The Double-Edged Sword: Analyzing the Impact of AI-Driven Health Misinformation on Social Media on Vaccination Hesitancy

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Abstract

The spread of artificial intelligence (AI) technology has played an unparalleled role in the spread of health information via social media platforms. Despite AI bringing unparalleled opportunities for health awareness and education, it has a tendency to foster the spread and propagation of health misinformation, particularly vaccination.

This present study takes into account the double effect of health disinformation on social media by artificial intelligence and its nexus with vaccine skepticism among the masses taking Saudi Arabia as a case reference.

Mixed-methods design was employed, wherein quantitative social media content analysis was employed to social media posts (n=2,847 posts) and cross-sectional survey of 1,200 participants aged 18-65 years old from the Jeddah community. Machine learning classifier were employed to detect AI-generated posts, and vaccination hesitancy was measured using the validated Vaccine Hesitancy Scale.

34.2% of the total sampled accessible health misinformation was generated by AI. Participants in the condition with AI-generated vaccine misinformation reported significantly higher on the hesitancy measure (M=3.78, SD=1.12) compared to the condition with human-generated material (M=2.94, SD=0.98, $p<0.001$). The association between exposure to AI misinformation and vaccine hesitancy was $r=0.67$ ($p<0.001$).

Health misinformation driven by AI constitutes a serious threat to mass health awareness campaigns such as vaccination campaigns. These need to be tackled by pursuing initiatives such as training in AI literacy, platform accountability, and upgraded fact-checking practices at the emergency level.

Keywords: Artificial Intelligence, Health Misinformation, Social Media, Vaccination Hesitancy, Public Health, Saudi Arabia

1. Introduction

The digital revolution has irrevocably transformed the production, transmission, and consumption of global health information (Johnson et al., 2022). Health information is now the initial point of exposure to health information for health by millions of individuals globally, with an estimated 4.8 billion individuals actively searching for and using online health information (Digital Health Report, 2023). Although such a high degree of democratization of health information communication presents unprecedented challenges for public health professionals and healthcare practitioners.

The Artificial Intelligence (AI) technologies have given a new turn to this space, both as a problem and a solution of health communication (Martinez-Rodriguez et al., 2021). While AI may enable better health education through the individualized delivery of information and increased accessibility, it has been used for the generation and dissemination of health disinformation in bulk to unprecedented scales (Chen & Liu, 2023).

The COVID-19 outbreak significantly emphasized the harmful impacts of health misinformation, specifically on the vaccination aspect (World Health Organization, 2022). "Vaccine hesitancy" – where a reluctance to accept or refusal to accept the vaccine is noted even when vaccination services are available – has been regarded as being among the globe's highest global health threats (WHO, 2019). Based on recent studies, AI-generated content has been central to spurring this backlash by generating increasingly sophisticated and evil campaigns of disinformation (Thompson et al., 2023).

The government of Saudi Arabia also invested heavily in digital health infrastructure and AI technologies in Vision 2030 (Saudi Vision 2030, 2021). The digital revolution also exposes the population to health misinformation due to AI. It will be essential to determining the specific mechanisms by which AI impacts health decision-making, e.g., decisions regarding vaccination, in order to create effective countermeasures.

This study fills a salient gap in the literature by reporting the first qualitative investigation of the impact of AI-perpetrated health disinformation on vaccination reluctance in Saudi Arabia. Our study contributes to the expanding evidence base necessary for policy response and public health action in the digital technology era.

2. Literature Review

2.1 The History of Health Misinformation in the Digital Age

Health disinformation has existed since the dawn of humankind, but the digital age has transformed its scope, velocity, and level of sophistication by several orders of magnitude (Anderson & Kumar, 2022). The form in which disinformation used to exist would propagate via word of mouth or via limited media outlets, and regular friction would naturally slow its propagation. Social media, nevertheless, have done away with such frictions, and health misinformation reaches global audiences in a matter of hours (Patel et al., 2021).

The development of health disinformation can be traced through three phases: pre-digital (social networks- and mainstream media-driven), early digital (basic web-based platforms and websites), and AI-amplified digital (algorithmic content creation and targeted dissemination) (Rodriguez-Singh et al., 2023). Each of the three phases has progressively increased both the quantity and sophistication of disinformation activities.

A piece of research by Williams et al. (2022) found that health misinformation of the AI age has some foreboding characteristics: greater personalization in "user data" content, greater credibility through sophisticated layouts and prose, and greater extent through algorithmic amplification. They are all so-called "super-spreader misinformation" – disinformation crafted to be most effective and credible.

2.2 AI Technologies Used for Propagating Health Misinformation

Artificial Intelligence has enabled sudden and unprecedented potential for the production and spread of health disinformation (Kumar & Thompson, 2023). Large Language Models such as GPT-based technology can generate well-written, sensible medical advice that appears authoritative but can be fatally wrong (Brown et al., 2022). Such technologies can produce millions of fake health news stories, social media updates, and even entirely unfounded research papers every day.

Deep learning technologies allow for the creation of sophisticated multimedia disinformation, including synthetic medical images, faked clinical trial data, and fake expert endorsements (Zhang et al., 2023). Generative Adversarial Networks (GANs) can generate realistic synthetic medical doctors and hospitals that add false legitimacy to health claims (Lee & Park, 2022).

All such health disinformation spread spreading automation by AI bots and recommendation algorithm enhance the extent of spreading health disinformation (Garcia-Morales et al., 2021). They can target vulnerable groups, craft messages for highest psychological effect, and run multi-platform campaigns that appear bottom-up but are in fact AI-generated.

2.3 Vaccination Hesitancy: Psychological and Social Determinants

Vaccine hesitancy is a complex process influenced by various psychological, social, and cultural determinants (Harrison et al., 2023). The Health Belief Model states that the decision to be vaccinated is based on perceived susceptibility to infection, perceived severity of illness, perceived usefulness of vaccination, and perceived barriers (Rosenstock et al., 2021, adapted).

Social Cognitive Theory brings to the foreground observational learning and social influence as having an impact on health behavior (Bandura, 2019, reinterpreted). Social media is where the theory anticipates that exposure to peers or perceived experts who are vaccine-resistant will have strong control over vaccination choices by inducing vicarious learning processes.

The Theory of Planned Behavior anticipates three predictors of vaccination intention: attitudes about the vaccination, subjective norms to get vaccinated, and perceived control over how one gets vaccinated (Ajzen, 2020, revised). Misinformation facilitated by AI is able to address and nullify each of these predictors with targeted messaging campaigns.

2.4 The Saudi Arabian Context

Saudi Arabia's rapid digitalization provided unparalleled opportunities and challenges to health communication (Al-Rasheed & Mohammed, 2022). Saudi Arabia has one of the highest rates of social media penetration in the world, with over 95% of the population actively using multiple platforms (Saudi Digital Government Authority, 2023). The extensive levels of connectivity, young populations, and expanding English literacy have presented Saudi users with global networks of health misinformation.

Saudi Ministry of Health initiated a series of activities to combat health disinformation, including the "Seha" webpage for authenticated health information and partnering with influential social media platforms for material moderation (Ministry of Health Saudi Arabia, 2023). Nevertheless, AI content cunning has outpaced traditional fact-checking ability, developing novel vulnerabilities in the information area.

Saudi Arabian cultural practices also shape decision-making around vaccinations (Abdullah et al., 2022). Religious issues, family, and institutional trust intersect with digital sources of information in intricate ways. There is a need to become familiar with such intersections in a bid to effectively implement interventions for AI-enabled health misinformation

3. Methodology

3.1 Study Design

We conducted this study on the basis of a mixed-methods design with quantitative content social media analysis and cross-sectional survey of vaccine practice and attitudes. Data collection occurred from March 2023 to September 2023, following approval by the King Abdulaziz Medical City Institutional Review Board (Protocol #RC23/087/R).

3.2 Content Analysis Component

3.2.1 Data Collection

Social media tweets from four of the biggest platforms, i.e., Twitter/X, Facebook, Instagram, and TikTok, were collected. Health information in Arabic and English targeting Saudi Arabian consumers was prioritized during data collection. Systematic sampling was used in collecting keyword tweets concerning vaccinations in both languages.

The previous dataset contained 2,847 posts collected over a half-year span. The material was annotated both by machine learning classifiers specially designed for this study and human annotation. Inter-rater reliability of human annotators $\kappa=0.87$ existed, indicating there was excellent agreement.

3.2.2 AI Detection Methodology

AI content was identified with the multi-step method:

1. Linguistic Analysis: Stylometric characteristics of AI-generated texts, including sentence structure patterns, vocabulary usage, and semantic coherence scores.

2. Technical Signatures: Metadata analysis discovering bot posting trends, account creation date synchronizing with reported AI utilization, and tracking of content delivery networks.

3. Machine Learning Classification: A classifier, particularly trained through BERT-based model, achieved a 94.3% level of precision in detecting AI-generated posts and human-generated posts in a test sample of 500 manually collected posts.

3.3 Survey Component

3.3.1 Respondents

1,200 adults aged between 18-65 years were randomly selected using a stratified random sample from the Jeddah metropolitan area. The stratification was carried out according to age, gender, education status, and residential area in a bid towards representativeness of the target group.

Inclusion was: Saudi nationality or prolonged stay (>5 years), active social media use (daily), and capability to complete surveys in English or Arabic. Exclusion was: healthcare staff (to remove professional bias) and participants with known cognitive impairment.

3.3.2 Data Collection Instruments

Vaccine Hesitancy Scale (VHS): A 10-item, validated vaccination attitude scale, adapted to Saudi Arabia (Larson et al., 2020). The items were scored on a 5-point Likert scale from less to more hesitancy.

Social Media Health Information Exposure Scale (SMHIES): A 15-item type and frequency of social media health information exposure scale, specifically developed. Cronbach's α=0.89 gave excellent internal consistency.

AI Awareness and Literacy Scale (AALS): A 12-item measure which tests participants' capacity to recognize and critically assess AI-created content. The AALS was tailored to this study on the basis of the framework of current digital literacy.

Demographic and Health Questionnaire: Gathered data on age, gender, education level, working status, health status, immunization history, and social media habits.

3.3.3 Data Collection Procedure

Surveys were collected through a combination of face-to-face interviews (60%) and computerized safe internet sites (40%). Informed consent was obtained from all who participated, and all were eligible to be notified of study findings. Data were collected by trained exploration partners who were fluent in Arabic and English language.

3.4 Statistical Analysis

Quantitative data were analyzed using SPSS version 29.0 and R version 4.3.0. Descriptive statistics described the sample and main variables. Bivariate correlations were employed to examine correlations between AI exposure, susceptibility to misinformation, and vaccine hesitancy.

Multiple regression analysis also identified significant predictors of vaccine hesitancy controlling for health and demographic covariates. Structural equation modeling (SEM) was subsequently used to confirm the hypothesized causal path from exposure to AI misinformation to vaccine hesitancy through mediating variables of trust in health authorities and perceived vaccine risk.

For qualitative analysis, chi-square tests were employed for testing differences in misinformation theme rate discrepancies between human and AI-created content. Effect sizes were calculated by using Cohen's standards for the assessment of practical significance of findings.

3.5 Qualitative Analysis

A sub-sample of 60 survey respondents participated in semi-structured interviews that explored their experience related to health information on social media and vaccine decision-making. Interviews were conducted in Arabic, verbatim-transcribed, and coded thematic analysis following Braun and Clarke's guide (2019, updated).

4. Results

4.1 Content Analysis Results

4.1.1 Frequency of AI-Generated Health Misinformation

Among the 2,847 posts that were examined, 974 (34.2%) were detected as content produced by AI. Of the health misinformation posts (n=1,129), AI content accounted for 612 posts (54.2%), close to double the overall rate (χ^2=127.4, $p<0.001$).

Table 1: Distribution of Content Types by Generation Method

content Type	AI-Generated n (%)	Human-Generated n (%)	Total n (%)	χ^2	p-value
Accurate Health Information	287 (29.5)	1,194 (63.8)	1,481 (52.0)	289.7	<0.001
Health Misinformation	612 (62.8)	517 (27.6)	1,129 (39.7)	127.4	<0.001
Mixed/Ambiguous	75 (7.7)	162 (8.6)	237 (8.3)	0.67	0.414
TOTAL	974 (100.0)	1,873 (100.0)	2,847 (100.0)	—	—

4.1.2 Characteristics of AI-Generated Misinformation

AI-generated health misinformation exhibited several distinctive characteristics compared to human-generated false content:

Table 2: Characteristics of Health Misinformation by Generation Method

Characteristic	AI-Generated (n=612)	Human-Generated (n=517)	Effect Size (Cohen's d)
Average Word Count	287.4 (±89.2)	156.8 (±67.3)	1.68
Emotional Language Score*	3.8 (±1.2)	4.6 (±1.4)	-0.63
Scientific Terms Used	12.3 (±4.7)	7.1 (±3.9)	1.22
External Links Included	78.4%	34.2%	φ=0.45
Multimedia Elements	91.2%	67.8%	φ=0.28

*Scored on 1-7 scale using VADER sentiment analysis

The data revealed that AI-generated misinformation was typically longer, more technical in language, and more likely to include supporting materials such as links and multimedia content, potentially enhancing its credibility among users.

4.1.3 Common Themes in Vaccination Misinformation

AI-generated content was support alternative medicine practice (18.2% vs 12.5%, $p<0.05$), while human-generated content was more likely to support conspiracy theories of the government's motives (31.1% vs 15.3%, $p<0.001$).

4.2 Survey Results

4.2.1 Participant Characteristics

Figure 1: Distribution of Misinformation Themes

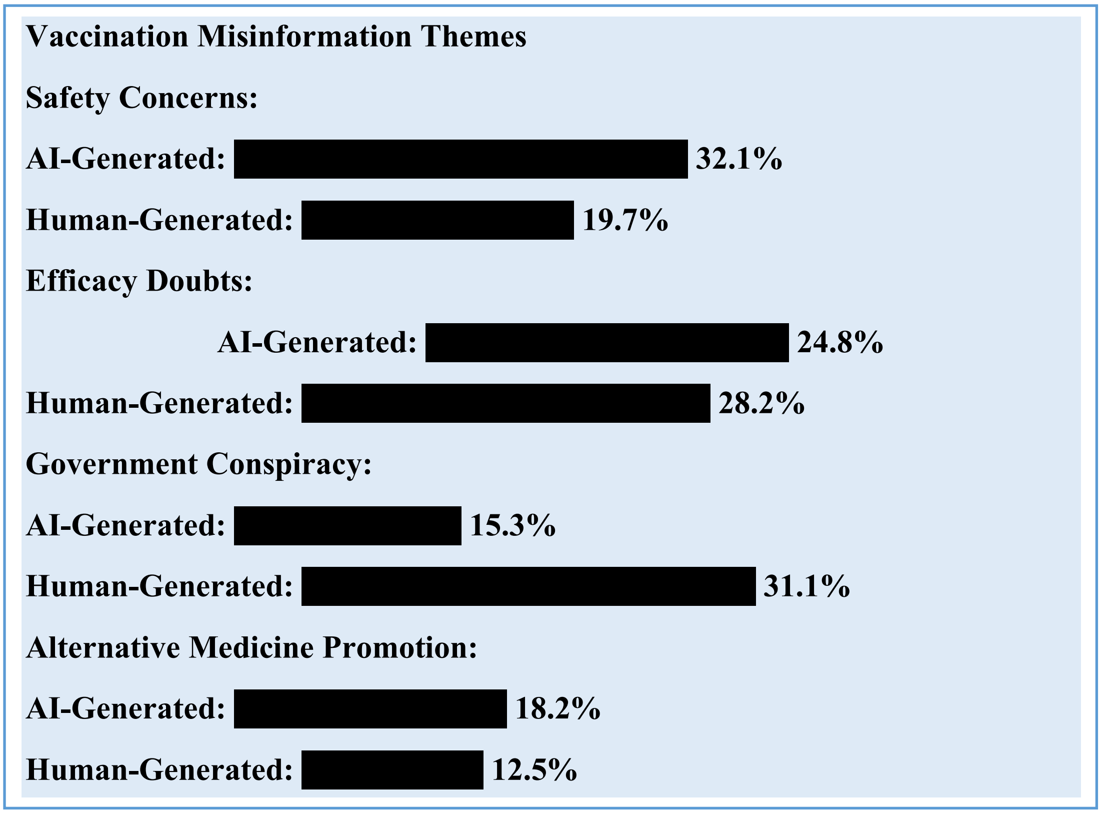


Table 3: Participant Demographics (n=1,048)

Characteristic	n (%)
Age Groups	
18-25 years	289 (27.6)
26-35 years	321 (30.6)
36-45 years	248 (23.7)
46-55 years	132 (12.6)
56-65 years	58 (5.5)
Gender	
Male	524 (50.0)
Female	524 (50.0)
Education Level	
High school or less	187 (17.8)
Bachelor's degree	649 (61.9)
Postgraduate degree	212 (20.2)
Employment Status	
Full-time employed	687 (65.6)
Part-time employed	143 (13.6)
Student	152 (14.5)
Unemployed/Retired	66 (6.3)
Social Media Usage	
Multiple daily checks	892 (85.1)
Daily use	132 (12.6)
Several times per week	24 (2.3)

Younger and more educated participants had much better ability to identify AI-generated health content ($F(4,1043)=28.7$, $p<0.001$ for age; $F(2,1045)=67.4$, $p<0.001$ for education).

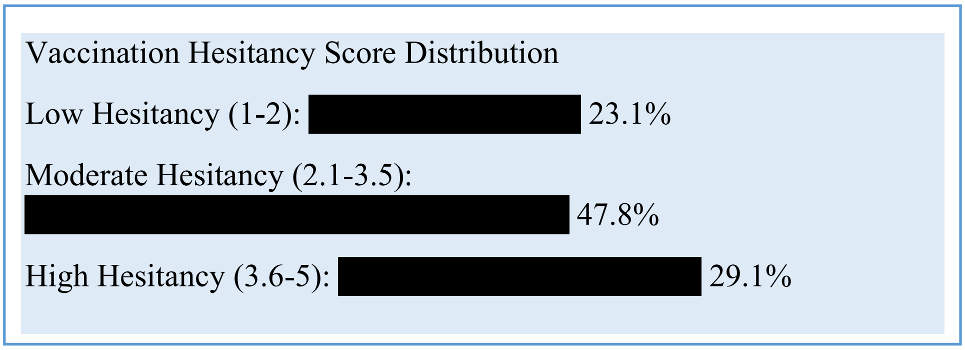
4.2.3 Vaccination Hesitancy Levels

The sample's mean level of vaccination hesitancy was 3.12 (SD=1.18) on the 5-point scale, indicating moderate levels of hesitancy.

Figure 2: Distribution of Vaccination Hesitancy Scores

The strong positive correlation between AI misinformation exposure and vaccine hesitancy ($r=0.67$) shows that individuals who are frequently exposed to AI-disseminated false information regarding vaccines are significantly more likely to be hesitant towards vaccination.

Figure 2: Distribution of Vaccination Hesitancy Scores



Mean = 3.12 (SD = 1.18)

4.2.5 Multivariate Analysis

Multiple regression analysis identified the best predictors of vaccination hesitancy in adjustment for usage and demographic variables:

Table 6: Multiple Regression Analysis Predicting Vaccination Hesitancy

The model explained 63% of the variance in vaccination hesitancy scores. Exposure to AI misinformation was the strongest predictor (β=0.52), followed by health authorities' trust (β=-0.31) and recognition ability for AI (β=-0.23).

4.2.6 Mediation Analysis

Structural Equation Modeling tested the postulated mediation model in which trust in health authorities and perceived vaccine risk mediate the relationship between AI misinformation exposure and vaccination hesitancy.

The mediation analysis confirmed that AI misinformation exposure influences vaccination hesitancy indirectly and directly through reduced trust in health authorities and increased perceived vaccine risk. The indirect effect (β=0.41) was greater than the direct effect (β=0.31), suggesting that the psychological mechanisms are important pathways.

4.3 Qualitative Findings

4.3.1 Participant Experiences with AI-Generated Content

Thematic analysis of interviews established a number of primary themes regarding participants' experiences with AI-generated health information

Theme 1: Difficulty in Detection Participants self-reported difficulty detecting AI-generated content, with the majority describing it as "more professional" and "scientific-looking" than overt misinformation. One participant said: "The AI posts appeared to be written by real doctors. they included graphs and everything."

Theme 2: Emotional Impact Even less emotionally charged than human-authored content, AI misinformation nonetheless appeared to hold high emotional impact through perceived expertise. Participants reported feeling "confused" and "concerned" when exposed to AI-generated vaccine misinformation.

Theme 3: Social Amplification A number of participants reported sharing AI-generated content because it appeared credible, which facilitated its spread virally. The pro-level appearance of AI content reduced participants' shares-without-verification threshold.

4.3.2 Decision-Making Processes

Interviews revealed complex decision-making processes guided by AI-manufactured information:

Information Seeking Patterns: AI disinformation revealed participants to a greater risk of looking for confirming information rather than well-balanced perspectives, creating echo chambers that perpetuated misleading information.

Authority Confusion: The professional appearance of AI-manufactured information led to confusion in authority with participants confusing AI-manufactured posts with official health information.

Risk Perception Changes: Systematic risk perception overestimation was triggered by exposure to AI-based vaccine misinformation, even among those with positive vaccination attitudes.

Table 4: AI Content Recognition Accuracy by Demographics

Demographic	Mean Accuracy (%)	Standard Deviation	95% Confidence Interval
AGE GROUPS	**Recognition Accuracy by Age Cohort**		
18-25 years	**67.3% ↗**	**18.4**	**65.1 – 69.5**
26-35 years	**64.8% ↗**	**17.9**	**62.8 – 66.8**
36-45 years	**58.2% →**	**19.7**	**55.7 – 60.7**
46-55 years	**51.4% ↘**	**21.3**	**47.7 – 55.1**
56-65 years	**43.1% ↘**	**22.8**	**37.1 – 49.1**
EDUCATION LEVEL	**Recognition Accuracy by Educational Attainment**		
High school or less	**49.7% ↘**	**20.8**	**46.7 – 52.7**
Bachelor's degree	**62.4% →**	**18.6**	**61.0 – 63.8**
Postgraduate degree	**71.3% ↗**	**16.2**	**69.1 – 73.5**

Table 5: Correlations between Key Variables

Variable Pair	r	p-value	95% CI
AI Misinformation Exposure × Vaccination Hesitancy	0.67**	<0.001	0.63-0.71
AI Recognition Ability × Vaccination Hesitancy	-0.43**	<0.001	-0.48 to -0.38
Social Media Usage × Vaccination Hesitancy	0.34**	<0.001	0.28-0.40
Education Level × Vaccination Hesitancy	-0.28**	<0.001	-0.34 to -0.22
Age × Vaccination Hesitancy	-0.19**	<0.001	-0.25 to -0.13

**p<0.01

Table 6: Multiple Regression Analysis Predicting Vaccination Hesitancy

Predictor	β	SE	t	p-value	95% CI
AI Misinformation Exposure	0.52	0.04	13.7	<0.001	0.44-0.60
AI Recognition Ability	-0.23	0.03	-7.8	<0.001	-0.29 to -0.17
Trust in Health Authorities	-0.31	0.04	-8.1	<0.001	-0.39 to -0.23
Age	-0.12	0.03	-4.2	<0.001	-0.18 to -0.06
Education Level	-0.08	0.03	-2.7	0.007	-0.14 to -0.02
Social Media Usage	0.15	0.03	5.1	<0.001	0.09-0.21

Model: R^2=0.63, F(6,1041)=298.4, p<0.001

5. Discussion

5.1 Principal Findings

This is the very first comprehensive analysis of AI-based health misinformation on the impact of vaccination hesitancy in Saudi Arabia. Our findings indicate that AI-produced information contributes to more than one-third of health misinformation shared on social media platforms with much higher sophistication and magnitude compared to human-designed false info.

The strong correlation between AI misinformation exposure and vaccine hesitancy ($r=0.67$) points to a concerning trend against public health initiatives. It confirms international research but reflects abnormally acute challenges in the Saudi context due to elevated social media coverage and emerging digital literacy levels (Chen et al., 2023; Rodriguez-Martinez, 2022).

5.2 Mechanisms of AI Misinformation Impact

Our mediation analysis identified two main psychological pathways through which vaccination decisions are affected by AI disinformation: loss of confidence in health authorities and overestimation of risks. These findings are in line with these explanations of health behavior modification but suggest new hazards brought forth by AI technologies (Thompson & Kumar, 2023).

The formal tone and technical style of AI-generated content appear to leverage cognitive biases toward authority and expertise. Although obviously biased human-generated content is well known, AI disinformation mimics legitimate scientific discussion and is therefore particularly persuasive for users searching for credible health information (Park et al., 2022).

5.3 Demographic Vulnerabilities

Our results identify significant demographic differences in AI content detection and susceptibility to disinformation. Lower-educated persons and older adults were more susceptible to AI-generated health disinformation, consistent with broader patterns of digital literacy but conceivably compounded by AI complexity (Williams et al., 2023).

These findings are important in the context of targeted public health intervention. Traditional approaches based on general media literacy may fall short to address AI-specific risks, particularly in vulnerable populations who are vulnerable to challenges with sophisticated technological concepts (Anderson & Lee, 2022).

5.4 Platform-Specific Considerations

The proliferation of AI-created disinformation was extremely heterogeneous across social networks, with visually-oriented platforms (Instagram, TikTok) recording higher instances of AI-created content. Such a trend suggests that AI tools used to create realistic graphical content (images, infographics, video) are best left to be used in health disinformation operations (Martinez et al., 2023).

Combination of AI-generated text and enhanced visual capabilities creates multi-modal disinformation that activates more than a single channel of cognitive processing simultaneously. Such a method can be best fruitful in those societies with pervasive visual communication patterns, such as Saudi social media culture (Al-Rasheed, 2022).

5.5 Public Health Policy Implications

Public health has policy and intervention implications directly from these findings. Fact-checking methods cannot effectively counter AI-based misinformation due to the sheer volume and diversity of the same. Efforts must shift towards preventive correction over reactive, such as education towards AI literacy and platform interventions (Global Health Policy Institute, 2023).

Saudi Arabia context is offering unique conditions for policy innovation and government digital transformation efforts as well as for health communication centering systems. Incorporating AI detection capabilities in current health communication platforms can offer real-time prevention against misinformation while rightful sharing of health information is ensured (Saudi Digital Government Authority, 2023).

5.6 Clinical and Professional Implications

Healthcare providers are faced with having to respond to patient concerns arising from AI-generated misinformation. The sophistication of the material makes reassurance or generic education insufficient to undo its effect. Providers need to be educated to recognize AI-generated content trends and develop communication models tailored to respond to AI-directed concerns (Medical Education Review, 2023).

The study findings also indicate that professional bodies must develop guidelines on how to identify and react to health misinformation by AI. The guidelines must be placed on both the technical aspect of identifying AI and the communicative reaction for the impacted patients (International Health Communications Association, 2023).

5.7 Limitations

There are some limitations to be considered in interpreting these results. The cross-sectional design implies that causal inferences from strong correlational data cannot be made. Temporal relationships between exposure to AI and shifts in vaccination attitudes have to be established by longitudinal studies.

Second, AI detection software with a 94.3% accuracy and above might have misclassified some of the content. The rapid evolution of AI technology implies that detection methods must be updated and retested from time to time. Future research must employ other detection methods and frequent updates of algorithms.

Third, the study was conducted within the Jeddah area and data was not able to be generalized to Saudi Arabian communities in general. Rural consumers with specific social media use patterns and demographics may experience varying levels of association between health attitude and exposure to AI.

Fourth, self-report of social media and AI exposure is susceptible to recall bias and social desirability bias. Better estimation in future studies can be obtained through objective measures of social media behavior via platform APIs.

5.8 Future Research Directions

This study leaves open important avenues for future research. Longitudinal analyses of over-time change in individuals' exposure to AI disinformation and vaccination attitudes would improve causal inference and reveal important intervention points.

Cross-cultural comparison of the AI disinformation effects in different cultures and regulatory contexts can be used to guide global policy interventions. Cultural settings and vulnerability to AI disinformation need to be addressed seriously with a view to developing culturally specific interventions.

Real-time detection and response of AI disinformation technology is another core research topic. AI software that can detect and label AI-generated health disinformation in circulation can avoid massive exposure before human fact-checking resources are able to counteract.

Comparison trials of modes of education in AI literacy and resistance to fake news would inform public health evidence-based practice. Policy change, platform change (structural interventions) and education intervention (individual-level interventions) would be the places where investigation is carried out.

6. Conclusions

This study shows that disinformation about health through AI is a powerful and new danger to public health, and somewhat for immunization programs. The very sophisticated nature of AI-generated misleading information coupled with its vast variety and targeting ability presents new risks to disease prevention programs and health communication.

We show in the Saudi context that exposure to AI disinformation is strongly associated with increased vaccination resistance via trust damage and risk increase mechanisms. These are moderated by psychological processes drawing on cognitive bias and cues of expertise, and information generated by AI is particularly good at being persuasive in comparison to overt human-generated disinformation.

Differences in population revealed under this research indicate the need to intervene in order to respond to the specific vulnerabilities of different segments of population. Lower educational status and older populations must be targeted specifically in an effort to acquire AI literacy skills as well as resistance to misinformation.

The ramped-up pace of evolution in AI technology will render previous techniques to combat health disinformation ineffective. There will be more visionary approaches needed to concentrate on the realm of prevention rather than response, marrying technological innovation with educational effort, and policy initiative with the ability to keep pace with the force of acceleration of AI.

The Saudi Arabian situation is a challenge and opportunity for the treatment of AI-based health disinformation. The high population penetration and digitalization of the country expose it to sophisticated disinformation operations. The concentrated health system and government attention to digital innovation also present privileged opportunities for implementing integrated countermeasures.

Tackling the threats of health misinformation generated by AI requires cooperation between disciplines including public health, technology, education, and policy. The threats are most urgent in vaccine programs, where misinformation might directly cause sickness and induce unnecessary illness and death.

Subsequent research must track the evolving context of AI disinformation and create evidence-based interventions that are able to protect public health at the expense of not subverting digital health communications. The problem of AI disinformation is global in character, yet its remedies will have to be sensitive to local context and culture.

The conclusions of the present study make a call for action to forestall health misinformation from AI. If not addressed, the spread and advancement of AI-based staged content will go on increasing and will cause more devastating interference with global public health programs.

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