AI-Driven Marketing Communications and Herbal Drugs Brand Awareness Among Retirees in Southwest Nigeria

Sadamoro, F. (Ph. D)[1], Olukorede, B. B. (Ph. D)[2], Ayodele, O. O[3]

Department of Business Administration, Faculty of Management Sciences, Ekiti State University, Ado-Ekiti

DOI: https://doi.org/10.51583/IJLTEMAS.2026.15020000075

Received: 24 February 2026; Accepted: 02 March 2026; Published: 17 March 2026

ABSTRACT

This study investigated the effects of AI-driven marketing communication messages on herbal drugs brand awareness among retirees in Southwest Nigeria. Specifically, AI-personalized advertising, AI-optimized promotional messaging, and AI-assisted interactive engagement were tested as the explanatory variables of brand awareness among retirees in Southwest, Nigeria. Using a survey research design and Multiple Regression analysis, the three proposed hypotheses were tested.

The findings revealed that AI-driven communication variables exert positive and statistically significant influence on herbal drugs brand awareness among retirees. AI-assisted interactive engagement showed the strongest predictive strength. The study concludes that AI-Driven marketing communication significantly affects brand recall and recognition among retirees. It recommends among others that herbal drug firms adopt AI-based personalization tools to improve message clarity, credibility, and audience targeting.

Keywords: Marketing Communications, Brand Awareness, Personalized Adverting, Optimized Promotion, Interactive Engagement

INTRODUCTION

Traditional advertising and promotional methods are no longer the only tools used in marketing communication. Businesses may now create data driven, customized messages that are sent via automated digital channels through artificial intelligence. To increase message accuracy and efficacy, AI-driven marketing communication combines machine learning algorithms, customer data systems, predictive analytics, and automated interaction platforms. A separate demographic group, retirees have particular health concerns, which call for reasons for making purchases, and ways of processing information.

Herbal medicine is a very common practice in Southwest Nigerian culture and health sector. However, inappropriate product communication, mistrust, ignorance, and brand confusion continue to pavade the populace. Therefore, platforms like automated health chatbots, WhatsApp messaging systems, SMS notifications, and targeted social media ads, AI-enabled technologies offer the chance to provide retirees with consistent, reliable, and personalized information.

There is dearth of empirical data on the efficacy of AI-enabled marketing in Nigeria's herbal drug sector, especially among retirees in Southwest Nigeria, despite the technology's explosive global growth.

The majority of earlier research ignored intelligent communication technologies in favour of traditional advertising, sales promotion, and human selling. This study fills that knowledge vacuum by examining how retirees' brand awareness of herbal drugs is influenced by AI-driven promotional platforms.

Research Objectives

The broad objective of this study is to examine the effects of AI-driven marketing communication messages on herbal drugs brand awareness among retirees in Southwest Nigeria.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

Specific objectives are to:

i. Determine the effect of AI-personalized advertising on herbal drugs brand awareness among retirees.

ii. Assess the influence of AI-optimized promotional messaging on herbal drugs brand awareness. iii. Evaluate the impact of AI-assisted interactive engagement on herbal drugs brand awareness

Research Hypotheses

H01: AI-personalized advertising does not significantly affect herbal drugs brand awareness among retirees in Southwest Nigeria.

H02: AI-optimized promotional messaging does not significantly affect herbal drugs brand awareness among retirees in Southwest Nigeria.

H03: AI-assisted interactive engagement does not significantly affect herbal drugs brand awareness among retirees in Southwest Nigeria.

LITERATURE REVIEW

Conceptual Review

AI-Personalized Advertising

Conventional advertising does not customize information for each receiver; instead, it conveys consistent messages to large audiences. Segmentation, such as tailoring according to demographic categories, was the initial step toward personalization (Kotler, 2014). But when compared to AI methods, this kind of segmentation is still crude. Higher engagement, greater memory, stronger brand attitudes, and better conversion outcomes are the objectives of AI-personalized advertising, which employs real-time data and computational models to deliver personally tailored content across digital platforms (Eisenbeiss & Bleier, 2015).

According to Bleier, Harmeling and Palmatier (2020), AI is revolutionizing targeted advertising in the automobile sector in a time when every click, search, and purchase is painstakingly documented. AI creates customized marketing messages that directly address the requirements and interests of potential customers by utilizing algorithms that sort through massive information. Dealerships can increase customer engagement and boost sales by knowing the preferences and habits of each individual consumer (Bleier et al., 2020).

According to Bleier and Eisenbeiss (2015), AI is transforming personalized advertising by anticipating consumer preferences, making tailored recommendations, and utilizing chatbots to respond to inquiries. Additionally, it supports customized shopping experiences, real-time data analysis, targeted advertising, and raising customer satisfaction levels. Artificial intelligence (AI) offers a number of benefits that have the potential to significantly influence marketing campaigns.

Delivering highly specialized and targeted marketing messages to prospective purchasers is one of the most noteworthy advantages. Businesses may learn a great deal about the tastes, actions, and historical purchase histories of their customers by employing AI-driven algorithms to analyze large databases. This thorough research makes it possible to create recommendations and offers that are unique to each customer (Bleier & Eisenbeiss, 2015).

AI-Optimized Promotional Messaging

AI optimized promotional messaging refers to the use of artificial intelligence systems in the creation, customization, and distribution of marketing communications. AI-driven solutions, in contrast to traditional messaging, create content automatically, customize messages for each user profile, and maximize distribution for engagement and conversion.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

AI-Optimzed promotion focuses on continual optimization via computational models, automation, and personalization. (Li, Monroe & Jurafsky, 2020). Li et al., (2020) state that AI-generated promotional content is based on Natural Language Generation (NLG).

While adjusting to contextual elements like user preferences, platform, or campaign objectives, NLG systems generate messages that represent brand voice. While contemporary methods use deep learning and transformer structures to produce more cohesive and contextually relevant material, early frameworks concentrated on structured text production (Reiter & Dale, 2000)

According to Radford, Wu, and Child (2019), Predictive models are used in AI-optimized messaging to foresee engagement and conversion results prior to message delivery. Machine learning is used by optimization frameworks to choose the best time, channels, and message variations. To study interaction patterns and optimize promotional content repeatedly, gradient boosting, ensemble models, and neural networks are commonly used (Nguyen, Li, & Zhao, 2021).

AI-Assisted Interactive Engagement

AI assisted interactive engagement, according to Zhao, Kumar, and Yang (2019), is the use of artificial intelligence systems to support, enhance, and sustain real-time or nearly real-time interactions between humans and digital systems, or between humans mediated by digital systems.

AI promotes engagement by deciphering user input, producing response actions, and modifying interactions according to context. Conversational agents, such as chatbots and virtual assistants, are at the heart of AI-assisted interactive engagement. They leverage user input to produce contextually relevant responses. These agents can comprehend, interpret, and generate human-like language at scale through Natural Language Processing (NLP) (Radford et al., 2019).

Radford, Wu, and Child (2019) added that adaptive content, targeted prompts, and interface modifications are examples of personalization in interactive engagement that match system outputs to user requirements and expectations. AI's capacity to comprehend changing user context is essential for real-time interactive interaction. Systems can instantly modify their interaction techniques through methods like intent identification, sentiment analysis, and multimodal input processing.

According to Mehrabi, Morstatter, Saxena (2021), sentiment analysis views user emotion as a signal that shapes the course of interactions. Supportive reactions may be elicited by negative signals, while promotional or reinforcing engagement may be guided by positive cues. AI-assisted interactive engagement differs from static scripted interaction systems in that it is always adapting (Nguyen et al., 2021).

Brand Awareness

Branding is a notable topic that has been extensively studied by researchers studying brand identification and the introduction of new products. Additionally, brands are more successful at creating profitable and enduring relationships with consumers than regular unbranded products (Heath, 2016).

Presenting brands to customers can increase brand awareness by causing a stimulus-like reaction in them that enables people to relate to, recognize, recall, and be generally aware of the brands, according to the reviewed literature.

Established brands often use brand reinforcement tactics to bolster their brand awareness campaigns. Conversely, the new products use advertising and promotion to increase product awareness among present and potential consumers. Companies can use brand image management and attitude advertising as tactics to increase brand recognition, claim (Heath, 2016).

The elements of consumers' value framework largely dictate how they behave in the marketplace. The value framework for customers includes factors such as pricing, class connection, brand image, and overall market awareness in relation to others (Heath, 2016).

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

Theoretical Review

Information Processing Theory

Information processing theory states that people selectively pay attention to, interpret, and retain messages. By tailoring material to customers' interests and requirements, personalized advertising lowers cognitive load and improves information retrieval and comprehension (Petty & Cacioppo, 1986).

Technology Acceptance Model (TAM)

In Technology Acceptance Model (TAM), new technology adoption is influenced by perceived utility and usability (Davis, 1989). Relevant content sent by AI-personalized systems is more likely to be viewed as helpful and less invasive, which increases engagement.

Elaboration Likelihood Model (ELM)

Elaboration Likelihood Model (ELM) stipulates that because customized messages are more likely to follow the core route of persuasion because they are seen as more credible and relevant, resulting in stronger attitude formation and deeper cognitive processing (Petty & Cacioppo, 1986).

Empirical Review of Related Literature

Bleier and Eisenbeiss (2015) conducted controlled experiments examining online display advertisements and found that personalized ad content significantly improved click-through rates and visual attention. Their results indicated that perceived relevance mediated the relationship between personalization and engagement. However, they also observed that overly intrusive personalization reduced trust, suggesting a non-linear relationship which raises concerns about generalizability, as the optimal level of personalization may vary across different populations and cultural contexts.

Similarly, Wedel and Kannan (2016) demonstrated that algorithmic targeting improves message-context congruence, thereby increasing engagement time and interaction depth. These findings underscore that AI-driven personalization operates through attention capture mechanisms rooted in perceived relevance. However, their study primarily emphasizes interaction metrics such as engagement time and depth, without examining downstream outcomes like brand awareness, recall, or purchase intention, which are crucial for assessing marketing effectiveness.

More recent large-scale digital experiments by Kumar et al. (2023) reported that machine learning–based ad optimization significantly improved consumer interaction metrics compared to rule-based targeting systems. Their study confirmed that predictive personalization yields measurable improvements in engagement quality, not merely quantity. However, the research relied on digitally savvy populations, leaving uncertainty about how predictive personalization performs among older adults or retirees, especially in contexts with lower digital literacy or differing cultural attitudes toward technology

Arora et al. (2021) observed that individualized product recommendations increased brand recall and recognition scores in experimental settings. Participants exposed to AI-tailored messages demonstrated stronger unaided recall than those exposed to generic advertising. However, much of this evidence comes from Western consumer samples, leaving open the question of whether similar cognitive responses occur among older adults or retirees in developing markets.

Huang and Rust (2021) argued that AI enhances persuasion effectiveness by dynamically adapting message framing to individual preferences. Empirical tests confirmed that adaptive framing increases purchase intentions and favourable brand attitudes. However, their study primarily measures intentions and attitudes, rather than actual behavioral outcomes such as brand awareness, product adoption, or long-term engagement, which limits the practical applicability of the findings.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

Mariani, Borghi and Gretzel (2023) found that AI chatbots in healthcare settings increased trust and engagement when compared with static website information. The interactivity element contributed significantly to user satisfaction. However, older populations exhibit mixed responses to digital health advertising. Studies suggest that retirees may require simplified language, visual clarity, and explicit trust cues to respond positively to AIpersonalized messages. This indicates the importance of contextual adaptation in markets such as Southwest Nigeria.

Martin and Murphy (2017) demonstrated that perceived data misuse significantly reduces trust in personalized advertising. When consumers believe their information is exploited without transparency, positive personalization effects diminish.

METHODOLOGY

Research Design

The study used a survey methodology known as the descriptive technique, which uses a questionnaire to gather data from participants about all of the explanatory variables being examined. It is generally accepted that this approach works best for gathering information about experiences, emotions, motivations, and thoughts that are hard to witness directly. Adoption of surveys is also seen to lessen the tendency toward manipulation.

The Population of the Study

According to Nigerian Union of Pensioners (2024), there are 145,232 retirees in the study's population. Taking into account a five-year life expectancy, these are the current retirees in Southwest Nigeria as disclosed by the pension boards and the Nigerian Union of Pensioners of several states. In particular, the population consists of 145,232 pensioners, including 19,080 from Ogun State, 18,600 from Ekiti State, 19,480 from Osun State, 24,740 from Oyo State, 39,398 from Lagos State, and 23,934 from Ondo State. This was based on the data the researcher collected from the Nigeria Union of Pensioners.

Table 1: Population of the Study

States	Number of Retirees
Ekiti state:	18,600
Ogun state:	19,080
Osun state:	19,480
Oyo state:	24,740
Ondo	23,934
Lagos	39,398
Total	145,232

Source: Nigerian Union of Pensioners 2026

Sample and Sampling Techniques

Arising from the population, the sample for the study, using Yamane (1967) is 398 respondents. This is considered to be the lowest level of acceptable responses to maintain a confidence level of 95% and a 5% error level. The sample size is arrived at through a formula developed by Yamane (1967) as stated below.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

N

n = $1+ N(e)_2$

For the population of 81,900, the sample size is computed below

$$n = \frac{145{,}232}{1+ 145{,}232(0.05)^2}$$

$$n = \frac{145{,}232}{1+ 145{,}232\ (0.0025)}$$

$$n = \frac{145{,}232}{1+ 363.08}$$

$$n = \frac{145{,}232}{364.08}$$

n = 398

In order to ensure appropriate administration of research questionnaire for this study, heterogeneous proportionate sampling technique was used. This is because the respondents are not in the same state. The respondents in the Southwest States are considered to be influenced by different factors. This means their experiences are influenced by heterogeneous factors. The population was grouped as:

$N!n!$

n =

N

Table 2: Sample Size for Each State

States	Computations	Sample Size
Ekiti state:	$n = \frac{18600(398)}{145{,}232}$	50
Ogun state:	$n = \frac{19080(398)}{145{,}232}$	53
Osun state:	$n = \frac{19480(398)}{145{,}232}$	54
Oyo state:	$n = \frac{24740(398)}{145{,}232} =$	68
Ondo	$n = \frac{23934(398)}{145{,}232} =$	65
Lagos	$n = \frac{39{,}398(398)}{145{,}232} =$	108
Total		398

Source: Author's computation, 2026

Research Instrument

Data were this study shall be gathered from primary sources by the use of a well structured questionnaire of four (4)-point Likert scale, adapted from Onyiengo (2014) which shall be divided into six sections of A – F. Section

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

A gathered information on the demographic characteristics of the respondents. Sections B,C and D focused on marketing communications and herbal drugs brand awareness variables.

Method of Data Analysis and Model Specifications

Analysing data for this study, a combination of descriptive and inferential statistics was employed. The descriptive statistics were employed include Frequency Table, Charts and Percentages while the inferential statistics employed was Multiple Regression Technique

Model Specification

$$BRAWA = \beta 0 + \beta 1AIPA + \beta 2AIPM + \beta 3AIIE + \varepsilon$$

Where:

BRAWA = Brand Awareness

AIPA = AI-Personalized Advertising

AIPM = AI-Optimized Promotional Messaging **AIIE** = AI-Assisted Interactive Engagement

β_0 = Constant

$\beta_1, \beta_2, \beta_3$ are the coefficients of the explanatory variables

RESULTS AND DISCUSSION

Analysis of Administered Questionnaire

Table 3: Distribution of Questionnaire by States

S/N	States	Nos Distributed	Nos Returned	Return Rate
1	Lagos	108	103	25.9
2	Ogun	53	52	13.1
3	Oyo	68	66	16.6
4	Osun	54	51	12.8
5	Ondo	65	62	15.6
6	Ekiti	50	50	12.6
TOTAL		398	384	96.6

Source: Researcher's Data Output (2026).

A total of 398 questionnaires were distributed across six states, resulting in 384 completed and returned responses. This impressive return rate of 96.48% signifies a strong level of engagement from the retiree population, which is critical for ensuring the validity and reliability of the study's findings. Such a high response rate suggests that retirees are not only interested in the topic but also actively engaged in discussions surrounding herbal drug usage influenced by AI-Driven marketing communications.

Examining the individual states reveals noteworthy variations in return rates that may reflect the effectiveness of AI-Driven MC in influencing purchasing behaviour. In Lagos, 108 questionnaires were distributed, with 103

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

returned, resulting in a return rate of 95.37%. This significant level of participation from retirees in this urban center indicates that integrated marketing communications may resonate well with this demographic, highlighting their awareness and interest in herbal drugs. Similarly, Ogun state exhibited a remarkable return rate of 98.11%, with 53 distributed and 52 returned. Such a high response rate suggests that the IMC strategies implemented in Ogun may be particularly effective in capturing the attention of retirees, potentially encouraging them to explore herbal drugs.

The state of Oyo also demonstrated strong engagement, with a return rate of 97.06% from 68 distributed questionnaires, of which 66 were returned. This high participation rate implies that the integrated marketing communications have likely made a positive impact on the retirees' perceptions and behaviours regarding herbal drug purchases.

In Osun, the return rate was slightly lower at 94.44%, with 54 distributed and 51 returned. While this rate is still commendable, it suggests that there may be specific factors at play influencing the level of interest among retirees in this state, warranting further investigation. Ondo showed a similar trend with a return rate of 95.38% from 65 distributed and 62 returned, reinforcing the overall pattern of high engagement across the states. Meanwhile, Ekiti achieved a notable 100% return rate, with all 50 distributed questionnaires returned. This complete participation indicates a particularly strong inclination towards herbal drugs among retirees in Ekiti, which may be indicative of effective marketing strategies that resonate deeply with this demographic.

Test of Research Hypotheses

Table 4: Linear Regression AI-Driven Marketing Communication on Herbal Drugs Brand Awareness among Retirees in Southwest, Nigeria.

Independent Variable	Unstandardised Coefficient		Standardised Coefficients	T	P-Value
	B	Std. Error	Beta		
(Constant)	2.291	.641		3.575	.000
AIPA	.361	.043	.145	3.183	.002
AIPM	.471	.044	.154	3.363	.001
AIIE	.601	.062	.479	9.765	.000
R = 0.721 R^2 = 0.520 Std Err. = 1.50679 **Dependent Variable: Brand Awareness**			Adj. R^2 = 0.514 F = 134.662 (0.000)		

Source: Data Output, 2026

R	R^2	Adjusted R^2	F	Sig.
.721	.520	.514	134.662	.000

communications on herbal drugs brand awareness among retirees in Southwest Nigeria with coefficient value (R) = 0.721 showed a positive and strong linear relationship among the dependent and independent variables of the model.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

The value of the coefficient of determination R^2 is 0.514 signifying that the regression model explained 52% variance in herbal drugs brand awareness among retirees in Southwest, Nigeria while the remaining changes were accounted for by other extraneous dimensions beyond the scope of the model.

The regression coefficients of the independent variables show that one unit change in AI-Personalized advertising will lead to 0.361 change in brand awareness; a unit change in AI-Optimized promotional messaging will lead to 0.471 change in brand awareness while a unit change in AI-Assisted interactive engagement will lead to 0.601 change in herbal drugs brand awareness among retirees in Southwest Nigeria. All coefficients revealed positive relationship with herbal drugs brand awareness among retirees in Southwest, Nigeria

Testing the hypotheses with consideration of the P-values of the independent variables, AI-Personalized advertising has a P-value of 0.002 which is less than 0.05 level of significance, the null hypothesis that AIPersonalized advertising does not significantly affect brand awareness is therefore rejected.

The P-value of AI-Optimized promotional messaging is 0.001 which is less than 0.05 level of significant. As a result of this, the null hypothesis that AI-Optimized promotional messaging does not significantly affect brand awareness is rejected

Finally, the P-value of AI-Assisted interactive engagement is 0.000 which is less than 0.05 level of significance. Thus, the null hypothesis that AI-Assisted interactive engagement does not significantly affect brand awareness id rejected.

RECOMMENDATIONS

i. Herbal drug companies should adopt AI-enabled personalization systems to tailor messages to retirees' health concerns.

ii. Firms should implement AI-powered interactive platforms such as chatbots to provide structured product explanations and build trust.

iii. Promotional campaigns should utilize predictive analytics to determine optimal timing and frequency of communication.

iv. Companies should ensure simplicity and clarity in AI-generated content to accommodate varying digital literacy levels among retirees.

CONCLUSION

The study concludes that AI-driven marketing communication significantly improves retirees' brand awareness of herbal drugs in Southwest Nigeria.

REFERENCES

1. Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., … Shankar, V. (2021). Putting one-to-one marketing to work. Journal of Marketing, 85(1), 109–127.
2. Bleier, A., & Eisenbeiss, M. (2015). The importance of trust in personalized advertising. Journal of Advertising Research, 55(1), 24–38.
3. Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2020). Creating effective online customer experiences. Journal of Marketing, 84(2), 98–119.
4. Davis, F. D. (1989). Perceived usefulness and user acceptance of IT. MIS Quarterly, 13(3), 319–340.
5. Heath, R. (2016). The hidden power of advertising. What really affects the choice of the brand? GWP
6. Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30–50.
7. Jachnis, A. (2022). Consumer psychology. Psychological and sociological determinants of consumer behaviour. Oficyna Wydawnicza Branta.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

8. Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. Computer, 42(8), 30-37.
9. Kotler, P. (2014). Marketing management: Analysis, planning, implementation and control (9th ed.). Prentice-Hall.
10. Kumar, V., Ramachandran, D., & Kumar, B. (2023). Influence of AI-driven personalization on consumer engagement. Journal of Business Research, 156, 113–124.
11. Li, J., Monroe, W., & Jurafsky, D. (2020). Deep reinforcement learning for neural dialogue generation. Transactions of the Association for Computational Linguistics, 8, 663-676.
12. Mariani, M., Borghi, M., & Gretzel, U. (2023). AI chatbots in healthcare marketing. Technological Forecasting and Social Change, 188, 122–134.
13. Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in personalization. Journal of Business Ethics, 152(1), 1–14.
14. Mehrabi, N., Morstatter, F., Saxena, N. (2021). A survey on bias and fairness in machine learning systems. ACM Computing Surveys, 54(6), 1-35.
15. Nguyen, T., Li, C., & Zhao, K. (2021). Predictive analytics for adaptive digital engagement. Journal of Marketing Analytics, 9(1), 45-60.
16. Petty, R. E., & Cacioppo, J. T. (1986). Communication and persuasion. Springer.
17. Radford, A., Wu, J., & Child, R.. (2019). Language models are unsupervised multitask learners. OpenAI Technical Report.
18. Reiter, E., & Dale, R. (2000). Building natural language generation systems. Cambridge University Press.
19. Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. Journal of Marketing, 80(6), 97–121.
20. Zhao, K., Kumar, A., & Yang, Q. (2019). Deep learning for user modeling and recommendation. Information Retrieval Journal, 22(1-2), 1-28.