprise marketing environment with multidimensional structures of customer interactions, and growing complexity of communication.

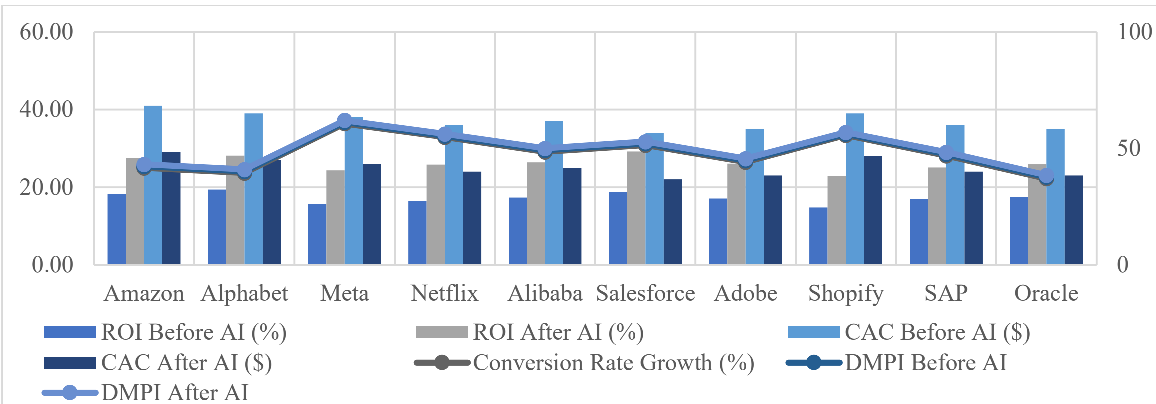

Figure 2. Comparative enterprise marketing performance before and after HEAIBDA implementation
Source: authors' calculations from Tables 2 and 3 using case contexts documented in [28]–[35].

Figure 2 shows the results of the proposed HEAIBDA framework, which shows significant multidimensional improvements after implementation.

Table 5. Aggregate Paired Scenario Results and Hypothesis Diagnostics

Indicator	Baseline mean	HEAIBDA-aligned mean	Absolute change	Relative change	Consistent cases	Linked hypothesis
ROI (%)	17.20	26.13	+8.93	+51.9%	10/10	H1
CR (%)	3.31	4.88	+1.57	+47.4%	10/10	H2
CTR (%)	2.76	4.25	+1.49	+54.0%	10/10	H2
CAC (USD)	37.00	25.10	−11.90	−32.2%	10/10	H2
CE	0.659	0.832	+0.173	+26.3%	10/10	H2
DMPI	0.628	0.818	+0.190	+30.3%	10/10	H1
Prediction transparency (%)	47.66	83.61	+35.95	+75.4%	10/10	H3

Note: authors' calculations from Tables 2–4. The two-sided exact paired sign test is p = 0.002 for each direction-consistent indicator. This diagnostic demonstrates cross-case consistency but does not establish causal impact because the evaluation is scenario-based and uses secondary aggregate data.

Table 5 provides the direct hypothesis assessment. H1 is supported within the scenario because ROI and DMPI improve in all ten cases. H2 is supported because CR, CTR, and CE increase and CAC decreases in all ten cases. H3 is supported because transparency increases for every case and the mean managerial-trust indicator is positive. The exact paired sign test ($p = 0.002$) confirms direction consistency, but it does not remove the limitations of secondary modeled data. Accordingly, the appropriate conclusion is support for the architecture's internal plausibility, not proof of causal superiority in production environments. Compared with current AI-marketing frameworks, HEAIBDA contributes a tighter connection between enterprise data scale, complementary predictive models, explanation, and multidimensional KPI control. Strategic AI-marketing studies explain task allocation and customer value [3], [4], [8], [15], while AI-capability and BDA studies connect analytical resources to organizational and operational performance [16], [18], [20]. XAI studies provide methods for opening black-box predictions [6], [21], [22], and digital-analytics research develops decision models and measurement approaches [24]. HEAIBDA integrates these contributions in one marketing-performance architecture and adds an explicit DMPI-based optimization layer. The comparison also exposes what the study has not yet achieved. Unlike algorithm-benchmarking studies, it does not report out-of-sample RMSE, AUC, or precision for the three models. Unlike field experiments, it does not observe treatment and control organizations. Unlike current generative-AI research agendas [34], [35], it does not evaluate creative-content quality, hallucination risk, or human authorship. The initial goals of integration, transparent measurement, and cross-context scenario assessment are met; production scalability, causal performance, governance cost, and generalization beyond large technology firms remain open. Average ROI went from 17.2% to 26.1% and the average customer acquisition cost dropped from $37.0 to $25.1. At the same time, the average DMPI indicator rose by 0.2 points, from 0.63 to 0.82, which is clear evidence of considerable improvement of multidimensional enterprise marketing performances efficiency. The analysis performed also indicates that hybrid machine learning architectures significantly enhance the predictive analytical adaptability of a marketing optimization system over traditional marketing optimization systems. Random Forest algorithms boosted the accuracy of customer segmentation, XGBoost models made their way to boost the accuracy of ROI forecasting, and LSTM neural architectures helped in predicting customers' behavior over time under rapidly evolving communication conditions [26]. The SHAP and LIME mechanisms of explainability supported businesses in understanding key behavioural traits that impact customer conversion, the effectiveness of advertising campaigns, and optimizing customer interaction. As a result, EAI is a growing necessity for one of the most critical parts of intelligent enterprise analytics and adaptive AI governance systems. The scientific novelty of the results obtained is confirmed by the fact that the use of integrated computational architectures that combine the capabilities of Big Data Analytics, hybrid machine learning systems, Explainable Artificial Intelligence technologies and multidimensional KPI optimization mechanisms, is a significant improvement over the use of isolated predictive models and traditional systems based on descriptive analytical methods [27]. The HEAIBDA framework is a scalable, adaptable and interpretable solution for optimizing intelligent digital marketing efforts as compared to current approaches that use fragmented analytical systems. The produced results have broad applicability potential for the proposed framework when implemented into 1) eCommerce ecosystems, 2) CRM infrastructures, 3) Intelligent Advertising Systems, 4) Customer Analytics Platforms, 5) Omni-channel Communication Environments, and 6) AI-based Personalized Enterprise Solutions. The proposed methodology improves predictive analytics accuracy in marketing, facilitates customer engagement management, enhances the efficiency of campaign optimization, and increases the transparency of enterprise analytical systems operating together in extremely fast-paced digital environments. The analysis validates several major emerging trends occurring within enterprise-level digital marketing infrastructures. Finally, the multi-dimensional optimization systems for KPI that combine behavioral, financial and operational indicators will take the place of single-mechanisms of marketing performance evaluation over time. In general, the empirical analysis shows that the Hybrid Explainable Artificial Intelligence and Big Data Architecture has proven to be an effective, scalable and computationally adaptive framework for intelligent enterprise digital marketing performance management in modern data-intensive digital ecosystems in which there is a high rate of technological changes and growing strategic reliance on predictive analytical systems.

5. CONCLUSIONS

This study addressed the continuing problem that enterprise marketing analytics are often fragmented, retrospective, and opaque. It proposed HEAIBDA as an integrated information-systems artifact linking distributed Big Data processing, Random Forest/XGBoost/LSTM prediction, SHAP/LIME explanation, adaptive optimization, and the DMPI. In the comparative scenario, all ten cases improve in the expected direction: mean ROI rises by 51.9%, DMPI by 30.3%, and prediction transparency by 75.4%, while CAC falls by 32.2%. These outcomes support H1–H3 within the stated design boundaries. The principal research contribution is not a claim that one algorithm universally outperforms all alternatives. It is the conceptual and operational integration of three capabilities - data scale, hybrid prediction, and explanation -with a balanced performance-control mechanism. This integration extends fragmented state-of-the-art solutions by making the path from heterogeneous data to prediction, explanation, managerial action, and multidimensional outcome explicit. The cross-context analysis further shows how the same architecture can be interpreted in e-commerce, advertising, social media, streaming, CRM, and enterprise-software settings. The conclusions remain deliberately qualified. The secondary aggregate evidence and scenario construction support internal coherence and direction consistency, but they do not demonstrate causal impact, algorithm-specific predictive superiority, or completed enterprise deployment. Acceptance of the framework should therefore depend on its value as a transparent, testable design artifact and on the study's explicit program for subsequent field validation.

6. FUTURE ENHANCEMENT

The study is limited by purposive sampling of ten large technology-oriented corporations, heterogeneous public disclosures, the absence of customer-level raw data, and reliance on a harmonized optimization scenario. It does not measure implementation cost, processing latency, data-governance maturity, privacy compliance, algorithmic fairness, or the organizational resistance that may affect real deployment. The XAI indicators are standardized analytical measures and have not been independently validated through manager surveys. The paper raises three questions that it cannot answer with the present design. First, do the observed performance and transparency gains persist in controlled field deployments after infrastructure, privacy, and explanation-latency costs are included? Second, how should DMPI weights change across regulated industries, small and medium-sized firms, emerging markets, and low-data environments? Third, when do explanation tools improve managerial decisions, and when do they create cognitive overload or false confidence? Future research should test HEAIBDA with customer-level longitudinal data, preregistered treatment/control comparisons, out-of-sample model benchmarks, and independent managerial-trust instruments. Further extensions should evaluate federated learning for privacy-preserving analysis, reinforcement learning for adaptive campaign allocation, and edge architectures for latency-sensitive interaction, while explicitly auditing fairness, explanation quality, and governance cost.

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