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Boosting insurance sales performance with marketing strategy: the power of artificial intelligence, chatbot engagement and machine learning

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Abstract

Purpose – This study examines how marketing strategy influences insurance sales performance by integrating artificial intelligence (AI) chatbot engagement and machine learning into the analysis. It aims to uncover how digital technologies transform the effectiveness of marketing strategy in Ghana's insurance sector, an underexplored context in emerging economies.

Design/methodology/approach – A quantitative, cross-sectional survey was conducted among 246 employees of licensed insurance companies in Ghana. Data were collected using structured questionnaires, which were analyzed with Structural Equation Modelling (SEM) to test the direct, mediating and moderating relationships among the variables.

Findings – Results reveal that marketing strategy alone does not significantly predict insurance sales performance. However, AI chatbot engagement fully mediates this relationship, demonstrating that marketing strategy becomes effective only when implemented through technology-driven customer engagement. Moreover, machine learning positively moderates the link between AI chatbot engagement and sales performance, indicating that higher levels of machine learning capability strengthen the impact of chatbot interactions on sales outcomes.

Practical implications – The study provides a strategic roadmap for insurance firms to embed AI chatbots and machine learning into their marketing systems. Managers are encouraged to develop digital competencies and data-driven cultures that enhance customer experience, personalization and decision-making in competitive insurance markets.

Originality/value – This research is among the first to integrate AI chatbot engagement and machine learning within the Resource-Based Theory framework to explain marketing performance dynamics in an African insurance context. It advances theoretical understanding by conceptualizing AI technologies as strategic resources that convert marketing capabilities into measurable performance gains, offering novel and context-specific insights for digital transformation in emerging markets.

Keywords Marketing strategy, Insurance sales performance, Artificial intelligence chatbot engagement, Machine learning, Insurance companies, Resource-based theory

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Introduction

The actions of consumers in acquiring and utilizing goods and services are significantly influenced by the marketing strategies employed by firms (Deepak & Jeyakumar, 2019; Mattar & Hanna, 2024). In an era of digital disruption, marketing strategy has evolved beyond traditional promotion and pricing mechanisms to encompass data-driven and customer-centric approaches that directly shape business performance (Ghobakhloo & Jafarian, 2019). As consumer behavior becomes increasingly complex and dynamic, organizations must continuously rethink how they develop, implement and adapt marketing strategies to remain competitive (Khalayleh & Al-Hawary, 2022).

Empirical research confirms that strategic marketing positively influences business outcomes, particularly in small- and medium-sized enterprises (SMEs) and emerging sectors such as insurance (Amin, 2021; Dibb, Simkin, Pride, & Ferrell, 2019; Syaifullah, Syaifudin, Sukendar, & Junaedi, 2021). However, much of the existing literature has treated marketing strategy as a static set of tools rather than a dynamic capability that must integrate with evolving technologies to yield sustained performance outcomes (Varadarajan, 2020). In response, scholars have called for deeper exploration into how artificial intelligence (AI) chatbot engagement and machine learning can be embedded within marketing strategy to enhance performance metrics such as customer acquisition, engagement and revenue growth (Govindan, 2024; Makhlooq & Al Mubarak, 2024; Kumar, Ashraf, & Nadeem, 2024).

Despite growing scholarly attention, current studies often examine AI chatbot engagement and machine learning in isolation or treat them as ancillary technological tools rather than strategic resources within a marketing framework (Madhuri, Rajesh, & Kumar, 2024; Singh, Das, Jha, Kumar, & Rani, 2024). Few studies have examined how AI-powered chatbot engagement, as an operational interface and machine learning, and also as a back-end learning capability, can jointly transform marketing efforts and improve insurance sales performance outcomes. Moreover, most of the available research has been conducted in developed market contexts, leaving a significant gap in understanding how these technologies operate within emerging markets such as Sub-Saharan Africa, where patterns of digital adoption, customer engagement and strategic needs differ substantially (Akter, Bandara, Wamba, Foropon, & Papadopoulos, 2021; Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021).

Research gap and justification

While insurance firms across Ghana are progressively embracing digitalization, empirical studies linking AI chatbot engagement, machine learning and marketing strategy to sales performance remain limited. Existing research has mainly focused on the operational efficiencies of AI systems rather than their strategic contribution to firm performance. In addition, there is little evidence explaining how AI chatbot engagement mediates the link between marketing strategy and sales performance, or when machine learning strengthens this relationship. These gaps are critical because emerging markets like Ghana, face resource and infrastructural constraints that influence the adoption and effectiveness of digital technologies. Understanding these dynamics can therefore provide actionable insights for both academia and industry.

This study addresses these gaps by investigating the pathways through which marketing strategy influences insurance sales performance, emphasizing the mediating role of AI chatbot engagement and the moderating role of machine learning. Grounded in the Resource-Based Theory (RBT), the study conceptualizes AI and machine learning not merely as tools but as strategic organizational capabilities that are valuable, rare, inimitable and nonsubstitutable (Barney, 1991; Wamba-Taguimdje, Wamba, Kamdjoug, & Wanko, 2020). This perspective shifts the focus from technology – as infrastructure to technology-as-strategy, highlighting how internal digital competencies can be leveraged to build sustainable competitive advantage.

To address the identified gaps in the literature and achieve the study's objectives, the following research questions are examined:

(1) What is the effect of marketing strategy on insurance sales performance?

(2) To what extent does AI chatbot engagement mediate the relationship between marketing strategy and insurance sales performance?

(3) How does machine learning moderate the relationship between AI chatbot engagement and insurance sales performance?

Contribution of the study

This study makes several theoretical and practical contributions. First, it extends the Resource-Based Theory by reconceptualizing marketing strategy as a dynamic organizational capability that derives value not only from internal resources but also from the integration of digital technologies. By empirically testing whether marketing strategy alone predicts insurance sales performance, the study provides evidence on the sufficiency or limitations of conventional marketing resources in a technology-driven environment. This advances theoretical understanding of how resource configurations affect performance when external technological capabilities are introduced.

Second, the study makes a novel contribution by positioning AI chatbot engagement as a mediating mechanism that translates marketing efforts into measurable performance gains. While previous studies have treated AI primarily as an operational tool, this research conceptualizes chatbot engagement as a strategic resource that enables real-time interaction, personalization, and customer relationship strengthening. By demonstrating its mediating role, the study provides empirical evidence that marketing strategies yield meaningful outcomes only when executed through technology-driven customer engagement processes. This extends RBT by showing how digital engagement capabilities bridge the gap between marketing intentions and sales outcomes.

Third, the study contributes to the growing literature on machine learning as a boundary condition in marketing–technology relationships. Machine learning is theorized as a moderating capability that amplifies the positive impact of AI chatbot engagement on insurance sales performance. This introduces an important theoretical refinement to RBT by highlighting resource complementarities, the idea that technological resources interact to produce superior performance outcomes. When machine learning capabilities are high, AI chatbots become more adaptive and predictive, enabling deeper customer insights and more effective personalization. This moderating insight positions machine learning as an enabling capability that determines the strength of AI's contribution to organizational performance.

Collectively, these contributions advance both theory and practice. Theoretically, the study integrates strategic marketing, AI engagement chatbot and machine learning within a coherent resource-based framework. This offers a richer understanding of how firms convert technological assets into competitive advantage. Empirically, it provides one of the first studies within Sub-Saharan Africa's insurance context to test a moderated mediation model linking marketing strategy, AI chatbot engagement and sales performance. Practically, it offers a digital transformation roadmap for insurance firms, showing that sustained sales growth requires not only an effective marketing strategy but also the strategic embedding of AI engagement chatbot and machine learning capabilities within those strategies.

Theoretical background and literature review

Digitalization has fundamentally reshaped how firms design and execute marketing strategy, particularly in electronic business environments where customer interactions are increasingly mediated by data-driven and automated technologies. Prior research shows that an effective digital marketing strategy, characterized by data-driven targeting, omnichannel coordination and personalized communication, can enhance sales performance by improving responsiveness and customer alignment (Varadarajan, 2020; Morgan, 2012). In service-oriented digital markets, however, strategic success depends not only on strategy formulation but also on the capabilities through which strategies are executed at digital customer touchpoints.

To explain performance differences arising from such capabilities, this study draws on resource-based theory (RBT), which posits that firms achieve competitive advantage by deploying resources that are valuable, rare, inimitable and nonsubstitutable (Barney, 1991). In marketing and information systems research, RBT has been used to explain how organization's specific resources, such as digital infrastructure, customer analytics and technological know-how enable superior strategic execution and performance (Bharadwaj, 2000). Extensions of RBT emphasize the importance of dynamic capabilities, highlighting firms' abilities to integrate and reconfigure resources in response to changing digital environments (Ruiz-Carrillo & Fernández-Ortiz, 2005; Madhani, 2009).

Despite these advances, much of the digital marketing literature continues to model the strategy–performance relationship as direct and linear, paying limited attention to the execution mechanisms through which strategies are enacted in electronic channels. As customer interactions increasingly occur through automated interfaces, this limits understanding of how marketing strategies translate into observable economic outcomes, such as sales performance, in electronic business settings.

AI-powered chatbots have emerged as prominent digital interfaces for customer interaction, enabling scalable communication, continuous availability and personalized engagement. Existing studies demonstrate that chatbot design features and interaction quality influence customer engagement, satisfaction and purchase-related behaviors (Araujo, 2018; Luo, Tong, Fang, & Qu, 2019; Wirtz *et al.*, 2018). However, chatbot research remains largely adoption and perception-focused, offering limited insight into firm-level economic outcomes. Moreover, chatbots are often examined as standalone tools rather than as firm-specific engagement capabilities embedded within broader marketing strategy, leaving their role in driving sales performance under-explored.

Customer engagement has become a central construct in digital business research, reflecting interactive processes through which firms and customers co-create value in online environments. Digital engagement mechanisms, such as responsiveness, interactivity and personalization, are associated with favorable behavioral outcomes, including conversion and repeat purchase (Hollebeek & Macky, 2019). Yet, engagement is frequently measured using attitudinal indicators, with limited linkage to objective performance measures, restricting understanding of its economic implications.

Machine learning further shapes digital marketing by enabling predictive analytics, adaptive personalization and real-time optimization of customer interactions. Prior studies suggest that machine learning enhances marketing effectiveness by supporting continuous learning from customer data (De Mauro, Sestino, & Bacconi, 2022). Nevertheless, machine learning is typically treated as a technical capability, and few studies examine its role as a boundary condition that strengthens or weakens the performance impact of AI-enabled engagement.

These gaps are particularly salient in the insurance sector, where products are complex, trust-sensitive and increasingly marketed through digital channels. Existing research focuses primarily on technology acceptance and service efficiency, offering limited evidence on how AI-enabled engagement contributes to sales performance.

Overall, the literature reveals three interrelated gaps: limited understanding of how digital marketing strategy is executed through AI-enabled engagement capabilities; insufficient evidence linking chatbot engagement to firm-level sales outcomes and under-exploration of machine learning as a moderating capability. Addressing these gaps, the study conceptualizes AI chatbot engagement as a firm-specific capability mediating the relationship between marketing strategy and insurance sales performance, while modelling machine learning as a moderating capability that conditions this effect. In doing so, the study advances understanding of how digital interaction technologies generate economic value in the contemporary electronic business environment.

Key concepts

Marketing strategy

Marketing strategy encompasses the coordinated use of organizational resources and tools to achieve superior market performance. In the digital era, businesses increasingly integrate AI and machine learning into their marketing strategies to drive personalization, improve targeting and enhance customer experience (Verma *et al.*, 2025; Reddy, 2024).

In marketing, AI and machine learning have been applied to several functions, including market segmentation, targeting, positioning, pricing and customer relationship management. Wedel and Kamakura (2000) and Haleem, Javaid, Qadri, Singh, and Suman (2022) highlight how AI-driven analytics facilitate precise customer segmentation and better targeting. Similarly, Babatunde, Odejide, Edunjobi, and Ogundipe (2024) and Kamal and Himel (2023) show that AI tools enhance positioning strategies by enabling personalized messaging, improving brand perception and customer loyalty.

Studies confirm a strong correlation between well-defined marketing strategies and improved insurance sales performance (Ahmad, Ahmad, Farhan, & Arshad, 2020; Harry & Purwanegara, 2021). However, while existing studies have explored AI and machine learning in marketing, most treat them as standalone technologies rather than firm-specific capabilities embedded within strategy (Madhuri *et al.*, 2024; Singh *et al.*, 2024). This study therefore examines how marketing strategy interacts with AI chatbot engagement and machine learning to improve insurance sales performance within Ghana's emerging digital environment, grounded in the Resource-Based View (Barney, 1991; Ruiz-Carrillo & Fernández-Ortiz, 2005).

Artificial Intelligence Chatbot Engagement

Artificial Intelligence Chatbot Engagement refers specifically to the extent to which employees and organizations use AI-driven chatbots to enhance customer communication and service efficiency. Within the insurance industry, AI chatbots are increasingly deployed to manage customer inquiries, policy renewals and claims processing, providing consistent and responsive service experiences. These chatbots learn from customer interactions, enabling them to deliver personalized assistance and targeted product recommendations that strengthen the customer–firm relationship (Madhuri *et al.*, 2024).

Incorporating AI chatbot engagement into marketing strategies facilitates the automation of tasks such as email campaigns, lead nurturing and ad targeting, thereby improving operational efficiency and freeing marketing professionals to focus on strategic planning (Haleem *et al.*, 2022). AI-driven analytics also offer deep insights into customer behavior and preferences, which enable marketers to design data-informed campaigns and enhance brand engagement (Kumar *et al.*, 2024). As firms deploy AI chatbots in customer-facing roles, they not only achieve cost efficiency but also generate real-time customer intelligence that can be used to refine marketing strategies, optimize customer journeys and ultimately boost sales performance.

Machine learning

Machine learning is a subset of AI that enables systems to improve their performance over time through data-driven learning and predictive modeling (Agrawal, Gans, & Goldfarb, 2020). It enhances organizational decision-making by identifying patterns, forecasting outcomes and refining operational processes based on empirical data. In marketing, machine learning plays a crucial role in customer segmentation, demand forecasting and dynamic pricing, providing businesses with adaptive intelligence that traditional analytical tools lack.

Machine learning acts as a moderating capability that strengthens the link between AI chatbot engagement and sales performance. By processing customer interaction data, machine learning algorithms improve chatbot responsiveness, accuracy and personalization. This allows chatbots to learn from past customer behaviors, predict future needs and tailor communication strategies accordingly. The synergy between AI chatbots and machine learning results in higher customer satisfaction, conversion rates and long-term loyalty.

Despite its growing global relevance, machine learning applications within Ghana's insurance sector remain limited. This study therefore operationalizes machine learning as an organizational capability that enhances the effectiveness of AI chatbot engagement, serving as a boundary condition that determines the strength of the relationship between AI engagement and insurance sales performance. At higher levels of machine learning integration, firms are expected to achieve more significant improvements in sales performance, while lower levels may constrain the effectiveness of AI-driven marketing initiatives.

The selection of these constructs is therefore justified on both theoretical and contextual grounds. From a theoretical perspective, AI chatbot engagement and machine learning meet the VRIN criteria and serve as dynamic capabilities that can enhance marketing effectiveness. Contextually, they are highly relevant as firms increasingly navigate digital marketing landscapes and need to integrate advanced technologies into their strategy to drive performance. Thus, this study contributes a holistic framework that reflects current realities while filling a gap in the literature.

Hypothesis development

Marketing strategy and insurance sales performance

Marketing involves all activities, organizations, and procedures for creating, communicating, delivering and exchanging valuable offerings for customers, clients, partners and society (Varadarajan, 2020). The main goal of a marketing strategy is to increase sales and gain a sustainable competitive advantage (Varadarajan, 2020; Ali, Ameen, & Tirwanshi, 2024). These strategies can involve short-term or long-term actions within the marketing domain (Webster & Lusch, 2013). Insurance sales performance measures the sales achieved within a specific period compared to targets, reflecting the effectiveness of a sales team and individual representatives (Rodriguez & Boyer, 2020; Ohiomah, Andreev, Benyoucef, & Hood, 2019). Marketing strategy is a framework for allocating resources to achieve organizational goals and gain a competitive edge (Harry & Purwanegara, 2021; Wijaya, Latanro, & Sugianitri, 2024). This approach helps establish and maintain high insurance sales performance within a specific timeframe (Chawla, Lyngdoh, Guda, & Purani, 2020). Achieving sales results involves analyzing strategic positions, strengths, competition and financial positions to select market-focused strategies (Ahmad *et al.*, 2020; Umamaheswari, 2024). This assessment aims to engage customers, add value, expand the customer base and increase sales through advertising and incentives (Darma & Noviana, 2020; Rodriguez & Boyer, 2020). Insurance sales performance reflects outcomes such as revenue growth, customer acquisition and achievement of sales targets within the insurance sector (Bag, Gupta, Kumar, & Sivarajah, 2021). Hence, this study proposes the following hypothesis:

H1. Marketing strategy has a positive effect on insurance sales performance.

The mediation role of AI chatbot engagement

Artificial Intelligence Chatbot Engagement refers to the extent to which employees use AI-powered chatbots to improve responsiveness, accuracy, and efficiency in customer service (Madhuri *et al.*, 2024). Research shows a growing trend in AI adoption in marketing, driven by its ability to analyze large volumes of data, automate tasks and personalize efforts (Wamba-Taguimdje *et al.*, 2020). Studies confirm a strong correlation between well-defined marketing strategies and improved insurance sales performance (Ahmad *et al.*, 2020; Harry & Purwanegara, 2021). AI-driven analytics provide insights into customer behavior and preferences, leading to better engagement, increased brand awareness and higher sales (Kumar *et al.*, 2024). Companies increasingly use AI for chatbots, predictive analytics, and content personalization (Patel & Trivedi, 2020). These capabilities help develop marketing strategies closely aligned with customer needs, potentially boosting sales (Wind & Rangaswamy, 2001). AI also automates tasks such as email campaigns, lead nurturing and ad targeting, enhancing efficiency and allowing greater focus on strategic planning (Haleem *et al.*, 2022). Importantly, recent studies highlight AI chatbot engagement, a key dimension of AI adoption as a critical mechanism linking marketing to sales outcomes. Vlačić, Corbo, e Silva, and Dabić (2021) argue that AI significantly mediates the relationship between digital marketing capabilities and firm performance, suggesting marketing alone may not yield performance gains without AI integration. Similarly, Dhamija and Bag (2020) showed that AI-enabled marketing improves insurance sales performance only when strategically implemented. Naslednikov (2024) emphasizes AI as a performance amplifier, enhancing marketing's impact on sales through better segmentation, predictive insights and personalization. Mu and Zhang (2025) further revealed that AI marketing usage enhances firm performance via customer acquisition and satisfaction, reinforcing its mediating role. Additionally, the 2024 State of Marketing AI Report indicates 88% of marketers use AI daily, with AI-powered campaigns delivering 32% more conversions (Marketing AI Institute and Drift, 2024). This widespread adoption and measurable impact further support AI chatbot engagement as a strategic channel through which marketing efforts translate into improved insurance sales performance. Therefore, this study hypothesizes that:

H2. AI chatbot engagement mediates the relationship between marketing strategy and insurance sales performance.

The moderating role of machine learning

Machine learning is defined as the use of data-driven algorithms that enhance decision-making over time (Anand, Velu, & Whig, 2022). In marketing and sales contexts, machine learning functions not merely as a technological tool but as a dynamic moderator that shapes the strength and direction of relationships between marketing strategies and performance outcomes. Specifically, machine learning moderates how effectively artificial intelligence (AI) systems such as chatbots, predictive analytics and automated customer engagement platforms translate marketing intelligence into measurable sales performance. Machine learning techniques are increasingly used in marketing to analyze large datasets, identify patterns and predict insurance sales performance (Saleem, Muhammad, Nizamani, Saleem, & Aslam, 2019). Studies show that the level of sophistication and integration of machine learning algorithms influences the magnitude of the relationship between AI-driven customer engagement and sales outcomes (Syam & Sharma, 2018; Helm *et al.*, 2020). For example, when machine learning capabilities are high, predictive models can more accurately identify high-potential leads, optimize pricing strategies and personalize offers, thereby strengthening the link between marketing efforts and insurance sales performance. Conversely, when machine learning capability is low, the predictive accuracy and responsiveness of AI systems decline, weakening this relationship. Machine learning algorithms aid predictive analytics and lead scoring, helping sales teams prioritize high-potential leads (Rane, Choudhary, & Rane, 2024). They also refine customer segmentation and personalize marketing content for more targeted sales strategies (Chaitanya, Saha, Saha, Acharya, & Singla, 2023). As a moderating variable, machine learning amplifies the effectiveness of AI-enabled marketing interventions by continuously learning from data feedback loops, reducing uncertainty and improving model precision. This means that firms with advanced machine learning adoption will experience a stronger positive impact of AI-driven marketing engagement on sales performance than firms with limited or rudimentary machine learning use. Machine learning enhances decision-making by extracting meaningful customer insights, leading to more informed marketing and sales strategies (Soori, Arezoo, & Dastres, 2023). This approach helps businesses understand customer behavior, preferences and purchase patterns (Shrirame, Sabade, Soneta, & Vijayalakshmi, 2020; Rane *et al.*, 2024). Thus, machine learning operates as a boundary condition that determines how efficiently AI-generated intelligence translates into performance outcomes.

At higher levels of machine learning capability, there will be an enhanced positive effect on insurance sales performance due to greater predictive accuracy and data adaptability; at lower levels, the relationship between AI engagement and sales performance will diminish or even flatten due to reduced learning precision and model responsiveness. Therefore, this study hypothesizes that:

H3. Machine learning moderates the relationship between *AI* chatbot engagement and insurance sales performance.

The conceptual framework of the study is presented in Figure 1, illustrating the proposed relationships among marketing strategy, artificial intelligence, chatbot engagement, machine learning and insurance sales performance.

Methodology

Research design

The study adopted a quantitative research design to investigate the effect of marketing strategy on insurance sales performance, focusing on the mediating role of AI chatbot engagement and the moderating role of machine learning. The design enables rigorous testing of direct, mediating and moderating relationships by assessing the mediating role of AI chatbot engagement and the boundary condition imposed by machine learning capability. This approach is particularly suited to the Ghanaian insurance context, where empirical evidence on the strategic performance implications of AI-driven marketing remains limited. The design enables rigorous testing of direct, mediating and moderating relationships by assessing the mediating role of AI chatbot engagement and the boundary condition imposed by machine learning capability. This approach is particularly suited to the Ghanaian insurance context, where empirical evidence on the strategic performance implications of AI-driven marketing remains limited.

A cross-sectional survey approach was used to collect data at a single point in time through a structured questionnaire, allowing for standardized responses and statistical analysis. This design was appropriate for examining associations among multiple variables within a defined organizational context (Rindfleisch, Malter, Ganesan, & Moorman, 2008). Given the study's aim to test both direct and indirect relationships, Structural Equation Modelling (SEM) using

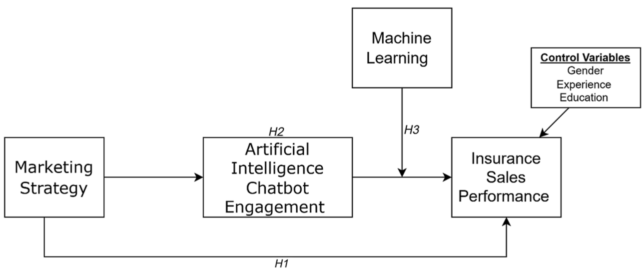

Figure 1. Conceptual framework: summary of hypothesized relationships between marketing strategy, AI chatbot engagement, machine learning and insurance sales performance

AMOS version 23 was employed. SEM is suitable for examining complex causal relationships and testing mediation and moderation effects within a unified analytical framework (Hair, Hult, Ringle, Sarstedt, Danks, Ray, . . ., & Ray, 2021). This analytical technique aligns with the study's objective of assessing how AI chatbot engagement and machine learning jointly shape the relationship between marketing strategy and insurance sales performance in Ghana's insurance sector.

Population, sampling frame and sample size

The target population consisted of employees of licensed insurance companies operating in Ghana. The sampling frame was drawn from the 2023 registries of the National Insurance Commission (NIC) and the Ghana Insurers Association (GIA), which included 28 life and nonlife insurance firms nationwide. Lists of employees from marketing, sales, customer service and information technology departments were obtained through organizational gatekeepers and used as the basis for questionnaire distribution. These departments were chosen because their staff are directly involved in marketing and customer service functions that utilize AI and machine learning tools. A purposive sampling technique was used to select firms that had adopted or were experimenting with AI technologies, such as chatbots, predictive analytics, or automated claims management systems. Within each selected firm, proportional stratification was applied across departments to ensure balanced representation of respondents. This combination of purposive and stratified sampling was justified because AI and machine learning adoption remain in the early stages within Ghana's insurance sector, making random sampling impractical (Campbell *et al.*, 2020). In total, 350 questionnaires were distributed, and 246 valid responses were retrieved after data cleaning, yielding a response rate of approximately 70%. This sample size exceeded the minimum threshold recommended by Hair, Risher, Sarstedt, and Ringle (2019) for SEM analysis, ensuring adequate statistical power.

Data collection procedure

Data were collected over a fifteen-working-day period using a dual-mode approach that combined Google Forms and printed questionnaires. This approach was designed to improve inclusivity and minimize nonresponse bias. Employees in urban locations such as Accra, Kumasi and Takoradi were reached through the electronic version due to their reliable internet access and familiarity with digital platforms. In contrast, staff in semi-urban and rural areas received printed questionnaires distributed through the human resource departments of their firms, as these locations often experience poor connectivity and limited digital literacy. The use of both online and offline modes ensured inclusivity, expanded geographic coverage and improved representativeness (Saunders, Lewis, & Thornhill, 2019). An independent-samples *t*-test was conducted to compare responses between the two data collection modes, and no significant differences were found ($p > 0.05$), confirming that merging the two datasets did not introduce systematic bias.

Instrumentation and measurement of variables

The research instrument was a structured questionnaire divided into five sections. Section A collected demographic data, while Sections B to E measured the main constructs: marketing strategy, AI chatbot engagement, machine learning and insurance sales performance. The items were adapted from validated scales in prior studies, marketing strategy from Amin (2021), AI chatbot engagement from Alsheibani, Cheung, and Messom (2018) and Basri (2020), machine learning from Anand *et al.* (2022), and insurance sales performance from Amin (2021) and Bag *et al.* (2021). All constructs were measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The instrument was pre-tested with 20 insurance employees to ensure clarity, face validity and internal consistency. Feedback from the pre-test led to the refinement of wording and the removal of ambiguous items before the main data collection. Machine learning was operationalized as an organizational capability representing the extent to which insurance firms in Ghana employ data-driven algorithms to enhance marketing, customer engagement and decision-making processes. This construct was contextualized to reflect the Ghanaian insurance environment, where firms such as Hollard Ghana, Metropolitan Life Insurance Ghana and Enterprise Group Plc have deployed machine learning tools for predictive analytics, claims processing and pricing optimization. Respondents rated items such as “Our company uses machine learning techniques to detect and eliminate insurance fraud”, “Our company applies machine learning to optimize pricing strategies” and “Our company leverages machine learning for customer segmentation and sales prediction”. This operationalization captured both the technological and strategic dimensions of machine learning as applied within Ghana’s emerging digital insurance ecosystem.

Ethical considerations

Ethical considerations were carefully observed throughout the research process. Participation was voluntary, and respondents were assured of anonymity and confidentiality. No personal identifiers were collected. Ethical approval was obtained from the university’s research ethics committee, and authorization letters were issued to participating insurance firms prior to data collection. Data were securely stored and used solely for academic purposes in accordance with data protection protocols.

Data screening and nonresponse bias assessment

Data screening was carried out using SPSS version 25 to identify missing values, outliers and inconsistencies. Incomplete responses were excluded from the final dataset. Normality tests confirmed that data distributions met the assumptions for SEM analysis. Nonresponse bias was examined by comparing early and late respondents across demographic characteristics, and no significant differences were observed ($p > 0.05$), suggesting the absence of nonresponse bias.

Common method variance (CMV) control

To control for potential common method variance (CMV), two diagnostic techniques were applied following Podsakoff, MacKenzie, Lee, and Podsakoff (2003). The first was the marker variable technique, where an unrelated construct, and organizational citizenship behavior, was included in the survey to assess potential common variance across items. The correlation between the marker and substantive variables was weak ($r = 0.08$, $p > 0.05$), suggesting minimal CMV influence. The second was the Unmeasured Latent Method Construct (ULMC) approach, implemented during confirmatory factor analysis (CFA) in AMOS by introducing a latent factor that loaded on all observed indicators. The standardized loadings of this latent factor were below 0.25, and its inclusion did not significantly improve model fit (ΔCFI <0.01), confirming that CMV was not a significant issue (Leong, Jaafar, & Ainin, 2018; Pavlou, Liang, & Xue, 2007). Together, these two approaches provided strong evidence that common method bias was negligible in the dataset.

Data analysis techniques

Data analysis followed three main stages. The first stage involved preliminary analyses, including descriptive statistics, normality assessment and reliability tests using Cronbach’s alpha. In the second stage, measurement model validation was conducted through Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The EFA ensured that items loaded appropriately onto their respective latent constructs, with factor loadings above 0.50. CFA results confirmed satisfactory reliability and validity, with composite reliability (CR) above 0.70, average variance extracted (AVE) exceeding 0.50, and model fit indices meeting conventional thresholds (CMIN/DF ≤ 3, CFI ≥ 0.90, TLI ≥ 0.90, RMSEA ≤ 0.08). In the third stage, Structural Equation Modelling (SEM) was used to test the hypothesized relationships, including mediation and moderation effects. The moderating role of machine learning was assessed through an interaction term (AI Chatbot Engagement × Machine Learning), and the results indicated a significant positive moderating effect ($\beta = 0.108$; $p < 0.05$), implying that higher levels of machine learning capability strengthened the positive influence of AI chatbot engagement on insurance sales performance. Control variables, including education, gender and work experience, were also tested and found to have no significant effects on the dependent variable.

Table 1 presents the demographic profile of the respondents in this study. The results indicate that male respondents constituted 47.6% ($n = 117$), while female respondents accounted for 52.4% ($n = 129$). Regarding work experience, 20.3% of respondents ($n = 50$) had less than 5 years of experience. Additionally, 25.6% ($n = 63$) had between 5 and 10 years of experience, 15.4% ($n = 38$) had between 11 and 15 years, 22.0% ($n = 54$) had between 16 and 20 years, and 16.7% ($n = 41$) had more than 20 years of experience. In terms of educational attainment, 68.3% of respondents ($n = 168$) held a first degree, 28.9% ($n = 71$) had a master's degree and 2.8% ($n = 7$) had a PhD. The demographic profile suggests a balanced gender distribution among respondents, diverse work experience levels, and a high level of educational attainment. This diversity provides comprehensive insights and enhances the robustness of the study's findings.

Data validity and reliability

We conducted an EFA to ensure the correct alignment of measurement items with their respective latent variables using SPSS (version 25). The study focused on three latent variables: marketing strategy (MS), insurance sales performance (ISP) and AI chatbot engagement. During EFA, items that loaded onto multiple constructs or exhibited weak factor loadings (less than 0.5) were excluded. The remaining items are presented in Table 2. The Total Variance Extracted (TVE) was 76.546%, exceeding the required minimum of 50%, indicating robust variance extraction. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy scored 0.903, above the recommended threshold of 0.6, confirming sample adequacy.

To validate the EFA, Bartlett's Test of Sphericity demonstrated the statistical significance of relationships between the variables. The data, with a Chi-square value of 5301.763 and a significance level of 0.000, confirmed EFA adequacy due to substantial correlations. The Determinant of Correlation was 1.837E−10, indicating positive definiteness. After EFA, CFA was conducted in Amos (version 23) to further check the

Table 1. Respondents' demographics

Variable	Response	Frequency (N)	Percent (%)
Experience	Less than 5 years	50	20.3
	5–10 years	63	25.6
	11–15 years	38	15.4
	16–20 years	54	22.0
	Above 20 years	41	16.7
	Total	*246*	*100.0*
Gender	Male	117	47.6
	Female	129	52.4
	Total	*246*	*100.0*
Education	First Degree	168	68.3
	Masters	71	28.9
	PhD	7	2.8
	Total	*246*	*100.0*

Table 2. Confirmatory factor analysis (CFA)

Model-fit indices CMIN = 375.209; DF = 197; CMIN/DF = 1.905; GFI = 0.884; TLI = 0.956; CFI = 0.966; RMSEA = 0.061; RMR = 0.052	Factor loading
Marketing Strategy (MS): CA = 0.941; CR = 0.926; AVE = 0.644	
The company builds the environmental benefits and/or costs into the insurance premium (MS1)	0.697
The company charges lower prices for environmentally friendlier versions of their service (MS2)	0.690
The company teams up with our channel members to develop appropriate insurance premiums for customers (MS3)	0.861
The company tends to modify its insurance policy decisions to emphasize any environmental benefits (MS4)	0.860
My insurance company sponsors educational programs in my community (MS5)	0.857
My insurance company sponsors sporting activities in my community (MS6)	0.840
My insurance company uses advertising to communicate its services (MS7)	0.792
Artificial intelligence Chatbot Engagement (AI): CA = 0.921; CR = 0.879; AVE = 0.593	
The company actively uses the AI chatbot as part of our daily work activities (AI1)	0.656
The company initiates interactions with the AI chatbot when handling customer service tasks (AI2)	0.802
The company depends on the AI chatbot to support decision-making during service delivery (AI3)	0.818
The AI chatbot is regularly incorporated into the company's workflow (AI4)	0.803
The company has integrated the AI chatbot into our routine to improve efficiency (AI5)	0.759
Machine Learning Usage (ML): CA = 0.937; CR = 0.949; AVE = 0.725	
Our company uses machine learning techniques to eliminate fraud in insurance *(ML1)*	0.829
Our company uses machine learning practices to detect fraud in insurance (*ML2)*	0.822
Our company uses machine learning techniques to automatically inspect insurance premiums (*ML3)*	0.874
Our company uses machine learning skills to process insurance claims (*ML4)*	0.879
Our company uses machine learning techniques to predict insurance prediction (*ML5)*	0.896
Our company uses machine learning techniques to predict customer lifetime value (*ML6)*	0.838
Our company uses machine learning techniques for insurance price optimization (*ML7)*	0.819
Insurance Sale Performance (SP): CA = 0.937; CR = 0.909; AVE = 0.715	
Our company sells insurance with a higher profit margin (SP1)	0.809
Our company produces a high market share for my company in my territory (SP2)	0.864
Our company generates sales of new company services quickly (SP3)	0.870
Our company exceeded the sales target and objective that were assigned to me *(SP4)*	0.839

reliability of measurement items in loading onto their respective latent variables using the retained EFA variables.

Confirmatory factor analysis

After meeting the designated thresholds, CFA results, as shown inTable 2, confirmed that the standardized factor loadings of the measurement variables consistently exceeded 0.5, indicating an effective representation of latent variables (Iddris, Dogbe, & Kparl, 2022). All latent variables had Cronbach's alphas (CA) above the 0.7 threshold, reflecting strong internal reliability. Convergent validity was established, with composite reliability (CR) and average variance extracted (AVE) both meeting the criteria of at least 0.7 and 0.5, respectively (Hair, Black, Babin, & Anderson, 2010). The model's goodness of fit was confirmed, with all criteria, CMIN/DF $\leq$ 3, GFI $\geq$0.8, PClose >0.05, TLI $\geq$0.9, CFI $\geq$0.9, RMSEA $\leq$0.08 and RMR $\leq$0.08, being satisfactorily met.

Discriminant validity

Discriminant validity was assessed by comparing the square root of the raw average variance extracted ($\sqrt{}$AVE) with the corresponding inter-correlation coefficients (Hair *et al.*, 2010; Iddris *et al.*, 2022). $\sqrt{}$AVE is highlighted in bold and italics and consistently exceeds the respective correlation coefficients. The results, as depicted in Table 3, indicate that the lowest

Table 3. Discriminant validity

Variables	Experience	Gender	Education	MS	AI	ML	SP
Experience	1						
Gender	0.053	1					
Education	0.040	−0.039	1				
MS	−0.019	0.068	0.049	*0.802*			
AI	−0.021	0.057	−0.005	0.498**	*0.770*		
ML	0.064	−0.009	0.039	0.011	0.014	*0.851*	
SP	−0.039	0.040	0.093	0.420**	0.473**	0.057	*0.846*

Note(s): ** ~ Correlation is significant at the 0.01 level (two-tailed); * ~ Correlation is significant at the 0.05 level (two-tailed); $\sqrt{\text{AVE}}$ ~ Italics

$\sqrt{\text{AVE}}$ was 0.770, and the highest correlation was 0.498 (between marketing strategy and AI chatbot), which was below 0.7. Consequently, it can be inferred that there was no multicollinearity in the dataset. In conclusion, the data obtained from the CFA analysis is valid for estimating the structural model. To address common method variance (CMV), this study employed two techniques as recommended by Podsakoff *et al.* (2003) and Leong *et al.* (2018, 2020). First, a marker variable unrelated to the core constructs was included to assess potential bias. Second, the Unmeasured Latent Method Construct (ULMC) approach was applied by introducing a latent factor loading on all observed items. Results from both methods indicated that CMV was not a significant concern. These steps align with established procedures for detecting CMV (Pavlou *et al.*, 2007).

Path analysis

The study utilized Amos (version 23) software for covariance-based structural equation modeling (SEM) to estimate route coefficients, employing 5,000 bootstrap samples and a 95% confidence level with the Bias-Corrected (BC) percentile bootstrapping technique. Analytical results are presented in Table 4 and Figure 2. The analysis controlled for work experience, education and gender. Education showed a positive impact on insurance sales performance, but this was not statistically significant ($\beta = 0.144$; $p > 0.05$). Gender had an insignificant negative effect on sales success ($\beta = -0.003$; $p > 0.05$), with gender coded as 1 for male and 2 for female. Work experience also had an insignificant negative effect on sales effectiveness ($\beta = 0.010$; $p > 0.05$).

Table 4. Path coefficients

Paths	Unstd. Estimates	S. E	C. R	*p*
M_S → A_I	0.628	0.066	9.568	***
M_S → S_P	0.109	0.075	1.446	0.148
A_I → S_P	0.662	0.097	6.844	***
M_L → S_P	0.081	0.060	1.363	0.173
MLxAI → S_P	0.108	0.045	2.368	0.018
Experience → S_P	−0.010	0.033	−0.289	0.772
Gender → S_P	−0.003	0.092	−0.033	0.974
Education → S_P	0.144	0.086	1.669	0.095

Indirect effect		Lower BC	Upper BC
MS→AI→SP	0.416	0.265	0.604

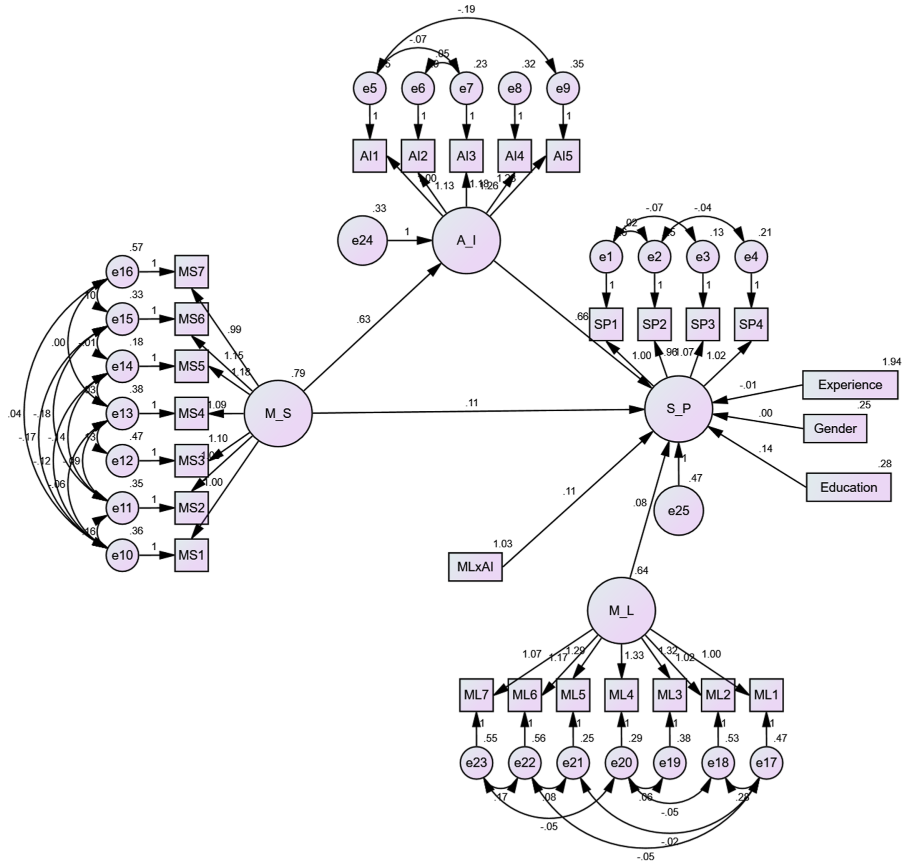

Figure 2. Structural equation model

The effect of marketing strategy on insurance sales performance was statistically insignificant (β = 0.109; $p > 0.05$), not supporting Hypothesis 1 (H1), which posited that marketing strategy affects insurance sales performance. This suggests that marketing strategy alone does not influence sales in the insurance sector significantly.

Conversely, marketing strategy had a significant positive effect on AI chatbot engagement (β = 0.628; $p < 0.01$), supporting Hypothesis 2 (H2), which proposed that AI chatbot engagement mediates the relationship between marketing strategy and insurance sales performance. Effective marketing strategies were found to increase AI chatbot engagement by 62.8%, which in turn positively impacted insurance sales performance (β = 0.662; $p < 0.01$), suggesting a 66.2% improvement in insurance sales performance with effective AI chatbot engagement.

Finally, Hypothesis 3 (H3) was supported, showing that machine learning positively moderates the relationship between AI and insurance sales performance. The interaction between machine learning and AI (MLxAI) had a significant positive effect on insurance sales performance (β = 0.108; $p < 0.05$) as depicted in Table 4 and Figure 3, indicating that high levels of both AI and machine learning improved insurance sales performance. Conversely, low AI chatbot engagement and machine learning levels led to decreased insurance sales performance. However, the effect of machine learning alone on insurance sales performance

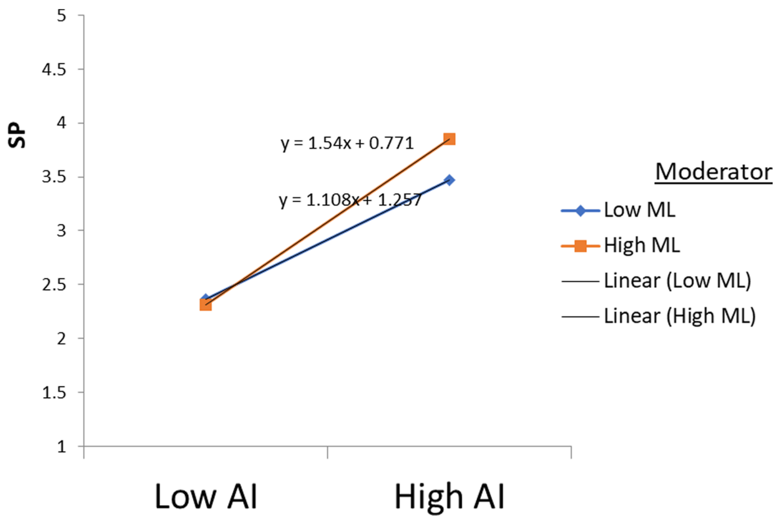

Figure 3. Interaction between AI and sales performance

was statistically insignificant but positive ($\beta = 0.081$; $p > 0.05$), suggesting that machine learning alone does not significantly affect insurance sales performance.

Discussion

This study offers unique contributions by integrating AI chatbot engagement into marketing strategies, demonstrating its mediating role in the relationship between marketing strategy and insurance sales performance. It also reveals the positive moderating effect of machine learning on the relationship between AI chatbot and insurance sales performance. It is conducted within Ghana's insurance sector and provides valuable context-specific insights and knowledge. Specifically, the empirical results reveal the following.

First, the effect of marketing strategy on insurance sales performance was not statistically significant, rejecting hypothesis (H1). The rejection of Hypothesis 1 indicates that marketing strategy, when considered as a standalone resource, does not exert a statistically significant direct effect on insurance sales performance. From a Resource-Based Theory perspective, this finding suggests that marketing strategy lacks performance-generating power in isolation unless it is effectively orchestrated with complementary digital resources. While prior studies (e.g. Obadia & Vida, 2024; Zega, Gea, Batee, & Zebua, 2024) report positive effects, these outcomes are typically observed in contexts where marketing strategies are enacted through technology-enabled engagement mechanisms. Consistent with the resource orchestration view, strategic resources create value not merely by their possession but through their coordinated deployment with complementary capabilities. In the Ghanaian insurance context, traditional marketing strategies appear insufficient to drive sales unless they are activated through AI-enabled customer interaction. The significant mediating role of AI chatbot engagement therefore indicates that marketing strategy contributes to performance indirectly, by shaping how firms deploy interactive, data-driven engagement resources. This finding extends existing literature by demonstrating that marketing strategy functions as an enabling resource whose value is realized through digital complementarities rather than through direct effects.

Second, AI chatbot was found to mediate the relationship between marketing strategy and insurance sales performance (H2). The effect of marketing strategy on AI chatbot engagement was statistically significant, aligning with the findings of Xie and He (2022), who also reported a positive effect of marketing strategy on AI chatbot engagement. Moreover, the effect of AI chatbot engagement on insurance sales performance was statistically significant, supporting studies by Basri (2020) and Pekkaya, Uysal, Altan, and Karasu (2024). This indicates that the marketing strategy adopted may lead to AI chatbot engagement, which in turn enhances insurance sales performance. Therefore, the effect of marketing strategy on insurance sales performance is realized through the mediation of AI chatbot engagement, supporting H2. AI chatbot engagement emerges as a critical factor for achieving higher sales through various marketing strategies. The study uniquely highlights the critical role of AI chatbot engagement in enhancing the effectiveness of marketing strategies. By demonstrating that AI chatbot engagement fully mediates the relationship between marketing strategy and insurance sales performance, it demonstrates the importance of adopting AI technologies to achieve better sales outcomes.

Third, although the direct effect of marketing strategy on insurance sales performance was not significant, marketing strategy significantly influenced AI chatbot engagement, which in turn had a significant impact on insurance sales performance. This indicates that AI chatbot engagement fully mediates the relationship between marketing strategy and insurance sales performance. In organizations where traditional marketing strategies no longer directly affect sales, integrating AI chatbot into operations can play a critical role in driving insurance sales.

Lastly, the study found that machine learning moderates the relationship between AI chatbot engagement and insurance sales performance, supporting Hypothesis (H3). This finding aligns with Zhang *et al.* (2024), indicating that the combined presence of machine learning and AI chatbot engagement has a superior effect on insurance sales performance in insurance company operations. When an AI chatbot is engaged, and employees are proficient in using machine learning, insurance sales performance is likely to improve significantly. The research brings a novel insight into the moderating effect of machine learning on the relationship between AI and insurance sales performance. This indicates that while AI chatbot engagement can significantly enhance insurance sales performance, the addition of machine learning further strengthens this effect, providing an understanding of how advanced technologies interact to influence sales outcomes.

Theoretical contributions

This study makes several important theoretical contributions by extending the Resource-Based Theory (RBT) into the realm of technology-enabled marketing performance. Traditionally, RBT emphasizes tangible and intangible firm resources as primary determinants of competitive advantage (Barney, 1991; Barney & Arikan, 2005). However, as firms operate in increasingly digitalized and data-driven markets, the nature of strategic resources is evolving. This research advances RBT by reconceptualizing artificial intelligence (AI) chatbot engagement and machine learning as strategic organizational resources that are valuable, rare, inimitable and nonsubstitutable (VRIN). These digital capabilities enable firms to develop adaptive, data-informed marketing systems that enhance responsiveness, customer engagement and performance outcomes (Wamba-Taguimdje *et al.*, 2020; Lubis, 2022).

First, this study broadens RBT's explanatory scope by showing that marketing strategy alone, a traditional internal resource, no longer guarantees superior sales performance in technology-intensive environments (Varadarajan, 2020). The empirical findings demonstrate that AI chatbot engagement fully mediates the relationship between marketing strategy and insurance sales performance. This finding supports the argument that digital engagement capabilities act as strategic bridges that convert marketing intent into measurable customer outcomes. By conceptualizing AI chatbot engagement as a dynamic capability, this study aligns with the digital transformation perspective, which views technological adaptation as a process of continuous capability renewal (Wamba-Taguimdje *et al.*, 2020; Misra, Sharma, Gupta, & Das, 2023).

Second, the study introduces machine learning as a boundary condition within the RBT framework, emphasizing the concept of resource complementarity. The moderating effect of machine learning shows that when predictive analytics and data-driven intelligence are high, AI chatbots become more adaptive, context-aware and capable of delivering superior sales outcomes. This aligns with Magrini (2023), who emphasized the transformative power of AI in shaping modern sales strategies, and with Hildebrand and Bergner (2019), who demonstrated how AI-driven sales automation enhances customer interaction and efficiency. Together, these findings contribute a theoretical refinement to RBT by illustrating that synergistic integration of digital resources magnifies competitive advantage. Firms achieve superior performance not from isolated technological capabilities, but from their interdependent configuration (De Mauro *et al.*, 2022).

Third, by empirically testing a moderated mediation model in Ghana's insurance sector, the study extends RBT's contextual relevance to emerging economies. The findings demonstrate that when firms strategically embed AI chatbot engagement and machine learning within marketing systems, digital resource configurations can offset structural market constraints and institutional inefficiencies typical of developing economies (Truong, Simmons, & Palmer, 2012). This evidence supports the argument that digitalization enables firms to reconfigure their internal processes and customer interfaces, thereby achieving performance advantages even under resource-scarce conditions (Alsheibani *et al.*, 2018).

Collectively, these insights position AI chatbot engagement and machine learning as strategic, capability-based resources that transform marketing from a functional activity into a dynamic, knowledge-intensive system for value creation and sustained competitiveness. The study thus enriches RBT by demonstrating how firms in emerging markets can leverage digital complementarities to build a more resilient and innovation-driven marketing architecture (Wamba-Taguimdje *et al.*, 2020; Varadarajan, 2020; Lubis, 2022).

Practical implications

From a managerial standpoint, this study underscores that marketing success in the insurance industry increasingly depends on digital integration rather than reliance on traditional promotional techniques. Managers should strategically embed AI chatbot systems within marketing workflows to enhance customer responsiveness, personalization and real-time engagement. These chatbots can automate repetitive customer interactions, streamline claim processing, improve lead nurturing and increase cross-selling opportunities, thereby transforming customer touchpoints into strategic value exchanges (Hildebrand & Bergner, 2019; Basri, 2020). As customers expect immediacy and precision, the adoption of AI-enabled chatbots allows insurance firms to strengthen relationships and enhance perceived service quality, contributing to improved sales performance and brand loyalty (Wamba-Taguimdje *et al.*, 2020).

Furthermore, managers should treat machine learning capabilities not merely as technical enablers but as adaptive learning systems that continuously refine marketing and sales processes. Machine learning supports predictive modeling for customer churn, fraud detection and risk assessment, ultimately improving sales targeting and conversion rates (Rane *et al.*, 2024; Anand *et al.*, 2022). Training employees to interpret and apply these insights promotes data-driven decision-making, enhances accountability and increases organizational agility. When marketing and sales personnel are empowered with analytical literacy, firms can move beyond intuition-driven strategies toward precision marketing and performance optimization (Chaitanya *et al.*, 2023).

Executives should also encourage cross-functional collaboration between IT, marketing and customer service teams to ensure that data analytics and AI-driven insights directly inform strategic objectives. This integration helps align customer engagement strategies with predictive technologies, thereby maximizing the impact of marketing investments (Bag *et al.*, 2021; Govindan, 2024). Finally, organizational culture must evolve toward digital literacy and experimentation. Creating a culture that supports innovation, iterative testing and responsible

AI deployment will help insurance firms sustain long-term competitiveness in an increasingly intelligent business landscape (Makhlooq & Al Mubarak, 2024).

Policy implications

At the policy level, this research highlights the need for robust institutional frameworks to facilitate the responsible adoption of artificial intelligence (AI) and machine learning within Ghana's insurance industry. Agencies such as the National Insurance Commission (NIC) and the Ghana Insurers Association (GIA) play a central role in accelerating digital transformation through regulatory innovation sandboxes and promoting ethical algorithmic governance to ensure transparency and consumer protection (NIC, 2023; GIA, 2022).

Furthermore, collaborative learning ecosystems between insurance firms, technology providers and academic institutions should be fostered to build local expertise in AI and machine learning. Such partnerships can help close Ghana's digital skills gap while ensuring that AI solutions are contextually relevant and socially responsible (Iddris *et al.*, 2022). Government-led incentive schemes, such as tax credits for AI investment, digital infrastructure grants, or targeted training programs, can further motivate firms to integrate these technologies into their strategic operations. These initiatives align with Ghana's Digital Economy Policy Framework (World Bank, 2019), which emphasizes digital inclusion, innovation-led growth and sustainable competitiveness in emerging sectors such as insurance.

Collectively, these policy measures would ensure that AI and machine learning adoption not only enhance firm-level marketing and sales performance but also contribute to national digital transformation goals, positioning Ghana as a model for technology-driven service innovation in Sub-Saharan Africa.

Limitations and directions for future research

Despite its significant contributions, this study has several limitations that create opportunities for future inquiry. First, the use of a cross-sectional design restricts the ability to establish causal relationships or capture temporal dynamics in AI and machine learning adoption. As suggested by Rindfleisch *et al.* (2008), future research could employ longitudinal or mixed-method designs to observe how digital transformation initiatives evolve over time and how learning effects or technological maturity influence sales performance trajectories.

Second, the study focuses exclusively on insurance firms in Ghana, which provides valuable contextual depth but limits external validity. To enhance generalizability, future research could conduct comparative cross-sectoral studies across key African service industries such as banking, telecommunications, and healthcare. Such comparative analyses would help identify sector-specific drivers and contextual moderators shaping the impact of AI and machine learning on marketing and sales performance (Akter *et al.*, 2021; Borges *et al.*, 2021).

Third, although rigorous diagnostic tests were conducted to mitigate common method variance (Podsakoff *et al.*, 2003), the study relies on self-reported survey data, which may introduce perceptual bias. Future studies should consider integrating multi-source data, including objective performance indicators such as customer satisfaction metrics, chatbot interaction analytics and sales transaction records. The triangulation of perceptual and behavioral data would strengthen the robustness and validity of empirical findings.

Finally, future research could expand the current conceptual model by incorporating additional boundary conditions that shape the relationship between marketing strategy, AI chatbot engagement and sales performance. Constructs such as organizational culture, digital leadership, and data governance may reveal how human, structural and strategic factors jointly enhance or constrain technology-enabled marketing advantages.

Conclusion

This study provides both empirical and theoretical clarity on how marketing strategy, AI chatbot engagement and machine learning collectively enhance insurance sales performance in Ghana's emerging digital economy. The findings demonstrate that while marketing strategy alone no longer guarantees superior outcomes, its integration with AI chatbot engagement significantly improves firm performance through enhanced personalization, customer responsiveness and data-driven decision-making (Vlačić *et al.*, 2021). Moreover, machine learning acts as a performance amplifier, reinforcing the positive impact of AI chatbot engagement on sales outcomes by enabling predictive insight and adaptive learning (Zhang *et al.*, 2024).

Theoretically, this research extends the RBT by demonstrating that technology-enabled capabilities, rather than static resources, represent the new sources of sustainable competitive advantage. By conceptualizing AI chatbot engagement as a dynamic capability and machine learning as a complementary resource, the study advances understanding of how firms orchestrate digital assets to achieve superior marketing and performance outcomes.

Empirically, this study is among the first to test a moderated mediation model linking marketing strategy, AI chatbot engagement and sales performance within the Sub-Saharan African insurance context. The findings provide actionable insights for firms operating in resource-constrained environments, illustrating how digital transformation can close performance gaps and position firms for sustained competitiveness in the Fourth Industrial Revolution.

Collectively, the study reinforces the imperative for insurance firms and by extension, other service organizations to transition from traditional marketing logics to data-driven strategic architectures, where AI and machine learning are embedded as integral, synergistic elements of value creation.

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