



Article

Evaluation of an Artificial Intelligence-Generated Health Communication Material on Bird Flu Precautions

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Simple Summary

Public health crises necessitate the rapid dissemination of health communication materials to mitigate public confusion and misinformation. Here, we applied artificial intelligence (AI) to accelerate the development of a health communication material on bird flu precautions in response to the 2025 bird flu outbreak in the United States. We surveyed 100 United States adults to assess the effectiveness of a health communication material created with ChatGPT, Leonardo.AI, and Canva for text, illustration, and design, respectively. Our findings show a positive perception of the AI-generated health communication material, with a 77% effectiveness rating. This evidence suggests that AI-generated health communication materials may provide rapid and efficient tools for health communication during disease outbreaks.

Abstract

The 2025 avian influenza A(H5N1) outbreak has highlighted the urgent need for rapidly generated health communication materials during public health emergencies. Artificial intelligence (AI) systems offer transformative potential to accelerate content development pipelines while maintaining scientific accuracy and impact. We evaluated an AI-generated health communication material on bird flu precautions among 100 U.S. adults. The material was developed using ChatGPT for text generation based on CDC guidelines and Leonardo.AI for illustrations. Participants rated perceived message effectiveness, quality, realism, relevance, attractiveness, and visual informativeness. The AI-generated health communication material received favorable ratings across all dimensions: perceived message effectiveness (3.83/5, 77%), perceived message quality (3.84/5, 77%), realism (3.72/5, 74%), relevance (3.68/5, 74%), attractiveness (3.62/5, 74%), and visual informativeness (3.35/5 67%). Linear regression analysis revealed that all features significantly predicted perceived message effectiveness in unadjusted and adjusted models ($p < 0.0001$), e.g., multivariate analysis of outcome on perceived visual informativeness showed $\beta = 0.51$, 95% CI: 0.37–0.66, $p < 0.0001$. Also, mediation analysis revealed that visual informativeness accounted for 23.8% of the relationship between material attractiveness and perceived effectiveness. AI tools can enable real-time adaptation of prevention guidance during epidemiological emergencies while maintaining effective risk communication.



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1. Introduction

Effective risk communication during emerging infectious disease outbreaks is critical for mitigating public confusion, curbing misinformation, and promoting protective behaviors [1]. The United States has been grappling with a severe avian influenza A(H5N1) outbreak, with at least 70 human cases reported since April 2024, including 41 associated with sick dairy cows and 26 linked to infected poultry [2]. The crisis has dramatically impacted the agricultural sector, with the United States Department of Agriculture (USDA) reporting 989 infected dairy herds across 17 states and 543 affected poultry flocks since March 2024. The scale of the outbreak is staggering, with over 90.9 million birds affected, highlighting the urgent need for effective containment and prevention strategies to mitigate the spread of this highly pathogenic virus [3].

During such health crises, public demand for actionable information often outpaces health organizations' capacity to produce multimodal resources (text, visuals, audiovisuals) that address evolving transmission risks, prevention strategies, and susceptibility concerns. For example, the public's appetite for information on bird flu prevention has surged, as indicated by a 5900% increase in related Google searches between February 2024 and February 2025 [4]. If these information demands are unmet, the gap can create fertile ground for misinformation proliferation, particularly when dealing with novel exposure routes like raw milk consumption or backyard poultry handling [5]. Belief in health misinformation continues to be cited as a major predictor of distrust in healthcare systems, leading to a lack of compliance with health recommendations [6]. Therefore, there is an urgent need for scalable, cost-effective, and efficient methods to rapidly generate accurate, engaging, and visually appealing health communication materials.

The development of effective health communication materials involves several key processes, including content creation (e.g., scriptwriting, articles, infographics), selection of the communication mode/channel (e.g., text, audiovisual, multimodal formats), and message design/production. Traditional health communication workflows face three critical bottlenecks during outbreaks: (1) time-intensive expert curation of evidence-based content, (2) delayed translation of technical guidelines into lay-friendly formats, and (3) resource constraints in producing visually optimized materials for diverse literacy levels [7,8]. These limitations hinder the rapid creation of health communication materials that effectively convey evolving health information in visually compelling ways.

Generative artificial intelligence (AI) systems, a subset of AI that enables computers to generate media outputs based on natural language prompts, offer the transformative potential to accelerate this pipeline. These tools can synthesize peer-reviewed evidence into plain-language narratives, generate culturally tailored visuals, and output materials in multiple formats (infographics, FAQs, animated shorts) within hours rather than weeks [9–11]. While generative AI has been increasingly applied in areas such as marketing, education, and entertainment, its potential in public health communication remains largely unexplored [12]. Specifically, little research has systematically evaluated AI-generated health communication materials using validated psychometric measures, particularly in the context of an ongoing disease outbreak.

The goal of this study is to conduct a formative evaluation of the perceived message effectiveness of an AI-generated health communication material on bird flu precaution methods. Specifically, we assessed how specific health information determinants (i.e.,

perceived message quality, realism, relevance, material attractiveness, and visual informativeness) influence message effectiveness using robust psychometric measures. Additionally, we investigate the mediating role of perceived visual informativeness (i.e., the extent to which individuals believe that a visual (e.g., an image or graphic) helps them understand and retain health information presented in the message) [13] in the relationship between material attractiveness (i.e., the extent to which individuals rate the visual appeal or design of the communication materials) [14] and perceived message effectiveness. Our study seeks to advance risk communication research by providing empirical evidence for AI's capacity to produce materials that meet public health messaging standards during epidemiological emergencies. As health systems face growing pressures from zoonotic disease emergence [15], this work seeks to demonstrate how AI tools could enable real-time adaptation of prevention guidance while maintaining the scientific rigor and psychological impact required for effective risk communication.

2. Methods

2.1. Study Design and Procedure

This study employed an online cross-sectional survey to assess participants' perceptions of an AI-generated health communication message containing both text and images. After providing informed consent, participants were directed to a URL where they viewed the message content. Upon completion, they returned to the survey to answer validation questions confirming that they had reviewed the content before proceeding to assess its effectiveness and quality.

2.2. Message Development

The AI-generated health communication message (Figure 1) was developed in three stages, designed to ensure fidelity to evidence-based health information and maximize visual and narrative engagement.



Figure 1. AI-generated health communication message using ChatGPT (ChatGPT, Version 4, OpenAI, San Francisco, CA, USA), Leonardo.Ai (Version 2.11, Leonardo.Ai, Sydney, Australia), and Canva (Canva Pty Ltd., Sydney, Australia).

2.2.1. Text Development

Text content was generated using ChatGPT (ChatGPT, Version 4, OpenAI, San Francisco, CA, USA). The following prompt was used to guide content creation:

“Create a short script between a female vet doctor and an auto mechanic who has taken her car for an oil change. The conversation should have a maximum of 8 dialogue exchanges. The mechanic asks about precautions for bird flu since he keeps backyard chickens. The vet’s responses should apply the Health Belief Model, emphasizing perceived risk, benefits, and self-efficacy. All of the vet’s responses should be based on CDC guidance from this webpage: [<https://www.cdc.gov/bird-flu/about/index.html>, accessed on: 13 February 2025]. Format the script using a three-arc storytelling structure (setup, confrontation, and resolution).”

The research team then reviewed the resulting dialogue for length, clarity, content validity, and factual consistency with CDC information. Minor revisions were made to simplify language and ensure message accuracy.

2.2.2. Visual Development

Visuals for the dialogue were generated using Leonardo.Ai (Version 2.11, Leonardo.Ai, Sydney, Australia), with scenes designed to reflect the story’s context and emotional tone. The imagery was crafted to support the verbal message while preserving narrative continuity across the 8 dialogue panels.

2.2.3. Formatting and Comic Design

Text and visuals were integrated into a comic-style layout using Canva (Canva Pty Ltd., Sydney, Australia). The comic format was chosen for three reasons. First, comics offer an effective narrative medium for communicating complex health information in an accessible and engaging way [16]. Compared to prose messages, comics combine text and imagery to reduce cognitive load and improve message retention. Second, because the characters are AI-generated, the comic format clearly signals that the scenario is fictional and not based on real individuals, avoiding potential misrepresentation. Finally, this format allows us to creatively incorporate public health models (e.g., Health Belief Model) into an emotionally compelling and educational dialogue.

The final version was exported as a PDF for inclusion in the survey. All materials are available on request to support transparency and replication.

2.3. Participant Recruitment and Data Collection

This study used a sample size of 100 participants, consistent with prior formative evaluation studies in health communication. For example, Berman and colleagues conducted a community-based evaluation with 80 partners [17], and a scoping review by Sonke and colleagues reported sample sizes ranging from 4 to 2140 across similar studies [18].

The study sample was obtained via Prolific, a web-based participant recruitment platform commonly employed in behavioral science investigations [19]. Prolific has been validated as a reliable participant pool, with prior studies demonstrating that respondents exhibit high engagement, lower rates of dishonest behavior, and better attention to survey questions compared to other crowdsourcing platforms [19,20].

Prolific platform uses automated algorithms to invite individuals who meet the researcher-defined eligibility criteria. In this study, participants had to be 19 years or older and reside in the United States to be eligible. The survey was conducted on 14 February 2025, using Qualtrics. The research was approved by the University of Nebraska Omaha Institutional Review Board (IRB Protocol #0780-24-EX), approved on 20 December 2024. Respondents were compensated USD 0.69 upon completing the survey.

2.4. Measures

2.4.1. Dependent Variable

Perceived message effectiveness [21] was assessed using a two-item scale (Cronbach's $\alpha = 0.87$). One of the items included the question, "How confident did the information you just read make you feel about taking the right precautions to protect yourself from bird flu?" Responses were measured on a five-point scale ranging from 1 (strongly unconfident) to 5 (strongly confident). The second item included the question, "How convincing was the message in the information material?" Responses were measured on a five-point scale ranging from 1 (strongly unconvincing) to 5 (strongly convincing).

2.4.2. Independent Variables

Perceived message quality [22] was measured using a two-item scale ($\alpha = 0.81$) that assessed participants' perceptions of the persuasiveness of the material. An example item included "This information material was persuasive," with responses ranging from 1 (strongly disagree) to 5 (strongly agree).

Perceived realism [22] was assessed using a two-item scale ($\alpha = 0.79$) to determine how authentic the information appeared to participants. One item asked respondents to rate the statement, "The conversation in this information material was honest," using a five-point scale from 1 (strongly disagree) to 5 (strongly agree).

Perceived message relevance [23] was evaluated using a three-item scale ($\alpha = 0.84$). One of the items asked participants, "How well do you agree or disagree with the following statement: 'I found the message in the information material relevant to my life,'" with responses ranging from 1 (strongly disagree) to 5 (strongly agree).

Material attractiveness [14] was assessed using a single-item measure, which asked participants, "How attractive did you find the materials?" Responses were provided on a five-point scale from 1 (very unattractive) to 5 (very attractive).

Perceived visual informativeness [13] was measured using a two-item scale ($\alpha = 0.86$) to evaluate the role of imagery in conveying the message. One item asked participants to rate the statement, "The images in the information material helped me understand the rest of the content," with responses ranging from 1 (strongly disagree) to 5 (strongly agree).

2.4.3. Sociodemographic Covariates

We collected key demographic variables to account for statistical control, following established message-testing research practices [24]. Participants provided information on sociodemographic characteristics, including age (<45 years, ≥ 45 years), sex (female, male), and race/ethnicity (White, Black or African American, Asian, Hispanic, Native American or Alaska Native, Native Hawaiian or Other Pacific Islander, Mixed Race, or Other). Educational attainment was categorized as less than high school, high school diploma or GED, some college with no degree, associate degree, bachelor's degree, master's degree, or doctoral/professional degree. Household income was reported in the following brackets: <USD 20,000, USD 20,000–34,999, USD 35,000–49,999, USD 50,000–74,999, and $\geq$ USD 75,000.

2.5. Data Analysis

We summarized participants' characteristics using descriptive statistics (frequencies, proportions, means, and standard deviations). We calculated a composite score for perceived message effectiveness by averaging the responses to its two items. Given that the resulting variable was continuous, we used linear regression to examine its association with predictor variables. In the linear regression Model 1, bivariate or unadjusted associations between the dependent variable (perceived message effectiveness) and each independent

variable (perceived message quality, realism, message relevance, material attractiveness, and perceived visual informativeness) were examined. In Model 2, multivariate linear regression included adjustments for sociodemographic covariates (age, sex, race, education, and income).

A mediation analysis was conducted to assess whether perceived visual informativeness mediated the relationship between material attractiveness and perceived message effectiveness. Regression models were fitted in four steps following Sobel's procedures to evaluate the mediation effect [25]. Statistical tests were two-sided, with $p < 0.05$ considered statistically significant [25]. Effect sizes and 95% confidence intervals for indirect effects were estimated using bootstrapping methods [26]. All statistical analyses were performed using SAS version 9.4 (SAS Institute Inc., Cary, NC, USA).

2.6. Data Quality

To ensure data quality, participants were required to complete an open-ended attention check, in which they were asked to summarize the content of the information material in 2–3 words. One participant who failed this check was excluded. Prolific's platform also uses internal algorithms to prevent inattentive and unreliable participants or those with poor prior ratings from joining studies, further enhancing sample integrity [27].

3. Results

3.1. Participant Characteristics

The study included 100 participants (Table 1), the majority of whom were younger than 45 years (68%). The sample consisted of 51% females, 69% White individuals, 51% who reported a household income of USD 75,000 or more, and 73% had a bachelor's degree or more.

Table 1. Participant characteristics ($n = 100$).

Variable	<i>n</i> (%)
Age	
Less than 45	68 (68%)
45 or older	32 (32%)
Sex	
Female	51 (51%)
Male	46 (46%)
Race	
White	69 (69%)
Non-White	31 (31%)
Income	
Less than USD 75,000	49 (49%)
USD 75,000 or more	51 (51%)
Education	
Less than a bachelor's degree	27 (27%)
Bachelor's degree or more	73 (73%)
Most liked message feature	
Message clarity	36 (36%)
Simplicity	39 (39%)

Table 1. *Cont.*

Variable	n (%)
Relatability/visuals/overall design	13 (13%)
None of the above/others	13 (13%)
	Mean (SD)
Perceived message quality	3.83 ± 0.98
Perceived realism	3.84 ± 0.97
Perceived message relevance	3.64 ± 1.02
Material attractiveness	3.35 ± 1.15
Perceived visual informativeness	3.48 ± 1.15
Perceived message effectiveness	3.83 ± 0.99

3.2. Message Characteristics

Participants identified simplicity (39%), message clarity (36%), and relatability/visuals/overall design (13%) as the most favorable features of the message. Mean scores on a 5-point scale were 3.83 ± 0.98 for perceived message quality, 3.84 ± 0.97 for perceived realism, 3.64 ± 1.02 for perceived message relevance, 3.35 ± 1.15 for material attractiveness, 3.48 ± 1.15 for perceived visual informativeness, and 3.83 ± 0.99 for perceived message effectiveness.

3.3. Bivariate and Multivariate Associations with Perceived Message Effectiveness

Bivariate linear regression (Model 1, unadjusted) demonstrated that perceived message quality ($\beta = 0.81$, 95% confidence interval [CI]: 0.69–0.92, $p < 0.0001$), realism ($\beta = 0.69$, 95% CI: 0.54–0.84, $p < 0.0001$), relevance ($\beta = 0.64$, 95% CI: 0.49–0.78, $p < 0.0001$), material attractiveness ($\beta = 0.61$, 95% CI: 0.47–0.74, $p < 0.0001$), and perceived visual informativeness ($\beta = 0.51$, 95% CI: 0.38–0.65, $p < 0.0001$) were all significantly and positively associated with perceived message effectiveness.

In the adjusted multivariate model (Model 2), which controlled for age, sex, race, education, and income, these associations remained statistically significant. Perceived message quality ($\beta = 0.83$, 95% CI: 0.71–0.95, $p < 0.0001$), realism ($\beta = 0.71$, 95% CI: 0.56–0.87, $p < 0.0001$), relevance ($\beta = 0.66$, 95% CI: 0.51–0.79, $p < 0.0001$), material attractiveness ($\beta = 0.61$, 95% CI: 0.47–0.74, $p < 0.0001$), and perceived visual informativeness ($\beta = 0.51$, 95% CI: 0.37–0.66, $p < 0.0001$) all remained significantly and positively associated with perceived message effectiveness (Table 2).

Table 2. Bivariate and multivariate linear regression on perceived message effectiveness.

Exposure Variables	Model 1		Model 2	
	Estimates β (95% CI)	p-Value	Estimates β (95% CI)	p-Value
Perceived message quality	0.81 (0.69–0.92)	<0.0001	0.83 (0.71–0.95)	<0.0001
Perceived realism	0.69 (0.54–0.84)	<0.0001	0.71 (0.56–0.87)	<0.0001
Perceived message relevance	0.64 (0.49–0.78)	<0.0001	0.66 (0.51–0.79)	<0.0001
Material attractiveness	0.61 (0.47–0.74)	<0.0001	0.61 (0.47–0.74)	<0.0001
Perceived visual informativeness	0.51 (0.38–0.65)	<0.0001	0.51 (0.37–0.66)	<0.0001

Model 1 is unadjusted. Model 2 is adjusted for age, sex, race, education, and income.

3.4. Mediation Analysis of Visual Informativeness

Mediation analysis (Figure 2) indicated that perceived visual informativeness accounted for 23.8% of the total effect of material attractiveness on perceived message effectiveness ($b = 0.14$, $SE = 0.07$; bias-corrected 95% CI: 0.01–0.28), demonstrating a partial mediation effect.

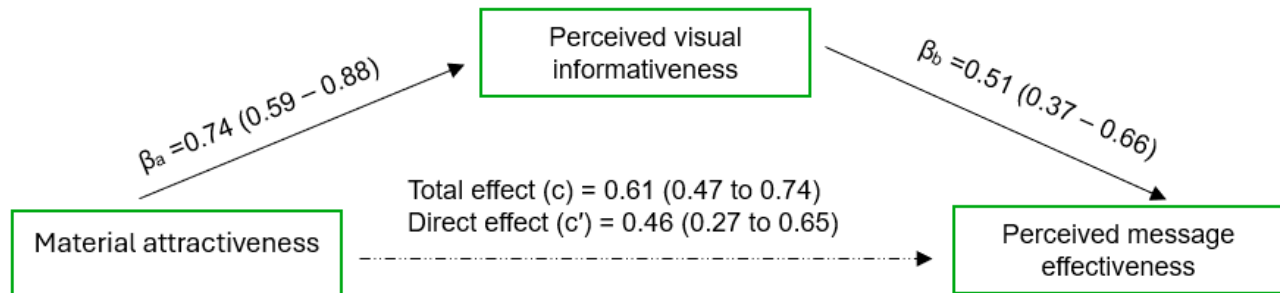


Figure 2. Mediation analysis: Perceived visual informativeness mediates 23.8% of the total effect of material attractiveness on perceived message effectiveness with 1000 bootstrap resamples, $b = 0.14$, $SE = 0.07$. Bias-corrected 95%CI = 0.01–0.28.

4. Discussion

Our formative evaluation of an AI-generated health communication resource on bird flu precautions revealed that, on average, participants rated its perceived message effectiveness (PME) at 3.83/5 (77%), with other critical attributes, perceived message quality (3.84), realism (3.72), relevance (3.68), attractiveness (3.62), and visual informativeness (3.35), scoring within a similarly robust range (all on a 1–5 scale). Our PME score of 3.83 exceeded the average PME scores reported across health communication resources in a recent review of 75 studies, which identified a mean of 1.68 PME measures per study [28]. These findings underscore AI's potential to support the rapid design of effective health communication tools during outbreaks, where timely, accurate messaging is critical for coordinating responses and mitigating risks [29]. For instance, during the COVID-19 pandemic, rapid communication strategies reduced misinformation spread by AI-enhanced campaigns [30], highlighting the urgency of scalable solutions like those explored here. Additionally, our perceived message effectiveness (PME) score of 3.83 aligns with the upper range of PME values (3.3–3.8) reported in a large pretesting study of e-cigarette prevention messages developed by the U.S. Food and Drug Administration [31]. These findings suggest that the AI-generated avian flu infographic may have performed comparably to professionally developed public health campaigns that underwent rigorous pretesting.

This study was designed as a formative evaluation, a process used to gather feedback on the quality, clarity, and relevance of health communication materials prior to broad dissemination. Formative evaluations do not require a control or comparison group, as their primary purpose is to refine materials based on perceptions of the target audience. Such evaluations are particularly critical in public health emergencies, where rapid feedback on message clarity, cultural appropriateness, and visual appeal can guide improvements before wide-scale deployment [32,33]. This approach has been used in diverse settings, from digital health tools to culturally inclusive health promotion campaigns [34,35]. By capturing participants' assessments of visual informativeness, realism, and message quality, our study contributes to the early-stage validation of AI-generated health communication content.

The emergence of generative AI presents unprecedented opportunities to address longstanding challenges in health communication, including personalization at scale and rapid resource deployment. Two recent studies demonstrated that AI saved message

creation time exponentially [36] and increased message relevance over time, with 86.2% of participants reporting improved message relevance [37]. However, AI's limitations, including algorithmic bias and hallucinations, necessitate rigorous human oversight [38]. By empirically testing AI-generated content with target populations, as performed here, public health practitioners can balance efficiency with evidence-based rigor.

The message features evaluated in this study are central to behavior change frameworks like the Elaboration Likelihood Model (ELM) [39]. We found PME correlated with attributes such as realism and relevance, which enhance persuasion by fostering transportation (immersion in narratives) and character identification. For example, situating bird flu guidance within a narrative dialogue between a healthcare provider and a mechanic with backyard poultry, a relatable, casual setting, likely amplifies engagement. This aligns with evidence that narratives grounded in everyday contexts increase message adoption on safe milk handling compared to didactic formats [40].

The mediation analysis revealed that perceived visual informativeness mediated 23.8% of the total effect of material attractiveness on perceived message effectiveness, suggesting that visually optimized content amplifies persuasive impact through enhanced information clarity. This finding aligns with prior research demonstrating that narrative-driven visual elements significantly improve health message adoption by fostering cognitive engagement and emotional resonance, as observed in studies of pandemic communication strategies during COVID-19 [41]. The partial mediation effect corroborates Vicari and Komendatova's framework for multimodal risk communication, which posits that visual components synergize with textual content to reinforce behavioral intentions while requiring complementary design elements [30]. These results underscore the critical need for AI-generated health materials to prioritize visual clarity and contextual relevance, particularly when addressing novel transmission risks like avian influenza's spread through dairy herds and poultry flocks.

4.1. Implications for Practice and Research

First, AI-generated materials require empirical validation using psychometrically robust measures before broad deployment. Our study demonstrates that AI can rapidly produce theory-driven content (e.g., HBM-based content) while preserving message quality, a critical advantage during fast-moving outbreaks. Second, AI enables hyperlocal personalization; for example, tailoring messages to high-risk groups like backyard poultry owners, as performed here, improves relevance and trust [42]. Third, in addition to evaluating the role of artificial intelligence in bridging Health, One Health, and zoonotic communication gaps, future work should examine how effectively these tools support the translation of technical content for non-technical audiences. This includes assessing whether key scientific messages are preserved while enhancing accessibility and engagement across diverse communities. Additionally, as this study was formative in nature and focused on perceived message effectiveness, future research should explore the explicit measurement of Health Belief Model constructs to more directly assess theoretical mechanisms of message impact.

4.2. Strengths and Limitations

We rapidly developed AI-generated health communication content, designed visuals, validated the message, and conducted an evaluation survey, all within 24 h, demonstrating the speed and feasibility of this approach during public health emergencies. Another strength includes the use of validated measures (Cronbach's $\alpha = 0.81\text{--}0.89$), ensuring reliability in assessing message attributes [43]. Another key strength of this study is the mediation analysis, which assessed the role of perceived visual informativeness in mediating the relationship between material attractiveness and perceived message effectiveness, provid-

ing valuable insights into the underlying mechanisms driving the impact of AI-generated health communication materials, even in the context of innovative interventions.

Limitations include the cross-sectional design; longitudinal assessments comparing AI-generated and human-developed health communication materials are crucial for evaluating sustained behavioral impacts, cultural adaptability, and information retention over time, particularly given findings that AI content may lag in cultural nuance despite matching human quality in other domains [44]. Although our outcome, perceived message effectiveness (PME), is not a direct measure of behavior, it satisfies the goal of this initial evaluation and is an established predictor of actual message effectiveness [28,45]. Future studies should assess the impact of AI-generated risk communication materials on protective behavioral outcomes.

Another limitation of our study is that our sample, though diverse in some respects, was skewed toward participants with higher education and income levels, which may affect how professionally designed health messages are received. As a result, the findings may not fully generalize to populations with lower socioeconomic status or limited health literacy. Future studies should also replicate our analysis with larger samples and include full diagnostic checks to confirm robustness and reduce the risk of overfitting. Also, although this study sampled from the general U.S. population, and not specifically poultry owners, our aim was to assess public-facing materials addressing broader zoonotic risk factors (e.g., raw milk consumption, unprotected animal exposure). Future research should evaluate similar materials among individuals with direct poultry exposure to assess differential message relevance and effectiveness [46]. Finally, we acknowledge that our use of a two-item measure to assess perceived message effectiveness (PME) does not fully capture the multidimensional nature of the construct, which includes cognitive, emotional, and anticipated behavioral components [47]. Future studies should consider using more comprehensive and validated PME scales to better assess message impact.

5. Conclusions

This study demonstrates AI's capacity to generate credible, engaging health communication resources during crises, with perceived message effectiveness scores averaging 77%. By integrating AI's scalability with empirical testing and narrative design, public health can meet evolving demands for rapid, equitable messaging. As outbreaks like bird flu test global preparedness, leveraging AI, while mitigating its risks, will be essential to safeguarding populations.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
CDC	Centers for Disease Control and Prevention
HBM	Health Belief Model
PME	Perceived Message Effectiveness
USDA	United States Department of Agriculture

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