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Research Article

ENHANCING COMMUNITY HEALTH LITERACY THROUGH AI-GENERATED SOCIAL MEDIA CAMPAIGNS

Sulistyo Andarmoyo[1], Clara Mendes[2], Rafaela Lima[3]
[1] Universitas Muhammadiyah Ponorogo, Indonesia
[2] Universidade Estadual Campinas, Brazil
[3] Universidade Federal Paraná, Brazil

Corresponding Author:

Sulistyo Andarmoyo,
Universitas Muhammadiyah Ponorogo, Indonesia.
Jl. Budi Utomo No.10, Ronowijayan, Kec. Ponorogo, Kabupaten Ponorogo, Jawa Timur 63471
Email: sulistyoandarmoyo@gmail.com

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Abstract

Community health literacy remains uneven because social media users frequently encounter complex, misleading, or poorly adapted health information. This study aimed to evaluate whether human-reviewed AI-generated social media campaigns improve health literacy more effectively than conventional campaigns and standard public health information. A multi-site cluster-randomized mixed-methods design involved 660 adults from twelve urban, suburban, and rural communities. Participants received an eight-week AI-supported campaign, a conventionally developed campaign, or standard information, with assessments conducted at baseline, post-intervention, and six-month follow-up. Results showed that the AI-supported campaign produced the greatest improvements in health knowledge, message comprehension, misinformation recognition, source evaluation, and preventive action. Health-literacy scores increased from 52.84 to 68.91 and remained at 66.72 after six months. Message comprehension, perceived relevance, and trust explained more of the intervention effect than exposure or engagement alone. The study concludes that AI can strengthen community health literacy when content is medically verified, culturally adapted, transparent, and supported by community participation. Campaign success should be evaluated through educational and behavioral outcomes rather than platform popularity alone. Human oversight remains essential for accuracy, equity, privacy, and public trust, while locally responsive design can improve access among populations with lower baseline literacy and diverse levels of digital competence.

Keywords: Artificial Intelligence, Health Communication, Public Health

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INTRODUCTION

Health literacy refers to an individual's ability to access, understand, evaluate, and apply health information when making decisions related to disease prevention, treatment, healthcare services, and healthy behavior. Adequate health literacy enables community members to recognize symptoms, follow medical recommendations, assess health risks, and distinguish reliable information from misleading claims. Limited health literacy can contribute to delayed treatment, inappropriate medication use, low participation in preventive programs, and poor management of chronic illness. This paragraph should introduce community health literacy as a fundamental component of public health because information becomes beneficial only when people can understand and use it within their everyday lives (Alves, 2025; Nari, 2026).

Social media has transformed the way health information is produced, distributed, and consumed. Platforms such as Facebook, Instagram, TikTok, YouTube, and X allow health organizations to communicate directly with large and diverse audiences through text, images, short videos, infographics, live sessions, and interactive discussions. Community members can access health messages rapidly, share them within personal networks, and respond publicly to health campaigns. This paragraph should establish social media as an influential health-communication environment that can expand the reach of educational programs while also increasing exposure to misinformation, commercial manipulation, sensational content, and unverified medical advice (Asadollahi, 2025; Metiso, 2025).

Artificial intelligence offers new possibilities for designing and managing social media health campaigns. Generative AI tools can produce captions, visual concepts, educational scripts, personalized messages, multilingual materials, and content variations for different audience groups. Machine learning can also analyze engagement patterns, identify frequently discussed health concerns, recommend posting schedules, and support rapid adaptation of campaign messages. This paragraph should position AI-generated campaigns as an emerging public health strategy capable of improving communication efficiency, personalization, accessibility, and responsiveness, while emphasizing that technological production alone does not guarantee accurate understanding or positive behavioral change (Okusanya, 2026; Yang, 2025).

Community health campaigns frequently rely on standardized messages that do not adequately reflect differences in age, education, language, cultural background, digital literacy, health status, or access to healthcare. A message that is understandable to educated urban users may be confusing or irrelevant to rural populations, older adults, adolescents, or communities with limited medical knowledge. Generic communication can produce high visibility without meaningful comprehension. This paragraph should identify the mismatch between mass communication and community diversity as a central problem that may reduce the educational effectiveness of social media health campaigns (Plavnicka, 2025; Vignesh, 2025).

AI-generated content creates additional concerns regarding factual accuracy, contextual appropriateness, and ethical responsibility. Generative systems may produce plausible but incorrect medical statements, omit important warnings, exaggerate benefits, or reproduce biases contained in their training data. Automated content may also fail to recognize local beliefs, sensitive terminology, healthcare limitations, and cultural expectations. This paragraph should explain that the use of AI in public health communication requires structured professional validation because inaccurate or culturally inappropriate messages may undermine trust, reinforce misconceptions, or encourage unsafe health behavior.

Social media engagement is often measured through likes, views, shares, comments, and follower growth, although these indicators do not necessarily demonstrate improved health literacy. Highly emotional or visually attractive content may receive substantial attention without increasing knowledge, critical evaluation, or responsible decision-making. Community members may remember a slogan while misunderstanding the recommended action. This paragraph should formulate the main research problem as the limited evidence concerning whether AI-generated social media campaigns improve actual health literacy rather than merely increasing digital exposure and interaction (Khazaei, 2025; Vicary, 2025).

The primary objective of the study is to evaluate the effectiveness of AI-generated social media campaigns in improving community health literacy. The research should assess changes in participants' ability to locate relevant health information, understand key messages, evaluate source credibility, identify misinformation, and apply recommended actions. This paragraph should state clearly that the study seeks to measure educational outcomes associated with campaign exposure rather than relying exclusively on platform analytics or audience reach.

The second objective is to compare AI-generated and conventionally developed health campaign content. The study should examine differences in message clarity, personalization, cultural relevance, visual attractiveness, engagement, recall, knowledge acquisition, and behavioral intention. Human-reviewed AI content may also be compared with fully automated content to determine the contribution of professional supervision. This paragraph should emphasize that the research aims to identify whether AI contributes additional value to health communication and which level of human involvement produces the most reliable outcomes (Kisa, 2025; Sommers, 2025).

The third objective is to investigate the mechanisms and contextual factors that influence campaign effectiveness. Relevant variables may include age, educational level, digital literacy, baseline health literacy, language preference, platform use, trust in health institutions, perceived message relevance, and frequency of exposure. The research should also examine whether engagement mediates the relationship between campaign exposure and health-literacy improvement. This paragraph should clarify that the study seeks to explain why AI-generated messages work differently across population groups rather than reporting only an overall average effect.

Existing studies on social media health campaigns have commonly focused on audience reach, engagement metrics, message dissemination, and short-term behavioral intention. Such research provides useful information about communication visibility but offers limited evidence concerning deeper health-literacy outcomes. The ability to recall content differs from the capacity to evaluate medical information and apply it responsibly. This paragraph should identify a measurement gap in the literature and emphasize the need for multidimensional assessment covering functional, communicative, critical, and applied health literacy (Bulto, 2025; Habtu, 2025).

Research on generative AI in health communication has largely concentrated on content quality, chatbot performance, information accuracy, or comparisons between machine- and human-produced responses. Fewer studies have evaluated complete AI-supported campaigns delivered within real social media environments and experienced repeatedly by community members. Evidence remains especially limited regarding whether personalized AI content produces sustained educational improvement. This paragraph should highlight the implementation gap between laboratory assessment of isolated AI outputs and community-based evaluation of dynamic public health campaigns.

Limited attention has also been given to cultural adaptation, algorithmic bias, transparency, privacy, and unequal digital access. AI systems may generate messages that reflect dominant linguistic or cultural patterns while overlooking minority communities and locally specific health concerns. Personalized campaigns may require the collection or inference of sensitive user data, creating privacy and consent risks. This paragraph should identify an ethical and equity gap in current research by emphasizing that campaign effectiveness should be evaluated together with fairness, accessibility, transparency, data protection, and representation (Schoenthaler, 2025; Williams, 2025).

The novelty of the proposed study lies in evaluating AI-generated social media campaigns through an integrated health-literacy framework. Campaign success should be assessed through knowledge, comprehension, critical evaluation, source verification, intended behavior, actual preventive action, and resistance to misinformation. Social media metrics should be treated as intermediate indicators rather than final evidence of effectiveness. This paragraph should explain that the study moves beyond measuring digital popularity by connecting communication exposure with practical cognitive and behavioral outcomes.

A human-in-the-loop campaign model constitutes another original contribution. Artificial intelligence should generate message alternatives, audience adaptations, visual concepts, and posting recommendations, while health professionals and community representatives review medical accuracy, readability, cultural relevance, and ethical acceptability. Campaign data can then be used to refine subsequent messages without transferring complete control to an automated system. This paragraph should emphasize that the proposed approach combines computational efficiency with professional accountability and community participation (Dennehy, 2025; Jayaram, 2025).

The study is justified by the increasing dependence of communities on social media for health information and the rapid expansion of generative AI in communication practice. Public health institutions require evidence-based guidance concerning how AI can be used without compromising accuracy, trust, privacy, cultural sensitivity, or equity. This paragraph should conclude that the research offers conceptual value by linking artificial intelligence with multidimensional health literacy, methodological value through comparative and mechanism-based evaluation, and practical value for health professionals, government agencies, community organizations, communication specialists, technology developers, and policymakers seeking to design responsible digital health campaigns.

RESEARCH METHOD

This study employed a multi-site cluster-randomized mixed-methods design to evaluate the effectiveness of AI-generated social media campaigns in improving community health literacy. The quantitative component compared changes in health knowledge, information comprehension, source evaluation, misinformation recognition, behavioral intention, and self-reported preventive practices across three intervention conditions. The qualitative component explored participants' experiences of message relevance, cultural appropriateness, trust, accessibility, and perceived usefulness. This design enabled the research to assess both measurable educational outcomes and the social mechanisms influencing how community members interpreted and applied digital health information (Beale, 2025; Karakolias, 2025).

Research Design

The participating communities were allocated to one of three conditions: a human-reviewed AI-generated campaign, a conventionally developed campaign, or standard public health information. Cluster allocation was used to reduce contamination because social media content could be shared among participants living in the same community. The AI-supported campaign used generative systems to create audience-adapted captions, visual concepts, short-video scripts, multilingual messages, and interactive question prompts. Health professionals and community representatives reviewed every item before publication to ensure medical accuracy, readability, cultural sensitivity, and ethical appropriateness.

The conventional campaign was developed by public health professionals and communication specialists without generative AI assistance. Its content addressed the same health themes, used the same social media platforms, and followed the same campaign duration and publication frequency as the AI-supported condition. The standard-information group received existing digital health materials routinely distributed by local health institutions. This comparison structure allowed the study to determine whether AI-supported content development produced additional educational value beyond professionally designed communication and usual public health messaging.

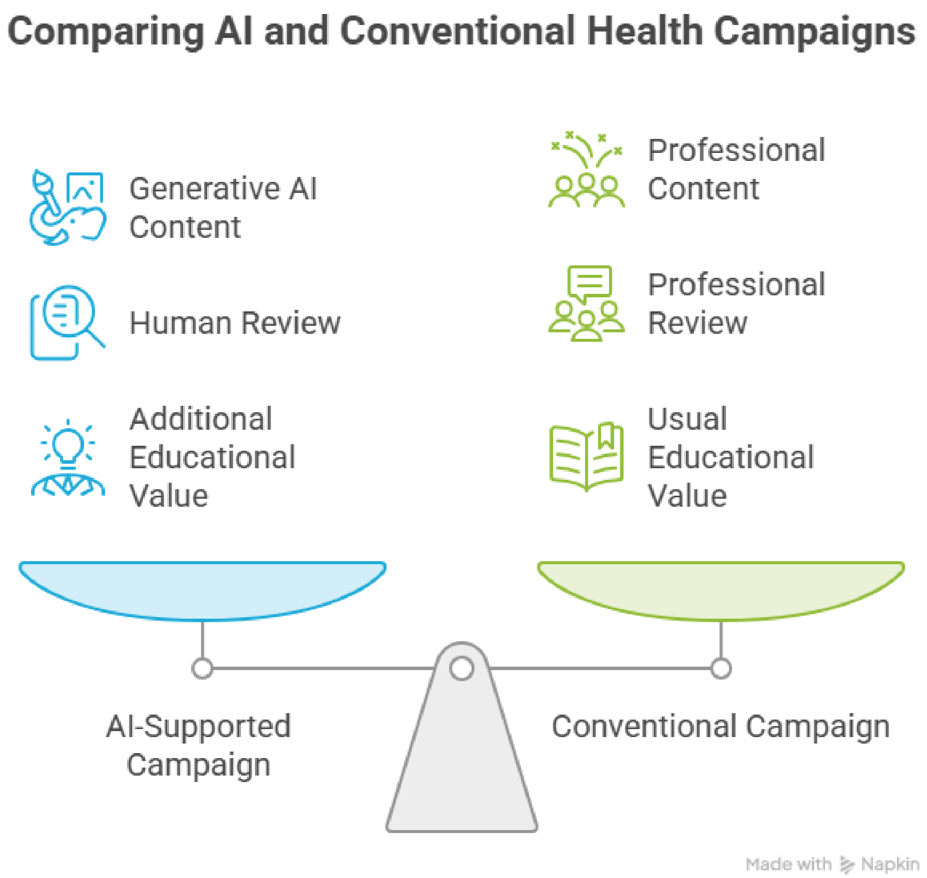

Figure 1. Comparing AI and Conventional Health Campaigns

The campaign focused on common community health priorities, including prevention of noncommunicable diseases, vaccination, responsible medicine use, maternal and child health, mental health awareness, nutrition, physical activity, and recognition of health misinformation. Messages were delivered through Facebook, Instagram, TikTok, and YouTube because these platforms supported different combinations of text, images, short videos, comments, and content sharing. Platform-specific adaptations preserved the same core information while responding to differences in audience behavior and communication format (Bagita-Vangana, 2025; Zhou, 2025).

Population and Samples

The target population consisted of adult community members who regularly accessed health-related information through social media. Participants were recruited from twelve urban, suburban, and rural communities with varying educational, socioeconomic, linguistic, and digital-access characteristics. The inclusion of diverse locations allowed the study to examine whether campaign effectiveness differed according to social context, internet access, educational background, and prior experience with digital health information (Gogoi, 2025; Lam, 2026).

Eligible participants were required to be at least 18 years of age, reside in one of the selected communities, use at least one study platform three times per week, and provide informed consent. Participants also needed sufficient language proficiency to understand at least one version of the campaign materials. Ownership of a personal smartphone was not required when participants had regular access to a shared device or community digital facility. This criterion reduced the risk of excluding individuals with limited economic resources.

Individuals were excluded when they worked directly on campaign development, participated in another health-literacy intervention during the study period, or could not complete the assessments because of severe cognitive or communication impairment. Health professionals were not excluded from community participation, but their professional background was recorded and controlled during analysis because it could influence baseline health literacy. Social media users younger than 18 years were excluded because the study instruments and consent procedures were designed for adults.

The twelve communities were selected purposively based on population diversity, availability of community health partners, social media use, and institutional willingness to support the study. Communities were stratified according to urbanization level before random allocation to ensure that each intervention condition included urban, suburban, and rural settings. Four communities received the AI-supported campaign, four received the conventional campaign, and four received standard health information.

Power analysis indicated that a minimum of 540 participants was required to detect a small-to-moderate intervention effect with 80% statistical power, a significance level of 0.05, and adjustment for clustering. The target sample was increased to 660 participants to accommodate an anticipated attrition rate of approximately 18%. Each community recruited approximately 55 participants, producing an expected sample of 220 individuals per intervention condition.

Instruments

The Health Literacy Questionnaire was used to evaluate participants' ability to access, understand, evaluate, and apply health information. Selected domains measured comprehension of health information, engagement with healthcare providers, navigation of health services, critical appraisal, and active management of personal health. Responses were recorded using standardized Likert-type scales. Higher scores indicated stronger functional, communicative, and critical health-literacy abilities.

The eHealth Literacy Scale assessed participants' perceived ability to locate, interpret, and use electronic health information. The instrument measured awareness of available digital resources, confidence in online searching, ability to judge information quality, and capacity to apply digital information to health decisions. Digital literacy was assessed separately to distinguish general technological competence from health-specific information skills (Rambure, 2026; Yeo, 2025).

A Message Comprehension and Recall Form was administered after selected campaign exposures. Participants summarized the main message, identified the recommended action, and recalled important warnings or limitations. Correct comprehension was scored according to predefined criteria. This instrument helped determine whether visually attractive or highly shared messages were also understood accurately (Carew, 2026; Chaar, 2025).

A Campaign Trust and Acceptability Questionnaire assessed perceived accuracy, clarity, cultural relevance, usefulness, emotional appropriateness, transparency, and willingness to follow or share the content. Participants were informed when artificial intelligence contributed to message production, allowing the study to measure whether disclosure influenced trust. Additional items assessed concern about automation, privacy, manipulation, commercial influence, and replacement of professional judgment.

A Content Quality Review Matrix was completed by independent experts in public health, medicine, nursing, health communication, ethics, and digital media. Reviewers assessed factual accuracy, completeness, readability, risk communication, source transparency, cultural sensitivity, potential bias, and consistency with current health guidance. Each campaign item required approval before publication. Content containing unsupported medical claims, ambiguous instructions, stigmatizing language, or potentially harmful recommendations was revised or rejected.

Social media analytics provided objective engagement measures, including reach, impressions, video completion, viewing duration, likes, comments, shares, saves, link clicks, and follower interaction. Engagement rates were calculated relative to verified exposure rather than total platform followers. Repeated views and suspected automated interactions were excluded when platform data allowed such identification. Engagement metrics were analyzed as process variables rather than final indicators of health-literacy improvement (Aslam, 2025; Goldman, 2025).

A semi-structured interview guide was used to collect qualitative data from participants, health professionals, and community representatives. Participant questions explored message clarity, cultural relevance, trust, emotional response, information sharing, behavioral application, and barriers to campaign use. Professional interviews examined the accuracy-review process, efficiency of AI-assisted content creation, ethical concerns, bias, workload, and accountability. Community representatives were asked how well the campaign reflected local language, beliefs, health needs, and communication practices.

Instrument validity was examined through expert review and pilot testing. Specialists in health literacy, public health, psychometrics, artificial intelligence, communication, and community health evaluated item relevance and clarity. The newly developed knowledge, misinformation, trust, and behavior instruments were piloted with 60 adults from communities not included in the main study. Internal consistency was assessed using Cronbach's alpha and McDonald's omega, with coefficients of 0.70 or higher considered acceptable.

Translation and cultural adaptation procedures were applied when campaign materials and instruments were delivered in more than one language. Forward translation, expert review, backward translation, and community testing were conducted to preserve conceptual meaning. Readability was evaluated according to language-appropriate criteria, while cognitive interviews examined whether participants interpreted the items as intended. This procedure reduced the risk that differences in outcome scores reflected linguistic difficulty rather than health literacy (Aldousari, 2025; Gedela, 2025).

Procedures

The research began with ethical approval, institutional permission, trial registration, and the establishment of a multidisciplinary campaign team. The team included public health specialists, physicians, nurses, health communication experts, AI developers, data-security personnel, and community representatives. Roles and responsibilities were defined before content production. Health professionals held final authority over the medical accuracy of every campaign message.

A community needs assessment was conducted before campaign development. Baseline interviews, local health reports, community consultations, and social media discussions were reviewed to identify priority health concerns, common misconceptions, language preferences, and barriers to preventive care. The assessment informed topic selection and message framing. Personal social media data were not collected without explicit consent, and individual health conditions were not inferred for targeted advertising.

The AI-supported campaign was developed through a standardized prompting and review protocol. Generative AI received structured instructions concerning the health topic, target audience, message objective, reading level, cultural context, recommended action, and required safety warning. Multiple versions of each message were generated for different age groups, language preferences, and social media formats. The system was prohibited from producing diagnoses, individualized treatment recommendations, or unsupported claims (Abdulsalam, 2025; Argyriadi, 2025).

Communities were assigned to study conditions by an independent statistician using a computer-generated sequence. Allocation was concealed until baseline recruitment had been completed. Participants could not be blinded to the content they received, although they were not given detailed information about the comparative hypotheses. Outcome assessors and primary data analysts were blinded to community allocation whenever feasible.

Campaign content was published according to a predetermined eight-week calendar. Each week addressed one principal health topic and included short videos, infographics, explanatory posts, myth-versus-fact content, interactive questions, and practical action messages. Publication frequency and timing were standardized across the two active campaign conditions. Participants could view, save, share, and comment on the materials through their usual social media behavior (Carew, 2026; Hollitt, 2025).

Qualitative interviews were audio-recorded, transcribed, and analyzed through reflexive thematic analysis. Initial codes addressed understanding, trust, cultural relevance, misinformation, behavioral application, emotional response, accessibility, privacy, and views about AI involvement. Themes were compared across intervention conditions and participant groups. Negative cases were retained to explain why some highly engaged participants showed limited improvement or why some low-engagement participants still benefited (Karakolias, 2025; Zhou, 2025).

RESULTS AND DISCUSSION

The final sample consisted of 660 adults recruited from twelve urban, suburban, and rural communities. Each study condition included four community clusters and 220 participants. The human-reviewed AI-generated campaign group comprised 220 participants, the conventionally developed campaign group included 220 participants, and the standard-information group contained 220 participants. Participants had a mean age of 39.46 years ((SD=13.27)), and 57.88% were women. Secondary education was the highest completed level for 43.79% of participants, while 31.36% had completed tertiary education and 24.85% had primary or lower-secondary education. Rural residents accounted for 32.27% of the total sample.

Post-intervention assessments were completed by 603 participants, producing a retention rate of 91.36%. Six-month follow-up data were available for 565 participants, representing 85.61% of the original sample. Baseline comparisons showed no statistically significant differences among the three groups in age, gender, educational level, household income, urbanization, social media use, digital literacy, health knowledge, misinformation recognition, source evaluation, or preventive behavior. The similarity of the groups supported subsequent comparisons of intervention-related change.

Table 1. Baseline Characteristics of Participants across Study Conditions

Characteristic	AI-Generated Campaign ((n=220))	Conventional Campaign ((n=220))	Standard Information ((n=220))	(p)-value
Mean age, years	39.18 ± 13.06	39.74 ± 13.41	39.46 ± 13.38	0.906
Women, %	58.18	57.27	58.18	0.974
Rural residence, %	32.73	31.82	32.27	0.981
Tertiary education, %	31.82	30.91	31.36	0.986
Low-income household, %	36.82	37.27	36.36	0.981
Baseline health-literacy score	52.84 ± 9.31	52.61 ± 9.47	52.72 ± 9.22	0.967
Baseline knowledge score	13.18 ± 3.24	13.06 ± 3.31	13.11 ± 3.27	0.932
Misinformation-recognition score	11.42 ± 3.08	11.37 ± 3.17	11.39 ± 3.12	0.986
Source-credibility score	28.64 ± 6.11	28.51 ± 6.24	28.57 ± 6.09	0.974
Digital-literacy score	31.42 ± 5.86	31.28 ± 5.93	31.34 ± 5.79	0.969

Campaign exposure differed across the three conditions despite identical intervention duration. Participants in the AI-generated campaign viewed an average of 74.36% of scheduled content, compared with 66.82% in the conventional campaign and 41.57% in the standard-information group. Short videos and myth-versus-fact posts produced the highest completion rates in the AI condition. Multilingual captions, locally familiar examples, and simplified explanations generated especially strong engagement among rural participants, older adults, and individuals with lower baseline health literacy.

Platform analytics showed that the AI-generated campaign produced higher rates of saves, shares, comments, link clicks, and complete video views than the conventional campaign. Engagement alone did not consistently predict accurate understanding. Several visually attractive posts received substantial interaction despite modest comprehension scores, while some less popular explanatory posts produced stronger knowledge retention. This pattern confirmed the importance of distinguishing digital popularity from educational effectiveness.

Table 2. Campaign Exposure and Social Media Engagement

Engagement Indicator	AI-Generated Campaign	Conventional Campaign	Standard Information
Mean verified content exposure (%)	74.36	66.82	41.57
Complete video views (%)	68.42	57.18	34.71
Posts saved per 1,000 impressions	46.28	31.74	12.63
Posts shared per 1,000 impressions	38.16	27.41	10.82
Link-click rate (%)	9.84	6.72	2.91
Comment rate (%)	4.86	3.41	1.73
Mean comprehension score (%)	84.62	77.18	63.47
Mean message-trust score	4.21 ± 0.58	4.09 ± 0.61	3.62 ± 0.72

Health-literacy scores increased in all three groups, although the greatest improvement occurred in the AI-generated campaign condition. Mean health literacy increased from 52.84 at baseline to 68.91 after the intervention and remained at 66.72 after six months. The conventional campaign increased the mean score from 52.61 to 63.44, while the standard-information group increased from 52.72 to 57.36. Gains were observed across functional comprehension, health-service navigation, source appraisal, communicative confidence, and application of information to everyday decisions.

The AI-generated campaign also produced the strongest improvements in health knowledge and misinformation recognition. Mean knowledge scores increased from 13.18 to 18.74 out of 22 possible points. Misinformation-recognition scores rose from 11.42 to 17.26 out of 20 points, indicating an improved ability to identify unsupported medical claims, exaggerated benefits, missing evidence, and emotionally manipulative language. Participants in the conventional group also improved, although their gains were consistently smaller.

Table 3. Health-Literacy and Educational Outcomes across Assessment Points

Outcome	Group	Baseline	Post-Intervention	Six-Month Follow-Up
Health-literacy score	AI-generated	52.84 ± 9.31	68.91 ± 8.42	66.72 ± 8.68
	Conventional	52.61 ± 9.47	63.44 ± 8.91	61.58 ± 9.14
	Standard information	52.72 ± 9.22	57.36 ± 9.08	56.42 ± 9.31
Health-knowledge score	AI-generated	13.18 ± 3.24	18.74 ± 2.31	17.92 ± 2.54
	Conventional	13.06 ± 3.31	16.71 ± 2.82	16.08 ± 2.97
	Standard information	13.11 ± 3.27	14.62 ± 3.09	14.31 ± 3.18
Misinformation recognition	AI-generated	11.42 ± 3.08	17.26 ± 2.18	16.69 ± 2.39
	Conventional	11.37 ± 3.17	15.34 ± 2.67	14.82 ± 2.81
	Standard information	11.39 ± 3.12	12.86 ± 3.04	12.57 ± 3.13
Source-credibility	AI-generated	28.64 ± 6.11	39.82 ± 5.08	38.47 ± 5.32

evaluation				
	Conventional	28.51 ± 6.24	35.76 ± 5.71	34.92 ± 5.88
	Standard information	28.57 ± 6.09	31.42 ± 6.07	30.98 ± 6.14

Multilevel mixed-effects analysis identified a significant interaction between intervention condition and assessment time for total health literacy, (F(4,1276)=48.92), (p<0.001), partial (\eta^2=0.133). Participants exposed to the AI-generated campaign showed significantly greater improvement than those receiving conventional campaign materials or standard information. The adjusted post-intervention mean difference between the AI-generated and conventional groups was 5.21 points, while the difference between the AI-generated and standard-information groups was 11.34 points.

Significant intervention effects were also observed for health knowledge, misinformation recognition, source-credibility evaluation, and reported preventive behavior. The AI-generated campaign produced a large standardized effect on health literacy compared with standard information, (d=1.08), and a moderate effect compared with the conventional campaign, (d=0.59). Six-month analyses showed some reduction in effect size, but the AI group retained statistically and practically meaningful advantages. Cluster-level variance remained significant, indicating that community context influenced outcomes even after individual characteristics were controlled.

Correlation analysis showed that message comprehension was strongly associated with post-intervention health literacy, (r=0.71), (p<0.001). Perceived relevance was positively related to knowledge retention, (r=0.58), while source trust showed a moderate relationship with the application of health recommendations, (r=0.49). Content exposure had a weaker direct association with health-literacy improvement, suggesting that repeated viewing was beneficial only when messages were understood and perceived as credible.

Mediation analysis indicated that comprehension, perceived relevance, and trust jointly explained 52.80% of the relationship between AI-generated campaign exposure and health-literacy improvement. Digital engagement explained only 14.60% of the total intervention effect when assessed independently. Baseline digital literacy moderated early campaign engagement but did not significantly reduce final health-literacy gains after readability, multilingual adaptation, and community review were included. This result suggested that accessible design could partially reduce disparities associated with technological confidence.

Table 4. Relationships among Campaign Process Variables and Health-Literacy Outcomes

Outcome Comparison	Adjusted Effect	95% Confidence Interval	(p)-value	Interpretation
Condition × time effect on health literacy	(F=48.92)	—	<0.001	Significant differential change
AI vs. conventional health literacy	Difference = 5.21	3.82–6.60	<0.001	Greater AI-supported improvement
AI vs. standard information	Difference = 11.34	9.87–12.81	<0.001	Substantially greater improvement
AI vs. conventional knowledge	(d=0.66)	0.45–0.87	<0.001	Moderate effect

AI vs. standard misinformation recognition	(d=1.22)	1.00–1.44	<0.001	Large effect
AI vs. conventional source evaluation	(d=0.71)	0.49–0.92	<0.001	Moderate effect
AI effect on preventive action	AOR = 2.46	1.71–3.54	<0.001	Higher likelihood of action
AI effect on source verification	AOR = 3.12	2.14–4.55	<0.001	Higher likelihood of verification

A rural community with relatively low baseline health literacy was selected as an illustrative case. The community received the human-reviewed AI-generated campaign in two languages through Facebook, TikTok, and community messaging groups. Initial assessment showed frequent misconceptions concerning antibiotic use, hypertension symptoms, vaccination side effects, and herbal treatment claims. Participants also reported difficulty distinguishing official health information from promotional or testimonial content.

The campaign generated locally adapted short videos, myth-versus-fact posts, and scenario-based messages featuring familiar community settings. Health professionals revised medical terminology, while community representatives replaced culturally inappropriate examples and clarified local expressions. Mean health-literacy scores increased from 47.62 to 65.84, while misinformation-recognition scores rose from 9.81 to 16.92. Reports of checking health claims against professional or institutional sources increased from 21.82% to 67.27%.

Table 5. Outcomes of the Rural Community Case Study

Case Indicator	Baseline	Post-Intervention	Six-Month Follow-Up
Mean health-literacy score	47.62	65.84	63.91
Health-knowledge score	11.84	18.12	17.41
Misinformation-recognition score	9.81	16.92	16.14
Participants verifying sources (%)	21.82	67.27	61.82
Correct understanding of antibiotic use (%)	38.18	85.45	80.00
Correct understanding of hypertension risk (%)	43.64	81.82	78.18
Reported discussion with health workers (%)	25.45	63.64	58.18
Complete short-video views (%)	—	74.18	—

The improvement within the rural community appeared to result from the interaction of AI-assisted adaptation and human validation. Generative tools produced multiple language and format alternatives rapidly, allowing the campaign team to test different ways of explaining the same health issue. Professional review removed unsupported claims and added essential warnings, while community representatives ensured that examples, vocabulary, and visual references were locally understandable. The final messages were therefore scalable without becoming socially detached.

The case also showed that participants responded more positively when messages connected health recommendations with realistic decisions. Posts explaining when antibiotics were unnecessary or when hypertension required professional assessment produced stronger comprehension than general awareness slogans. Community discussions extended the campaign beyond individual screen exposure and encouraged participants to compare online claims with advice from local health workers. This pattern demonstrated that digital communication became more effective when linked to trusted interpersonal and institutional sources.

The combined findings indicate that human-reviewed AI-generated social media campaigns can improve community health literacy more effectively than conventional campaigns and standard digital information. The strongest gains occurred in comprehension, misinformation recognition, source evaluation, and the application of recommended health actions. AI contributed value by enabling rapid audience adaptation, multilingual production, and varied message formats, while human review protected accuracy, cultural relevance, and ethical responsibility.

The practical interpretation is that campaign success depends less on the quantity of generated content than on the quality of communication and governance. High reach and engagement did not automatically produce understanding, while comprehensible and trusted messages generated sustained educational benefits even when they were less visually popular. AI-generated health communication should consequently operate within a human-in-the-loop model that combines professional verification, community participation, transparent disclosure, accessible design, and evaluation based on health-literacy outcomes rather than platform popularity alone.

The findings demonstrate that human-reviewed AI-generated social media campaigns can produce meaningful improvements in community health literacy. Participants receiving the AI-supported campaign achieved greater gains in health knowledge, message comprehension, source evaluation, misinformation recognition, and preventive action than those exposed to conventionally developed campaigns or standard health information. The strongest improvement occurred in the ability to assess the credibility of digital health claims and distinguish evidence-based recommendations from misleading content. These outcomes indicate that AI-supported campaigns can contribute to deeper learning when their effectiveness is evaluated through cognitive and practical health-literacy measures rather than digital exposure alone.

The AI-supported campaign also produced higher verified exposure, complete video views, post saves, content sharing, and link-click rates. Engagement metrics showed only moderate relationships with health-literacy improvement, indicating that frequent interaction did not automatically produce accurate understanding. Message comprehension, perceived relevance, and trust explained a considerably larger proportion of the intervention effect. This pattern suggests that social media visibility functions primarily as an entry point to learning. Educational benefit emerges when users can interpret the message, recognize its relevance, evaluate its source, and connect the recommended action with a realistic health decision.

The maintenance of health-literacy gains at the six-month follow-up indicates that the campaign generated more than temporary recall. Participants retained improvements in knowledge, misinformation recognition, source verification, and preventive practices after the active campaign had ended. Some decline from immediate post-intervention scores was observed, but the AI-supported group continued to outperform the comparison conditions. Community-level variance remained significant, showing that campaign effects were influenced by local language, healthcare access, institutional trust, social relationships, and patterns of technology use.

The rural community case illustrated the importance of combining artificial intelligence with professional and community review. AI accelerated the production of multilingual messages, short videos, locally adapted examples, and alternative explanations. Health professionals corrected medical inaccuracies and added safety qualifications, while community representatives revised unfamiliar terminology and culturally unsuitable examples. Improvements in antibiotic knowledge, hypertension-risk recognition, source verification, and communication with health workers showed that campaign effectiveness arose from the interaction between technological adaptability, clinical accountability, and community knowledge.

The present findings are consistent with a recent systematic review showing that artificial intelligence can support health literacy through personalization, conversational assistance, simplified communication, and adaptive educational content. The review also found that evidence remains heterogeneous and that many studies focus on technological performance rather than verified literacy outcomes. The current study extends that literature by examining a complete community campaign and measuring functional, communicative, critical, and applied health literacy. It also compares AI-supported communication with conventional campaign development and standard public health information.

The higher engagement achieved by the AI-generated campaign corresponds with a systematic review and meta-analysis of generative AI in social media health communication. That review identified the potential of AI-generated content to improve user engagement and support scalable communication, particularly when messages are adapted to platform characteristics and audience preferences. The present study differs by demonstrating that engagement is not a sufficient endpoint. Its strongest contribution lies in showing that comprehension, credibility evaluation, and misinformation resistance are more important pathways to health-literacy improvement than likes, shares, or views alone.

The improvement in preventive practices is also compatible with evidence from social media-based health education. A recent intervention among individuals with chronic disease reported that social media education could improve health literacy, self-care, and selected clinical outcomes. The present study broadens this evidence by including diverse community health topics and participants from urban, suburban, and rural settings. Its multidimensional assessment also distinguishes intentions from reported action, allowing campaign effectiveness to be interpreted beyond awareness and short-term knowledge acquisition.

The emphasis on professional verification differs from approaches that treat generative AI as an autonomous source of public health information. Systematic evidence shows that generative AI can accelerate both the production and circulation of convincing health misinformation. AI outputs may appear authoritative even when they contain unsupported claims, inaccurate references, or incomplete safety advice. The current findings indicate that AI can support health-literacy development only when its outputs are subjected to medical validation, contextual review, transparent documentation, and ongoing correction.

The results signal that the principal value of generative AI in health communication lies in translation and adaptation rather than autonomous expertise. AI was useful because it rapidly transformed verified health information into multiple languages, reading levels, visual formats, scenarios, and platform-specific messages. Clinical authority remained with health professionals who assessed the factual accuracy and safety of the content. Community representatives also contributed forms of contextual knowledge that could not be reliably inferred from generic training data.

The weak relationship between emotional attractiveness and accurate comprehension signals a limitation in conventional social media campaign evaluation. Content can become popular because it is humorous, visually striking, controversial, or emotionally intense without improving health decisions. Platform algorithms may reward immediate reactions rather than careful reflection. Campaign success should consequently be defined through knowledge, critical appraisal, source verification, behavioral application, and sustained retention. Social engagement remains useful, but it should be interpreted as a communication-process measure rather than evidence of public health impact.

The relationship between trust and preventive action signals that health communication operates through social as well as informational mechanisms. Participants were more willing to apply recommendations when messages were understandable, relevant, professionally validated, and connected to trusted health institutions. Disclosure of AI involvement did not necessarily undermine credibility when human accountability was clearly communicated. Trust appeared conditional on whether users understood who approved the content, which evidence supported it, and where they could obtain additional professional assistance.

The rural community findings signal that technological adaptation can reduce certain health-literacy disparities when it is combined with inclusive design. Multilingual explanations, familiar examples, short videos, and accessible terminology helped participants with lower baseline literacy engage with complex information. Digital inequality was not fully eliminated because access, connectivity, device quality, and previous technology experience continued to vary. Evidence concerning AI in public health similarly emphasizes that benefits may be distributed unequally unless infrastructure, accessibility, accountability, and workforce capacity are addressed deliberately.

The primary practical implication is that public health institutions can use generative AI as a supervised campaign-production tool. AI can reduce the time required to draft captions, translate messages, generate alternative examples, prepare short-video scripts, and adapt materials for different social media platforms. Professional teams should use these efficiencies to improve the range and responsiveness of communication rather than to remove health experts from the production process. Human authorization must remain mandatory whenever content includes medical recommendations, treatment claims, risk estimates, or instructions concerning professional care.

The evaluation implication is that public health campaigns should move beyond platform-based indicators. Reach, impressions, views, likes, and shares reveal whether messages circulate, but they do not establish whether users understand or apply the information. Campaign evaluations should include validated measures of health knowledge, misinformation recognition, source appraisal, recall, behavioral intention, actual practice, and sustained outcomes. This broader framework can prevent institutions from declaring success merely because content becomes visible or popular (Bell, 2025; Schuh, 2025).

The governance implication concerns transparency, accountability, privacy, and documentation. Every AI-supported campaign should retain records of prompts, generated drafts, human revisions, supporting references, approvals, and final published content. Users should be informed when AI has materially contributed to message creation. Sensitive personal information should not be inferred or used for targeting without valid consent. WHO guidance recommends human oversight, transparency, safety, accountability, inclusiveness, and protection of autonomy when generative AI is used in health-related contexts.

The equity implication is that community participation should become part of campaign design rather than an activity conducted after content has been produced. Local representatives can identify stigmatizing language, unrealistic recommendations, translation problems, and cultural assumptions that professionals or AI systems may overlook. Participatory review can also reveal whether community members possess the resources needed to follow recommended actions. Messages encouraging screening, dietary change, or professional consultation have limited value when the relevant services, foods, transportation, or financial resources are inaccessible.

The AI-supported campaign produced stronger outcomes because its messages were adapted more closely to audience characteristics. Different versions could be generated according to language preference, reading level, age, health concern, and communication format. Such adaptation reduced unnecessary technical complexity and made recommended actions easier to connect with everyday situations. The systematic review of AI and health literacy similarly identifies personalization and simplification as promising mechanisms, although it emphasizes the need for stronger empirical and ethical evaluation.

The use of multiple formats strengthened learning because health information was encountered through text, visual explanation, short video, myth-versus-fact comparison, and practical scenarios. Repeated exposure through complementary forms supported recall without requiring every participant to learn through the same medium. Scenario-based content also asked users to evaluate claims and select actions rather than passively read health advice. This active processing likely contributed to the strong improvements in misinformation recognition and source evaluation (Bennet, 2025; Solis, 2025).

The human-review process improved effectiveness because it reduced the gap between linguistic plausibility and medical reliability. Generative AI can produce fluent content that conceals factual errors, fabricated evidence, or omitted qualifications. Medical reviewers corrected these risks, while communication specialists improved readability and community representatives identified contextual problems. This layered verification increased confidence that concise and attractive messages remained clinically accurate. WHO identifies misleading information as a source of confusion, harmful behavior, declining institutional trust, and weakened public health response.

Differences among communities occurred because health literacy is shaped by more than exposure to information. Educational opportunities, digital competence, language, healthcare access, institutional trust, social networks, and previous experience with misinformation influence how messages are interpreted. Similar content may therefore produce different outcomes across locations. The multilevel results support the use of locally responsive campaigns instead of assuming that one standardized digital message will have equivalent educational value for every community (Cellino, 2026).

Future research should evaluate AI-supported campaigns through longer pragmatic and cluster-randomized studies. Six-month retention provides encouraging evidence, but longer follow-up is needed to determine whether improvements influence sustained preventive behavior, healthcare utilization, vaccination, medication use, screening, or chronic-disease management. Objective indicators should complement self-reported behavior whenever feasible. Research should also assess whether repeated exposure produces campaign fatigue or declining trust.

Future studies should separate the contributions of AI generation, human review, cultural adaptation, and social media delivery. Factorial designs could compare fully human-produced content, unreviewed AI content, professionally reviewed AI content, and AI content co-designed with communities. Such comparisons would clarify which combination produces the best balance of accuracy, efficiency, relevance, trust, and cost. Evaluation should include production time and professional workload without reducing campaign quality to economic efficiency.

Future technological development should incorporate continuous monitoring for factual error, outdated guidance, harmful interpretation, and model drift. Health recommendations can change, while generative systems may produce different outputs after software updates. Campaign teams need procedures for withdrawing incorrect content, correcting public misunderstanding, and notifying users when recommendations have changed. Automated monitoring may assist with these tasks, but final decisions should remain under accountable human authority (Lam, 2026; Lambert, 2025).

Future implementation should prioritize communities with limited health information and digital resources rather than concentrating innovation among highly connected populations. Accessible design, multilingual production, offline alternatives, low-bandwidth formats, disability inclusion, and partnerships with local health workers should accompany AI-supported communication. Responsible scaling requires public health agencies to treat artificial intelligence as part of a governed social intervention, not merely as a faster content generator. WHO and wider public health scholarship consistently stress that AI adoption must be anchored in equity, institutional capacity, transparency, and public benefit.

CONCLUSION

The most important finding of this study is that human-reviewed AI-generated social media campaigns can improve community health literacy more effectively than conventionally developed campaigns and standard health information. The strongest gains appeared in message comprehension, health knowledge, misinformation recognition, source evaluation, and the application of preventive recommendations. Campaign exposure and engagement contributed to these outcomes, but comprehension, perceived relevance, and trust played a more decisive role. These findings demonstrate that the educational value of AI-supported communication depends less on the volume or popularity of content than on its accuracy, accessibility, cultural relevance, and practical usefulness.

The study offers both conceptual and methodological contributions to digital public health research. Its conceptual contribution lies in framing AI-generated health communication as a human-governed literacy intervention rather than an automated content-production process. This perspective connects artificial intelligence, social media engagement, multidimensional health literacy, professional accountability, and community participation within one analytical framework. Its methodological contribution is reflected in the use of a multi-site cluster-randomized mixed-methods design, comparative campaign conditions, longitudinal assessment, multilevel analysis, mediation testing, platform analytics, content-quality evaluation, and qualitative inquiry. This integrated approach distinguishes digital visibility from genuine educational, critical, and behavioral outcomes.

The principal limitations of the study concern the use of self-reported preventive behavior, possible differences in social media exposure outside the intervention, reliance on selected platforms, and the relatively short six-month follow-up period. Campaign effectiveness may also vary according to language, internet access, algorithmic platform changes, institutional trust, local health services, and the quality of professional review. Future research should conduct longer pragmatic trials, include objective health-behavior indicators, and compare fully automated, professionally reviewed, and community-co-designed AI campaigns. Further studies should examine cost-effectiveness, algorithmic bias, privacy risk, low-bandwidth delivery, disability inclusion, multilingual communication, and the long-term influence of AI-supported campaigns on healthcare use and population health outcomes.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used Google Assisted to assist inimproving grammar, language quality, and overall readability of the text. After using this tool, the author(s) Carefully reviewed and edited the content as necessary and take full responbility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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