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The Role of Generative AI in Emergency Science Popularization: Disseminating Fluoride-Related Health Information for Effective Public Policy Interventions

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ABSTRACT

Background: The goal of this study is to explore our understanding of the effect of Generative AI Content on public health perceptions regarding Health Literacy on Fluoride Related Issues, Emotional Response to AI Content, Perceived Severity of Fluoride Related Health Impacts, and Support for Fluoride Related Health Policy Interventions.

Objectives: The study seeks to explore the impact of Generative AI Content exposure on health literacy, emotional responses as well as severity of designs, and the implications for health policy support.

Methods: To understand direct and indirect effects of Generative AI Content on our key constructs, we developed a conceptual model and tested using path analysis. Structural equation model (SEM) was applied for data analysis.

Results: Generative AI Content caused a significant increase in health literacy $\beta = 0.389$ ($p < 0.01$), emotional responses $\beta = 0.389$ ($p < 0.01$) and perception of severity $\beta = 0.402$ ($p < 0.01$). The relationship between AI content and Support for Fluoride-Related Health Policy Interventions was mediated by these factors. Significance was found for indirect effects through Health Literacy, Emotional Response and Perceived Severity.

Conclusion: Collectively, generative AI Content enhances health literacy to shape public health perceptions and emotional engagement thereby improving support for health policies. The findings imply that AI driven content can be a suitable public health communication and policy advocacy instrument.

Keywords: *Generative AI, Elaboration Likelihood Model (ELM), Health Literacy, Fluoride awarness, Policy intervention*

1. INTRODUCTION

Generative Artificial Intelligence (AI) is a disruptive technology that is already beginning to redefine how people engage with, interpret and interact with complex information. In the field of public health AI could fill up big gaps regarding literacy which affect health, especially where scientific knowledge is yet to be used completely because of lack of adequate communication [1]. The domain in which generative AI can have a great impact is related to fluoride-related health issues and policies. Although fluoride has been scientifically proven to be a critical dental caries prevention and public health intervention element, its application through public health policies (water fluoridation) has been scientifically contested [2]. Despite these measures, public misperceptions, emotional responses to fluoride related risks, and skepticism of policy interventions continue to obstruct the effective implementation of these mentions. But generative AI has opened up this possibility of creating adaptive, audience specific, emotionally resonant content that could solve these.

Understanding how fluoride policies are perceived involves navigating a complex interplay of public health literacy, emotional engagement, perceived severity of health impacts, and trust in the information source. The plethora of studies investigating traditional ways of communicating information relating to health do not cover the impact of emerging technologies, in particular, generative AI. In the case of fluoride-related health interventions, emotional conditions are of special concern in their ability to undermine emotional engagement and trust, as emotionally charged **Error!** misconceptions about risks, like dental fluorosis or systemic toxicity, tend to dominate despite their documented benefits. In Pakistan, where public health campaigns often struggle to counter misinformation, the introduction of fluoride in water supplies has faced resistance due to fears of toxicity and inadequate public health literacy. Leveraging generative AI to provide culturally relevant and emotionally engaging narratives could help address misconceptions and improve trust in fluoride-related health interventions, particularly in rural areas where awareness is limited [3, 4]. Presented with generative AI as an opportunity to knit together nuanced, evidence based narratives that help address these concerns and increase public understanding and support of fluoride policies. To enhance the narrative, Figure 1 illustrates a fluoride enhanced area to further this narrative and gives a clear visual representation of the health benefit of fluoride. This image pairs well with AI led content to help to contextualize that fluoride produces positives, reinforce how it works through AI led content, and support fluoride policies based on our understanding.

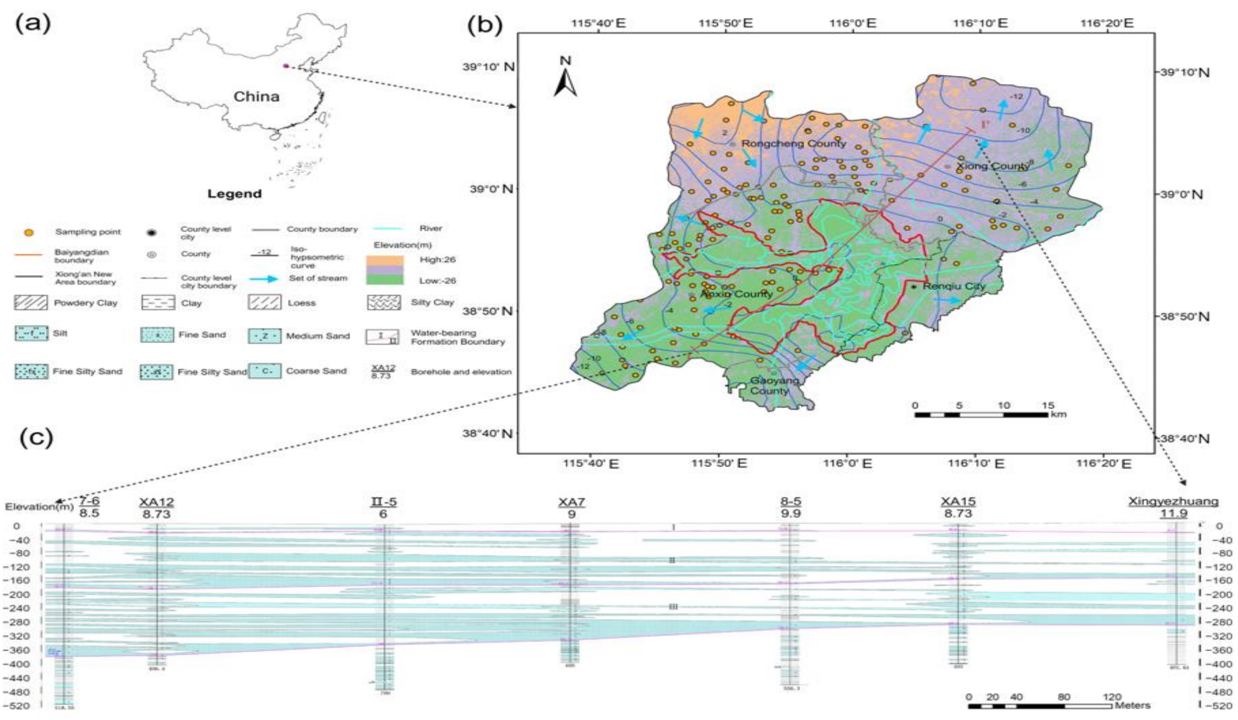

Figure 1: Fluoride rich areas in China [5]

A suitable theoretical lens for examining these dynamics is the Elaboration Likelihood Model (ELM). ELM posits two primary routes through which individuals process persuasive messages: central route: information processing in which message content is carefully evaluated in a cognitive way; peripheral route: information processing in which emotional cues and heuristics are processed. Take for instance, people with higher health literacy do have more tendencies towards taking in the central route, critical examination of AI generated content, i.e. fluoride related health information [6, 7]. Moreover, such ai content may trigger an emotional response on four occasions, and people with lower health literacy will voluntarily choose to act on one of these occasions (peripheral route). It is essential to understand how generative AI content captures cognitive and emotional engagement in order to better understand how to strategically communicate public health.

However, generative AI has not yet addressed several research gaps. While exploring gap current study aim to investigate that how emotional response to AI generated content affects public attitudes to fluoride health information and how differences in health literacy context leads people to assess the potential health risk associated with fluoride. Moreover, generative AI content has the ability to strengthen public backing for health policies, however the factors that enhance perceived credibility of that content are poorly understood. This gap needs to be addressed as an essential step to achieve the most optimal use of AI in health communication as well as maximizing ethical, impactful uses of information obtained through the dissemination of information through AI.

To address these gaps, this study focuses on two key research questions:

1. What is the impact of emotional response to generative AI content on public engagement and support for fluoride related health policies?

2. How does health literacy moderate the relation between generative AI content and perceived severity of fluoride-related health risks?

In this study, we explore how generative AI content impacts public understanding, emotional engagement and support of fluoride-related health interventions. The research will examine the interplay between emotional response to AI generated content, health literacy, perceived health impacts from fluoride and public support for policy interventions to understand how such content can maximise the effectiveness of popularizing science contents generated by AI. This investigation specifically aims to understand how emotional responses impact the engagement with fluoride information, health literacy's role in the perception of the severity of fluoride risks and determining how factors shape what is perceived as credible regarding generative AI content. The study also, through this lens, assesses how these variables jointly affect public support for fluoride related health policies.

The results from this study are of great meaning for public health policymakers, AI developers and communication strategists all. Resistance to fluoride related health policies is often influenced by misinformation and emotional skepticism, leading to an undermined implementation and effectiveness. By providing scientific evidence in a rewarding, understandable, emotional format, generative AI provides a unique, cost-effective way to help overcome these challenges. Through demonstrating how AI can enable public engagement with science and health policy this study helps to expand the body of research emerging at the intersection of technology, health communication, and public policy. The work also building on ethics work in the context of using AI for public influence and lays the groundwork for future work in this expanding realm.

2. THEORETICAL BACKGROUND

2.1. Elaboration Likelihood Model (ELM)

The Elaboration Likelihood Model (ELM) is a dual-process theory that explains how individuals process persuasive messages based on two distinct routes: central route and peripheral route [8]. Cognitive engagement with the message’s content defined the central route whereby effortful message processing and critical evaluation of information provided is required. In contrast, decision making through the peripheral route involves fewer effortful efforts due to the use of external cues (source credibility, appealing emotion, and heuristics) [9]. ELM assumes that people take different routes based on how motivated and able to process information they are. Central versus peripheral processing is a result of high motivation and ability and higher motivation and ability, respectively, lead to central route processing and peripheral route engagement [10, 11].

In particular, this theory is helpful to explain how people in different levels of health literacy and emotional engagement react to fluoride related health information in the context of generative AI content with the intent of science popularization. Generative AI content can be built with both peripheral route driven elements (emotionally engaging narratives or visual elements), as well as factual accuracy (central). For example, those with high health literacy tend to approach fluoride related health information by the central route, critically weighing scientific evidence about fluoride's benefits and risks compared to approaches through other channels. Meanwhile, people with lower health literacy may rely on peripheral cues, including the visual and emotional level of AI generated content but also the perceived credibility of the content.

In addition, ELM also gives emphasis on emotional involvement in practicing attitudes and behaviours. What determines if individuals are going to take a supportive position on fluoride related health policies—that is, what role do emotional responses to AI content (trust, skepticism, fear) play? Let's take the example of emotionally resonant AI content that simplifies fluoride science, tackles misconceptions, and helps engage and support public engagement and support for water fluoridation policies. At the same time, if the AI content doesn't address emotional concerns, or if it seems manipulative, then users will lose trust in it and stop supporting policy. Due to this, ELM offers a total view of how emotional and cognitive factors interact to shape public attitudes toward health interventions.

This study employs ELM as a base to understand how generative AI content engages the public on fluoride related health information. This study explores the interplay of emotional sensitivity towards AI salience in content (e.g. trust, fear, or curiosity), cognitive factors (e.g. health literacy) and these emotions in determining perceptions of fluoride linked health risks and support for fluoride related policies. The dual process framework of ELM gives us a more sophisticated picture of how people with different degrees of motivation and ability use both to engage to with AI generated content. Moreover, by considering both routes of persuasion, this study makes an additional contribution to nurturing tailored communication strategies for enhancing the effectiveness of generative AI in fostering science literacy and public health policies.

2.2. Application of ELM to Generative AI Content for Fluoride-Related Health Policies

ELM has been widely used already in studies of communications, marketing, and health, to better understand how messages affect attitudes and behaviors . As applied to generative AI content, ELM lays the ground for dissecting how people interpret AI generated health information, and what factors control how effective it is. For instance, such as AI content, that clearly, evidence based describes fluoride's benefits, may tap the central route of learning by health literate individuals, resulting in long term attitude change and reinforcement of support for policy interventions [12, 13]. However, for individuals with less motivation to process such content, peripheral route factors (such as infographics generated by AI with visually attractive design or perceived trustworthiness of this AI system) may be manipulative.

This two-fold application of ELM to this study uses the ELM efficacy to estimate the area inhomogeneity. It serves as a first explanation for how emotional reactions to the content of AI influence engagement in fluoride-related information. Peripheral cues of curiosity or trust can work as they cannot help but interact with content even if they don't know much about fluoride science. Second, ELM creates a framework to exploit how cognitive factors, including health literacy, mediate the spread of generative AI fluoride content to public beliefs about fluoride risks and benefits. For example, those with high health literacy may need more detailed evidence based content enabled by the central route, while less health literate persons may benefit more from emotionally appealing or visually engaging AI content [14].

ELM is particularly suitable for the present study as it offers insights into both cognitive and emotional engagement mechanisms, making it possible to design AI content that appeals to a wide range of individuals. The study also aligns with the theory that generative AI can help in improving public health literacy and policy support through making available the insights that ordinary peoples will have towards the development of communication strategies, which will be specific with what type of audience is being mentored in terms of motivation and ability to process information. This study leverages ELM to contribute to the growing body of research on the use of AI in science communication and offer actionable wisdom on how to best leverage AI generated content to optimize public health.

2.3. Research Model and Hypotheses

The theoretical framework for this study is the Elaboration Likelihood Model (ELM) from which a research model is developed and empirically tested to examine the effect of generative AI content on the public's engagement with fluoride related health policy intervention content. By providing a central, peripheral processing dual route perspective, ELM serves as an instrument for examining how users process AI generated content. In this model, Generative AI Content is hypothesized as the (independent) independent variable, its direct and mediated relationships with key independent variables including Emotional Response to AI Content, Health Literacy on Fluoride-Related Issues and Perceived Severity of Fluoride-Related Health Impacts, and, Support of Fluoride Related Health Policy Intervention. The research model shows a conceptual framework.

Generative AI content can inspire both emotional or cognitive reactions and influence public attitudes and policy support. Central route emphasizes on cognitive like aspects prevalent like health literacy and perceived severity where the information is critically evaluated while determining its validity and relevance. However, for the peripheral route, it is an emotional area where heuristics like trust, credibility or appeal affects an individual's response to the content. ELM supplies a strong theoretical backbone for understanding how both emotional (peripheral) and cognitive (central) relate to the formation of public opinion attitudes.

Hypotheses of this study answer both the questions of the direct effects of the generative AI content on outcome variables and the questions of the mediated relationships and their roles in explaining how the emotional and cognitive responses affect policy support. This first hypothesis suggests that generative AI content can be used to directly improve support for fluoride-related health policies by providing credible, accessible content. The following hypotheses concentrate on the role of the mediating variable of the emotional response, the health literacy, and perceived severity and how these intermediate variables affect the outcome. The development of these hypotheses is detailed below:

2.3.1. Generative AI Content and Direct Policy Support

Generative AI content is a transformational force to determine public support for fluoride-related health policies. Generative AI surfaces scientific, technical information into a format that "meets people where they are": in an understandable way. Its ability to produce dynamic, evidence-based, and personalized content that targets communication enables it to produce content addressing individual concerns while promoting the collective importance of policy and impacts. Consequently, such detailed messages widen trust and render health policies more connected to different demographics. In Pakistan, where misinformation about fluoride's health impacts is prevalent, particularly in rural areas, generative AI could play a critical role. By creating localized, culturally sensitive content in regional languages, it can bridge the gap between scientific knowledge and public understanding, fostering greater trust and acceptance of fluoride-related health policies across diverse populations [15, 16]. This hypothesis extends the argument of this premise, that credibility and potency reside on two sides of the same coin as relevance. In addition, generative AI content coordinates the alignment of the presented information with public health priorities by emphasizing a sense of urgency and responsibility. They result in a greater likelihood that certain fluoride-related health policies will be accepted and endorsed.

H1: Generative AI content positively influences public support for fluoride-related health policy interventions.

2.3.2. Emotional Responses to Generative AI Content

The particular strength of generative AI content is that it is able to generate emotional responses, a key determinant of public attitudes towards health policies. Trust, empathy and concern are important emotions while trying to convince people who do not opt to deal with technical matters but fall for 'real-life' narratives. For example, generative AI content could engage in impactful storytelling representing the challenges of those impacted with fluoride deficiency to create empathy and as well as drive action. ELM ensures emotional engagement of the public by processing the presented message through the emotional public through a peripheral route of persuasion [17, 18]. The hypothesis is that emotional responses can act as a catalyzer to bridge the gap between awareness and policy support, specifically among those audiences that value emotional connections over analytical evaluations.

H2a: Generative AI content positively influences emotional responses to AI content.

2.3.3. Health Literacy as an Outcome of Generative AI Content

Generative AI content improves health literacy by making complex scientific data on fluoride-related issues accessible and comprehensible to the general public. The cognitive engagement of AI generated content leveraging visual aids, interactive tools and simplified explanations for fluoride impact on dental, and overall health. Informed decision making depends on health literacy and people with health literacy are less likely to make the decisions that would lead to what are generally recognized as minimal benefits but are far from optimal, critically analyzing the benefits and implications of policy interventions[19, 20]. The hypothesis behind this echoes that generative AI content increases a greater connection towards the audience, allowing them to become actively involved in the choices of health. Besides, more health literate people resist misinformation which strengthens confidence in public health policies subsequently creating an informed and proactive society.

H2b: Generative AI content positively influences health literacy on fluoride-related issues.

2.3.4. Perceived Severity of Fluoride-Related Health Impacts

Generative AI content presents data driven insights about the dangers surrounding fluoride associated health problems and effective generation of such a content paints a realistic picture of just how bad the problem is and the severity of the same. It employs compelling narratives and evidence based scenarios in order to draw attention to the risk of dental caries and other oral health problems in order to instil an urgent sense of a risk. This heightened awareness helps to believe that fluoride related issues are serious public health concerns to mitigate and compensate under immediate action [21]. People are more likely to support policy interventions to reduce the perceived severity of health risks when the severity of these risks is high. With this hypothesis, we posit generative AI content improves the audience's ability to understand and prioritize the gravity of fluoride related challenges and, thus, modify their attitude towards health policies.

H2c: Generative AI content positively influences perceived severity of fluoride-related health impacts.

2.3.5. Mediating Role of Perceived Severity in Policy Support

The perceived severity of generative AI content mediates the relationship between generative AI content and public support for fluoride related health policies. It makes people aware of the major negative consequences of fluoride related health risks and urge them to keep fluoride out of the drinking water through policy measure. It suggests that how cognitive engagement affects public attitudes is important. Interventions to increase fluoride intakes are more likely to be endorsed if individuals perceive a severe amount of a deficiency [22]. Generative AI content magnifies this—creating a fair amount of new content that deals with how serious and what needs to be done about health risks, which amplifies this effect. Severity perception played a crucial role in translating awareness into policy support through the mediated relationship.

H3: Perceived severity of fluoride-related health impacts mediates the relationship between generative AI content and support for fluoride-related health policy interventions.

2.3.6. Mediating Role of Health Literacy in Policy Advocacy

Health literacy serves as another key mediator in the relationship between generative AI content and policy support. Fluoride health literacy promotes critical evaluation of fluoride related information and choices. Generative AI content makes scientific concepts easy and put in context for the audiences to understand the common implications of fluoride use and find relevance in related health policies [21]. According to this hypothesis, health literacy closes the gap between awareness and advocacy, leading people to do more than know they needed policy, but to really support policies. This mediation effect affirms the cognitive edges of ELM —the combination of knowledge increases engagement and promotes a positive attitude toward health interventions.

H4: Health literacy on fluoride-related issues mediates the relationship between generative AI content and support for fluoride-related health policy interventions.

2.3.7. Emotional Responses as a Mediator in Policy Support

Public attitudes toward fluoride related health policies are highly influenced by the emotional resonance of generative AI content. Trust, empathy and emotional engagement play as intermediaries to amplify persuasive power of AI content. The premises of this hypothesis is that emotional responses supplement cognitive engagement by increasing the relativity and impact of policy messages [23]. Generative AI content presents a balanced and compelling narrative, yet addresses both the emotional and informational needs of the audience, which all supports public advocacy. These are bridges really — helping us go from awareness to action, from place to place, through a deeply human lens.

H5: Emotional responses to AI content mediate the relationship between generative AI content and support for fluoride-related health policy interventions.

3. DATA AND METHODS

3.1. Data collection

Empirical data is collected to test the proposed research model using a structured survey questionnaire. Chongqing is an area in the southwestern parts of China known to be a region of fluoride high natural water sources concentrations and therefore very relevant to the context of fluoride related health issues, thus data collection was conducted in Chongqing. It was chosen specifically to capture real insight into the public perceptions and role of generative AI in health communication.

A broad cross section of participants ranging from educational institutions, health care organizations to local community groups were drawn. The number of institutions that volunteered to participate on that scale came to 30, and we contacted 20 of them, and they all agreed to participate. Meetings were held with organizational representatives prior to initiating the survey to inform them of rationale for doing so, and to ensure participants were informed of purpose of the study and confidentiality would be maintained. Surveying was conducted through a combination of online and offline methods, via the communication channels of WeChat (widely used in China) and email invitation, as well as in-person outreach.

A total of 600 surveys were distributed and 510 responses collected. A response rate of 75% was achieved by eliminating incomplete or invalid responses (such as inconsistent or identical responses to the different items) from the final dataset of 450 valid responses. The research model relationships were able to be tested using this robust dataset. See the detail of demographic description in Table 1.

Table 1: Demographich description

Category	Frequency	Percentage (%)
Gender		
Male	234	52
Female	216	48
Age (years)		
18–25	170	37.8
26–30	142	31.5
31–35	106	23.6
36–40	32	7.1
Education		
High School or Below	50	11.1
College	185	41.1
University	215	47.8
Designation		
Non-Managerial Employees	212	47.1
Manager	185	41.1
Senior/Executive Manager	53	11.8
Job Tenure/Experience		
<1 year	56	12.4
1–2 years	170	37.8
2–3 years	149	33.1
3–4 years	75	16.7
Experience using AI-generated content		
<1 year	120	26.7
1–2 years	156	34.7
2–3 years	135	30
3–4 years	39	8.7

3.2. Instrument

The survey questionnaire was constructed using pre-validated scales drawn from prior studies, tailored to the study's specific context. The constructs measured were Generative AI Content, Emotional Response to AI Content, Health Literacy around Fluoride Related Issues, Perceived Severity around Fluoride Related Health Impacts, and Support for Fluoride Related Health Policy Interventions. Items were measured using a 7-point sense of Likert scale with the value of 1 is 'strongly agree' and 7 is 'strongly disagree' to measure the intensity of respondents' perception and attitude. The detail survey is presented in Table 2. The questionnaire was translated to Chinese using the back translation method to ensure its grounding in (linguistic and cultural) relevance. The translated survey was reviewed by a group of experts from public health and AI communication areas, who determine its clarity and contextual appropriateness. They gave us feedback and the minor linguistic changes were made according to that. A sample of 30 members of the target population was also pilot tested to refine the questionnaire further as well as to assure its reliability and validity.

Table 2: Instrument of the survey

Constructs	Items (Questions)	References
Emotional Response to AI Content (ER-AI)	ER-AI1: I feel curious when I encounter AI-generated content.	[24]
	ER-AI2: I feel uneasy about the implications of AI-generated content.	
	ER-AI3: I feel excited by the potential of AI-generated content.	
	ER-AI4: I feel skeptical about the accuracy of AI-generated content.	
	ER-AI5: I feel positive about the role of AI in creating innovative content.	
Generative AI Content (GAIC)	GAIC1: I believe AI-generated content is comparable to human-created content in quality.	[25]
	GAIC2: I think AI content generation saves time in creative processes.	
	GAIC3: I consider AI-generated content as a valuable tool for education.	
	GAIC4: I trust the authenticity of AI-generated content.	
Health Literacy on Fluoride-Related Issues (HLF)	HLF1: I understand how fluoride benefits dental health.	[26]
	HLF2: I can identify the sources of fluoride exposure in daily life.	
	HLF3: I know how fluoride affects long-term health.	
	HLF4: I can explain the rationale for adding fluoride to public water systems.	
	HLF5: I understand the risks associated with excessive fluoride consumption.	
	HLF6: I can critically evaluate information about fluoride in public health debates.	
Perceived Severity of Fluoride-Related Health Impacts (PSF)	PSF1: I believe fluoride overuse can lead to serious health issues.	[27]
	PSF2: I consider dental fluorosis to be a significant concern for public health.	
	PSF3: I think the long-term exposure to fluoride could have serious consequences for health.	
	PSF4: I perceive fluoride-related risks as more harmful to vulnerable populations, such as children.	
	PSF5: I consider the risks of fluoride exposure when deciding on dental care products.	
Support for Fluoride-Related Health Policy Interventions (HPI)	HPI1: I support policies requiring the fluoridation of public drinking water.	[28]
	HPI2: I believe governments should regulate fluoride levels in consumer products.	
	HPI3: I support public health campaigns that promote fluoride awareness.	
	HPI4: I think fluoridation policies should consider individual choice and informed consent.	

Control Variables

To reduce the chance of being confounded, several control variables were incorporated to increase the robustness of the findings. It includes age, gender, educational background and digital literacy because they may influence the way that participants perceive generative AI-based content and health literacy [29]. Other critical variables in influencing individuals attitudes and knowledge were prior fluoride related health campaign exposure and frequency of AI technology use as well. Adding these controls was important in so that the study could separate out the effects of the primary constructs in the model.

3.3. Statistical Analysis

The data were analyzed using Smart PLS 4.0.1 as most of the software that is currently available for performing PLS structural equation modeling (PLS SEM). Current Study use this approach because it is able to model complex models with latent variables that are amenable to predictive research.

3.1.1. Common Method Bias

The data were collected from surveys that were self reported in a cross sectional design which raised concerns for Common Method Bias (CMB). Therefore, some procedural remedies were put in place, for example by assuring respondent anonymity including reverse coded items, and by varying the item presentation order. Furthermore, a Harman's single factor test was also per formed, showing no single factor accounting for greater than 24 per cent of the variance, well below the 50 per cent threshold [30]. The marker variable technique was used to further confirm the absence of significant CMB and the results are deemed valid.

3.1.2. Ethical Considerations

The study was ethically approved by a university ethics committee. Participants were also informed of voluntarity of their participation and assured that the responses would be used exclusively for academic purposes. Data analysis was performed with obtained written consent and personal identifiers removed to maintain confidentiality.

3.1.3. Measurment Model

To validate and estimate reliability of the constructs testing the measurement model was done. The results showed good psychometric properties, thereby satisfying the appropriateness of the constructs for further analysis. The factor loadings, composite reliability (CR) and average variance extracted (AVE) for each construct are shown in Table 3. Factor loading values ranged all from 0.758 to 0.986, which conform to accepted guideline of 0.7 from [31].This means that all creatd measurement items forcefully represented their respective constructs. AVE values (0.685 to 0.953) were greater than the minimum threshold 0.5 [32]. These results supported the convergent validity of constructs measuring the items on each construct were strongly correlated and shared a great deal of variance. The factor loadings further reinforced the validity of the measurement items. For instance, items within ER-AI had loadings ranging from 0.913 to 0.944, and items within GAIC exhibited exceptionally high loadings between 0.971 and 0.986. Constructs such as HLF and PSF also showed strong factor loadings, with values ranging from 0.758 to 0.974. These results confirmed that the Measurement items were appropriately designed and contributed meaningfully to their respective constructs. Table 3 presents the reliability statistics.

The CR ranged between 0.929 and 0.988 for all constructs, exceeding the suggested cut off of 0.7. This shows that the constructs are internally consistent, that the measurement items credibly represent the latent variables of interest. For instance, we had CR of 0.970 for Emotional Response to AI Content (ER-AI), and CR of 0.988 for Generative AI Content (GAIC), indicating high reliability of both. Other constructs, such as Health Literacy on Fluoride Related Issues (HLF) and Support for Fluoride Related Health Policy Intervention (HPI), had high CR values, too, suggesting fairly high reliability across all constructs. Figure1a-c present graphical representation of the reliability. Figure 2a-c illustrate the the graphichal representation of the reliability.

Table 3: Factor loading of the items

Constructs	Item	Loading	Cronbach alpha	CR	AVE
Emotional Response to AI Content (ER-AI)	ER-AI1	0.930	0.962	0.970	0.867
	ER-AI2	0.943			
	ER-AI3	0.913			
	ER-AI4	0.925			
	ER-AI5	0.944			
Generative AI Content (GAIC)	GAIC1	0.975	0.984	0.988	0.953
	GAIC2	0.972			
	GAIC3	0.986			
	GAIC4	0.971			
Health Literacy on Fluoride-Related Issues (HLF)	HLF1	0.823	0.907	0.929	0.685
	HLF2	0.764			
	HLF3	0.758			
	HLF4	0.876			
	HLF5	0.858			
	HLF6	0.877			
Perceived Severity of Fluoride-Related Health Impacts (PSF)	PSF1	0.966	0.944	0.984	0.927
	PSF2	0.974			
	PSF3	0.946			
	PSF4	0.965			
	PSF5	0.963			
Support for Fluoride-Related Health Policy Interventions (HPI)	HPI1	0.963	0.980	0.984	0.927
	HPI2	0.932			
	HPI3	0.897			
	HPI4	0.909			

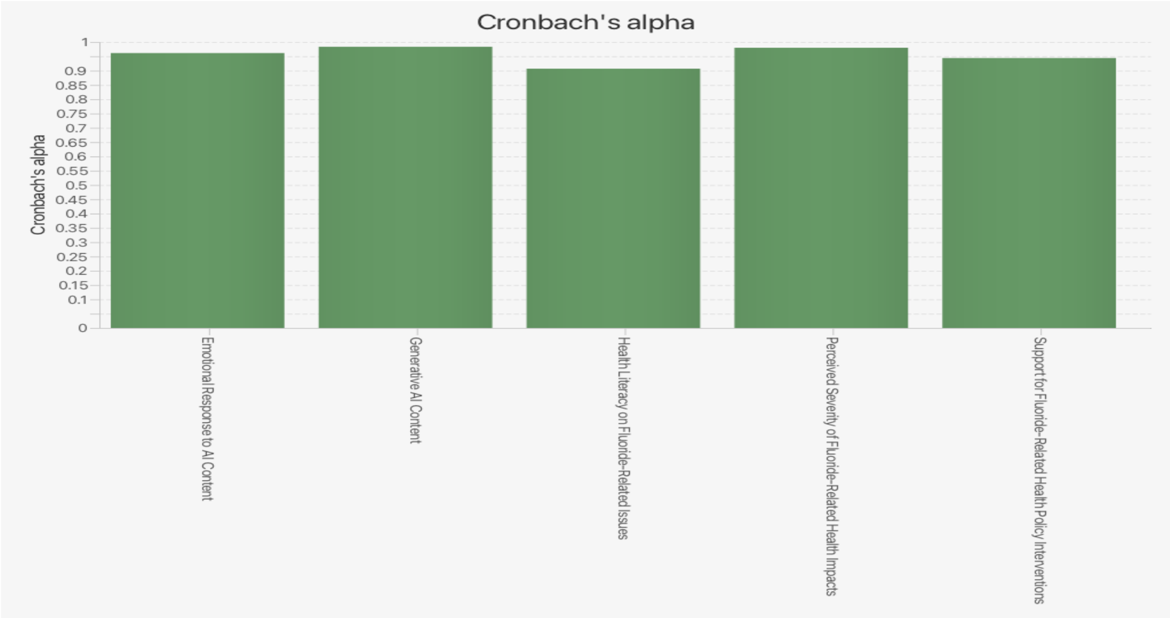

Figure 2a: Graphical representation of Cronbach Alpha

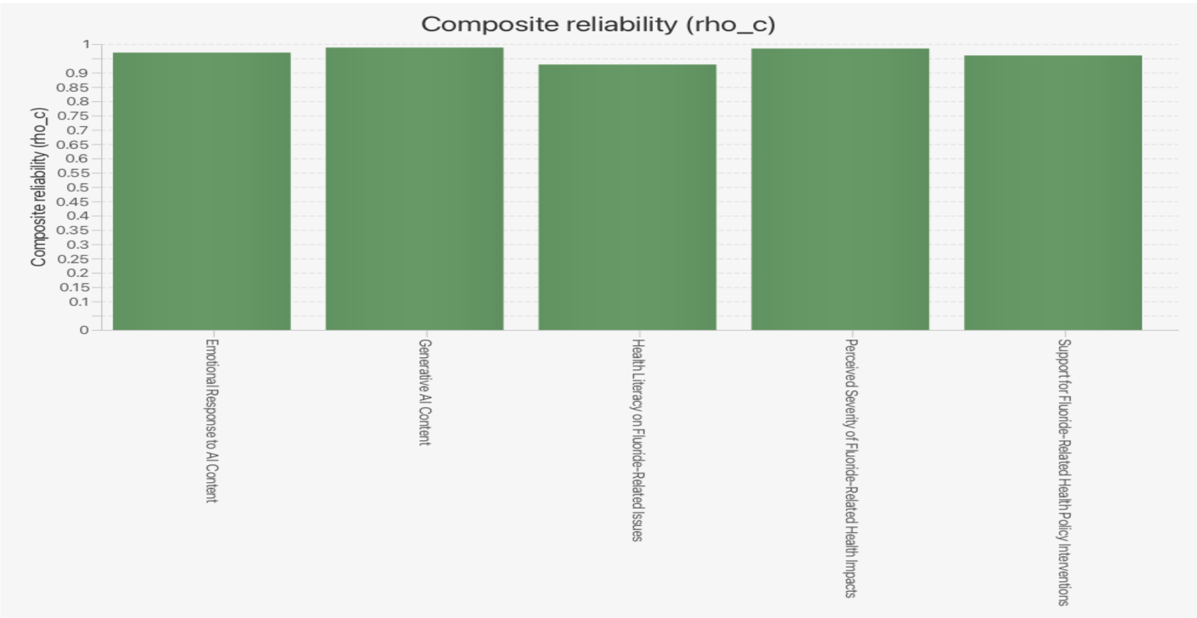

Figure 2b: Graphichical representation of Composite reliability

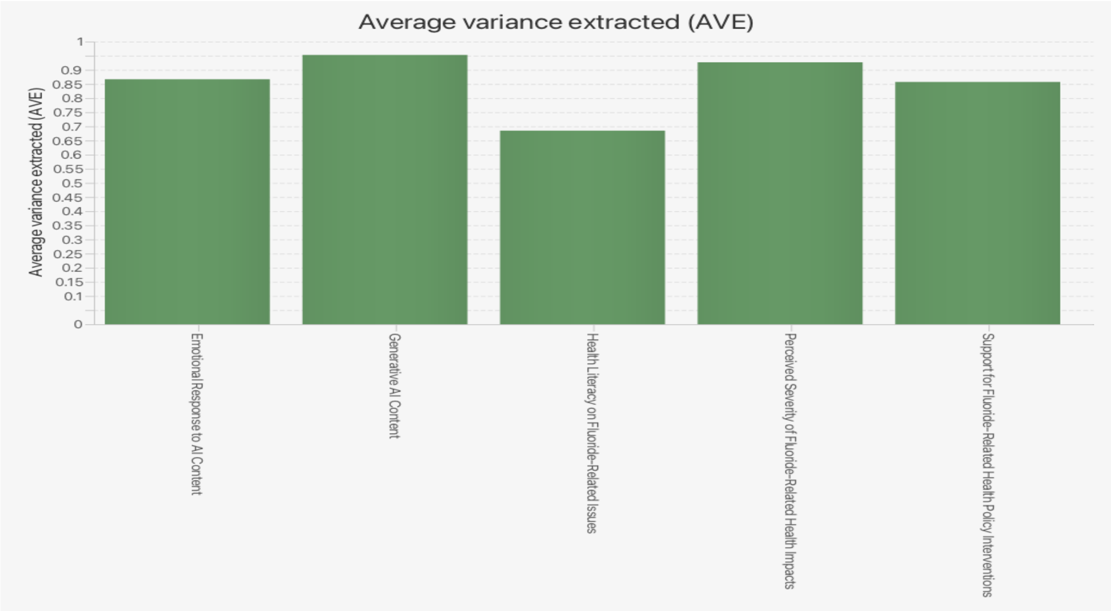

Figure 2c: Graphichical representation of AVE

We applied the Fornell-Larcker criterion in order to establish discriminant validity. In that current compared the square root of the AVE for each construct to its correlations with other constructs. By the Fornell and Larcker criterion [33] the square root of AVE for each construct was greater than the correlations of the construct with others. For example, the square root of AVE for HPI (0.963) was higher than the correlations of the construct with any other construct thus confirming its distinctiveness. Discriminant validity of all constructs was confirmed by this pattern in every construct. Table 4 presents fornell and larker criterian below.

Table 4: Fornell-Larcker criterion

	ER_AI	GAIC	HLF	PSF	HPI
ER_AI	0.931				
GAIC	0.389	0.976			
HLF	0.561	0.389	0.828		
PSF	0.342	0.402	0.367	0.963	
HPI	0.560	0.514	0.637	0.481	0.926

Discriminant validity was also reassessed using the heterotrait—monotrait (HTMT) ratio method, as suggested by Henseler, Ringle [34]. Further, all HTMT values were below the conservative threshold of 0.85, thus demonstrating the difference between the constructs. This showed us that the constructs were responding internally consistent, but importantly so much different from the other constructs to justify them in the model. Table 5 presents HTMT matrix.

Table 5: Heterotrait-monotrait ratio (HTMT) – Matrix

	ER_AI	GAIC	HLF	PSF	HPI
ER_AI					
GAIC	0.399				
HLF	0.599	0.412			
PSF	0.351	0.408	0.389		
HPI	0.587	0.533	0.687	0.499	

Also, the fit indices for the measurement model indicated a strong overall model fit. The chi-square to degrees of freedom ratio (χ^2/df) was 1.81 and was much lower than the acceptable threshold of 3. Fit indices other than the goodness of fit index (GFI = 0.98), adjusted goodness of fit index (AGFI = 0.95), normed fit index (NFI = 0.94), incremental fit index (IFI = 0.96), and comparative fit index (CFI = 0.97) were obtained and exceeded the recommended minimum of 0.9. The acceptable range of less than 0.08 is comfortably within the root mean square error of approximation (RMSEA) the value of which was 0.04 (Talwar et al., 2020). Finally, the measurement model fit of these indices was excellent. The detail of the measurement model of the study is presented in Figure 3.

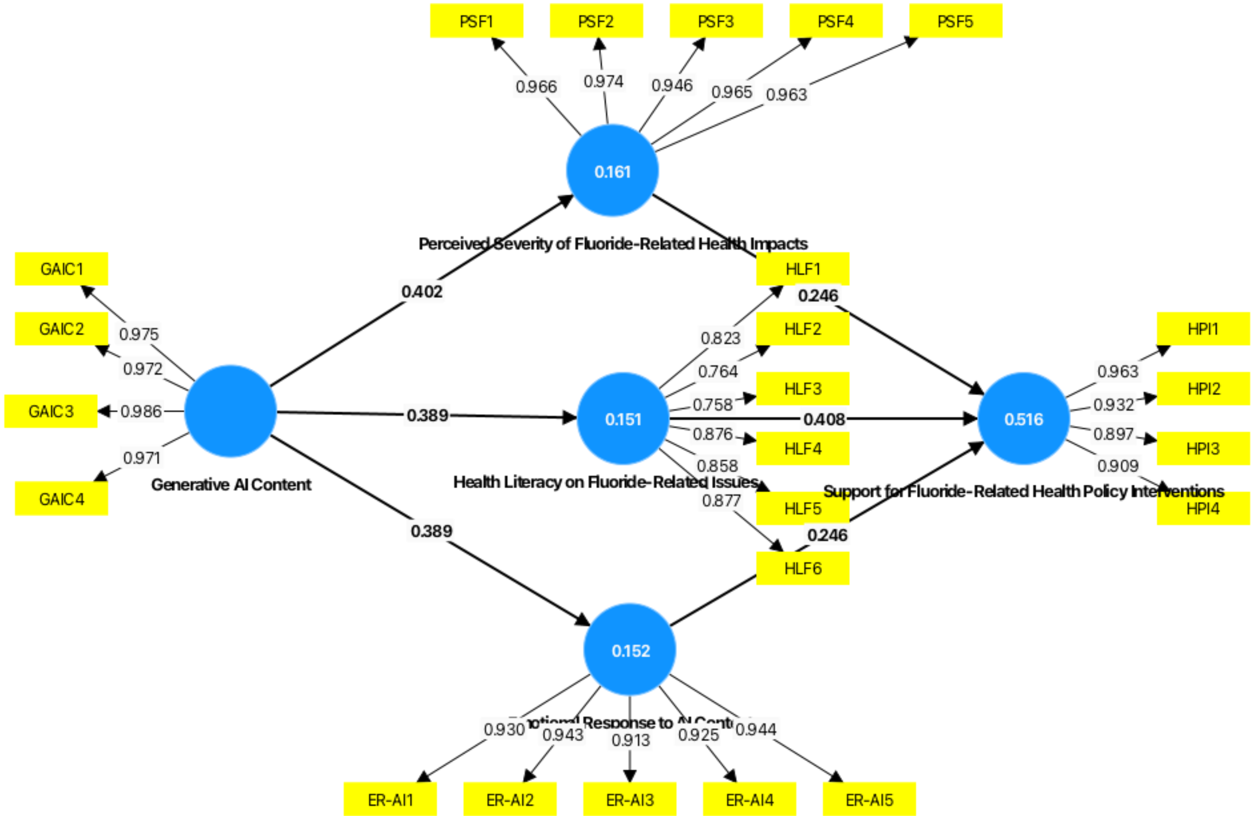

Figure: 3 Measurement model of the study

3.1.4. Structural model

As demonstrated in Fig. 4 the results from the structural model produced a good overall fit with the fitness indices above the acceptable thresholds. In particular, the chi square to degrees of freedom ratio (χ^2/df) of 1.72 is below the recommendation of 3 thus showing a good fit. Moreover, the goodness of fit index (GFI) and the adjusted goodness of fit index (AGFI) were 0.99 and 0.98 respectively, normed fit index (NFI) 0.92, incremental fit index (IFI) 0.96 and comparative fit index (CFI) 0.98 which exceeded the minimum value 0.9. The root mean square error of approximation (RMSEA) was 0.05, less than 0.08, one of the acceptable levels of fit for the model. These results tell us that the chosen structural model can satisfactorily explain which constructs are related to this study's constructs.

In terms of hypotheses, it referred to the effect of Generative AI Content on many outcomes, which included Support about Fluoride Related Health policy interventions; Emotional reaction to the AI content; Health literacy; related to Fluoride Related Issues; and its Perceived severity of Fluoride Related Health Impacts. As shown in Table 5, all direct effects were significant and positive, and so supported the proposed relationships. It appears that each of the outcome variables is greatly influenced by Generative AI Content.

Generative AI Content to Support Fluoride Related Health Policy Intervention (H1) path was important with a path coefficient of 0.354 ($t = 16.767$, $p < 0.01$). What this means, however, is that individuals exposed to more Generative AI Content are more likely to support fluoride related health policy interventions. What this strong positive relationship reveals is the impact of the AI powered content in shaping public opinion about health policy issues. As was the case with the Generative AI Content → Emotional Response → AI Content (H2a) path, a path coefficient of 0.389 ($t = 14.704$, $p < 0.01$) was also found. This finding suggests that exposure to Generative AI Content makes people emotionally react, and the more positive or impactful AI content is the stronger emotional response.

Path coefficient of 0.389 ($t = 15.461$; $p < 0.001$) indicated that Generative AI Content exposure explained a considerable contribution towards the increase in health literacy over fluoride related issues. Such a result is significant as it highlights how AI content can inform the public about important health issues, increase their awareness and knowledge around health risks and policy drivers. Additionally, the path from Generative AI Content to Perceived Severity of Fluoride-Related Health Impacts (H2c) illustrated that this was a path coefficient of 0.402 ($t = 14.617$, $p < 0.01$) showing that the more people are exposed to Generative AI Content, the more likely they are to perceive fluoride related health impacts as severe. This finding suggests that Generative AI Content may help amplify public concern of fluoride health risks.

The study also tests specific indirect effects and these are presented in Table 6. Finally, it was tested whether supporting fluoride related health policy interventions was mediated by intermediary variables in the relationship between Generative AI Content and Support. An indirect effect of 0.099 ($t = 7.949$, $p < 0.01$) in H3, that is, that Generative AI Content affects Perceived Severity of Fluoride-Related Health Impacts and Perceived Severity of Fluoride-Related Health Impacts also affects Support for Fluoride-Related Health Policy Interventions. This suggests that partially one mechanism by which generative AI content affects support for health policy interventions is partially mediated by the perception of severity of fluoride related health impacts. Perceptions of the health impacts are the more severe the more likely that they will support associated health policies. H4 also proposed that Generative AI Content affects Health Literacy on Fluoride Related Issues and that in turn does affect Support for Fluoride Related Health Policy Interventions, but the indirect effect was 0.159 ($t(\sim)= 10.069$, $p < 0.01$). This finding points to the fundamental mediation of health literacy between Generative AI Content and policy support. Health literacy is the variable that is associated with the probability of supporting fluorine health intervention policies. Finally, H5, whether Emotional Response to AI Content will mediate the effect of Generative AI Content in terms of Support for Fluoride Related Health Policy Interventions shows an effect of 0.096 (7.529, $p < 0.01$). This result shows that emotional responses to AI content affect support for health policy interventions.

Table 6: Path coefficient

	Original sample (O)	T statistics (|O/STDEV|)	P values
H1: Generative AI Content -> Support for Fluoride-Related Health Policy Interventions	0.354	16.767	0.000
H2a:Generative AI Content -> Emotional Response to AI Content	0.389	14.704	0.000
H2b:Generative AI Content -> Health Literacy on Fluoride-Related Issues	0.389	15.461	0.000
H2c:Generative AI Content -> Perceived Severity of Fluoride-Related Health Impacts	0.402	14.617	0.000
H3:Generative AI Content -> Perceived Severity of Fluoride-Related Health Impacts -> Support for Fluoride-Related Health Policy Interventions	0.099	7.949	0.000
H4: Generative AI Content -> Health Literacy on Fluoride-Related Issues -> Support for Fluoride-Related Health Policy Interventions	0.159	10.069	0.000
H5: Generative AI Content -> Emotional Response to AI Content -> Support for Fluoride-Related Health Policy Interventions	0.096	7.529	0.000

Collectively, these results suggest that Generative AI Content directly impairs and indirectly supports public health perceptions and policy support. And the study makes clear how important that type of AI content is to forming public opinions — especially in areas such as health literacy, emotional response and understanding of health risks. Implications of these results for use of Generative AI Content in public health communication and policy advocacy, as well as encouraging broader public engagement with health issues are far reaching.Figure 4 presents structural model in detail

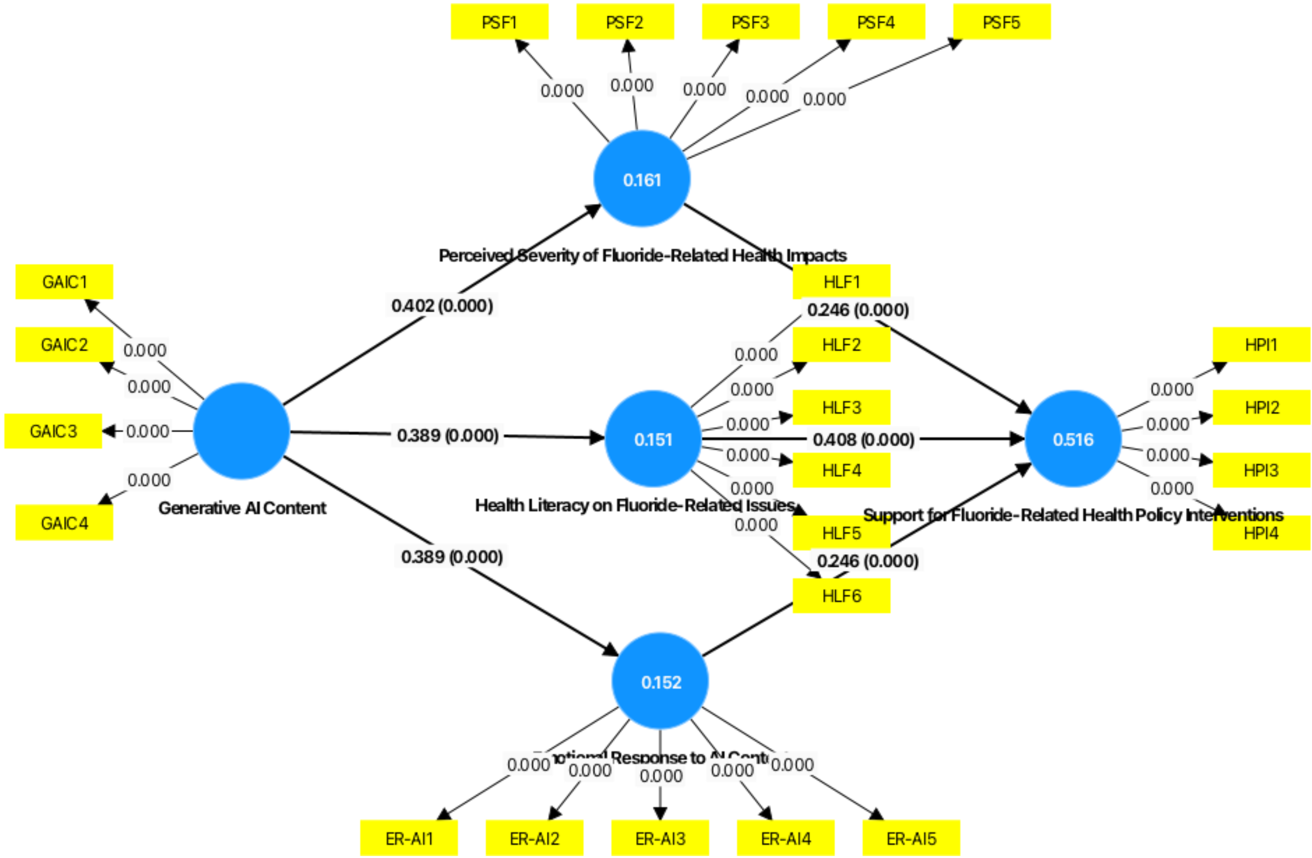

Figure 4: Structure model of the study

4. DISCUSSION

This current study aimed to understand the impact of Generative AI Content on to public health perception and support for health policy through Health Literacy on Fluoride issues, Emotional Response to AI Content, Perceived Severity of Fluoride related health impacts, and Support for Fluoride related health policy interventions. Two primary research questions were posed: Our research studied (RQ1) How does exposure to Generative AI Content affect health literacy, emotional responses, and perceptions of severity, and (RQ2) What factors, and their indirect effect, influence how these shape support for health policies?.

In response to RQ1, we find that Generative AI Content positively impacts Health Literacy, Emotional Response to AI Content and Perceived Severity of Fluoride Related Health Impacts. As shown in Table 5, these results show that exposure to Generative AI Content helps people understand the fluoride health risk better, heightens their emotional reaction to such risks, and increases the weight they attach to such risks. They are consistent with previous research highlighting media in shaping awareness of public health [24].The study found that Generative AI Content significantly influenced Health Literacy on Fluoride-Related Issues with a path coefficient of 0.389 ($t = 15.461$, $p < 0.01$), suggesting that increased exposure to AI content improves public understanding of health risks. Health literacy enables individuals to make informed decisions regarding health policies. As knowledge of fluoride-related risks increases, so does the understanding of the need for policies addressing these risks.

In addition, Emotional Response to AI Content was impacted (with path coefficient of 0.389, $t = 14.704$, $p < 0.01$) by Generative AI Content as well. The emotional fit between health content and an individual's emotional response to policy can be an emotional motivator to contribute to the creation of the policy. We find that AI driven content generates emotional response and, if that response is enacted, could galvanize public support for health interventions. Attitudes towards policy support are strongly influenced by emotional responses, namely when content emphasizes health risks' severity [35].

In addition, the new study discovered a robust correlation between Generative AI Content and

Perceived Severity of Fluoride-Related Health Impacts (path coefficient = 0.402, $t = 14.617$, $p < 0.01$), suggesting that AI-driven content heightens awareness of those health risks. If we think of perceived health risks as becoming more severe, the more people are likely to support policy aimed at limiting the risks.

In response to RQ2, we looked at second-order indirect effects of Generative AI Content on Support for Fluoride Related Health Policy Interventions through Health Literacy, Emotional Response to AI Content, and Perceived Severity of Health Impacts. Table 6 shows that Generative AI Content has a substantial impact on supporting policy through these intermediary constructs. A significant finding (as $t = 10.069$, $p < 0.01$) was the indirect effect of Generative AI Content on policy support via Health Literacy, indicating that those with greater health literacy were more likely to support policy addressing fluoride-related health risks. This finding emphasizes again the indispensable role of health education in the adoption of the aims of policy support, if the AI content helps disseminate and inform the intended audience. In Pakistan, studies have shown that regions with higher levels of health literacy, such as urban areas, exhibit more support for health interventions, including water fluoridation, compared to rural regions where knowledge gaps persist. AI-generated content could help bridge this gap by providing accessible, localized information.

Additionally, We found the indirect effect of Emotional Response to AI Content on policy support was 0.096 ($t = 7.529$, $p < 0.01$). That means emotional reaction to AI content is a key means through which it shapes policy support. Individuals with strong emotional reactions to health-related content are more prone to advocate for policies that they think will address risks. Furthermore, this finding agrees with theories that underline the importance of emotional engagement to people's support for policies supporting their concerns. In the Pakistani context, emotional responses to health campaigns have been shown to significantly influence public opinion, particularly when addressing health risks like fluoride exposure. Emotional appeals, combined with scientifically sound content, have been effective in mobilizing communities and influencing policy acceptance, as seen in previous public health interventions in the country [36].

Finally, Generative AI Content also mediated the relationship between Support for Fluoride-Related Health Policy Interventions and Fluoride-Related Health Impacts (indirect effect = 0.099, $t = 7.949$, $p < 0.01$). These findings indicate that increasing the perception for severity of health risks can stimulate support for policies designed to address health risks. The risks people believe make a health issue serious — not whether it actually is — matters because people who perceive health risks as serious are more likely to call for action on a health issue, indicating you need to worry less about what the risks are and focus instead on whether people perceive them to be serious [37].

Finally, Generative AI Content has an important effect on the formation of perceptions on public health, strengthening of health literacy and changing emotional response. Together, these factors result in increased Support for Fluoride Related Health Policy Interventions. To provide an example of how machine learning can be used to enhance public health education that elicits emotional responses and promotes support for health interventions, the study shows. Additionally, as it shows that those who believe that health risks are severe are more likely to support health policy proposals to reduce them, risk perception is also brought to the fore as a determinant of individuals' support for health policy. This gives a good insight into the double meanings of using Generative AI Content, the positive and negative effects of it and if we are to use this, it must be done with care to maximize the benefits, without doing excess damage to all our emotions and our brain.

5. IMPLICATIONS

5.1. Implications for Research

Our current study adds value to the ongoing research on how public health perceptions and support for policy change are influenced by Generative AI Content. These contributions build on how Generative AI Content affects successful emotional and cognitive responses, thus positively influencing the public engagement with health policies.

This first study responds to the gap in the extant literature to the dual impact of AI-promoted content. Much of the prior research on technology has been limited to understanding how it can produce positive outcomes such as improving health literacy and accessing policy support; this study adds important attention to the negative outcomes, including emotional exhaustion and cognitive overload, that can develop from too much exposure to AI driven health content. This study extends the research on how content affects people along central and peripheral routes by leveraging the Elaboration Likelihood Model (ELM). Findings indicate that the central route improves health literacy, while the peripheral route may result in emotional fatigue, diminished policy support, especially when people do not deeply engage, with the content. This study presents the concept, 'the dark side of AI use', in which the excessive use of AI health content leads to undesirable outcomes of emotional burnout, and less cognitive engagement with the AI health content, and promotes a more balanced perspective of AI's role in health communication.

Second, this research contributes to our knowledge of how Generative AI Content impacts public policy support by discovering novel mediating mechanisms. This research, in particular, investigates the role of Health Literacy, Emotional Response to AI Content, and Perceived Severity of Health Impacts between Generative AI Content and support for Fluoride Related Health Policy Interventions. This study builds empirically upon previous studies on the direct effects of AI on health literacy and policy support, but expands to the indirect effects through these intermediary concepts. ELM framework points to an opportunity for AI content to be encountered by people through central (cognitive) or peripheral (emotional) routes, and such encounters affect people's attitudes and policy preferences. By exploring indirect effects, this exploration provides new ways to study not only how digital content mediates knowledge acquisition, but emotional responses that can drive or impede action.

Third, the study contributes to the understanding of the ELM framework in health communication. While previous research on ELM has typically looked at how content quality impacts attitude change, this study shows that different results may follow if particular type of processing (central or peripheral) is utilized instead. These results indicate that Generative AI Content should improve Health Literacy through central processing but can impact policy support through peripheral processing and negative emotional response. Using this research as an illustration, the ELM theory is further put to use to show how AI driven content can initiate both central and peripheral routes of influence on public health perceptions and support for policy interventions.

The study also investigates the moderating influence of regulatory focus, a personality trait that affects how employees interact with AI content. The variability in ELM processing is exposed through the study of how promotion and prevention focused employees respond variability differently to AI driven health content. In another, promotion focused individuals might be more likely to engage with the content in an emotionally driven way, generating more emotional responses but may be cognitively depleted; prevention focused employees are more likely to engage less frequently, resulting in lower emotional responses but better cognitive focus and engagement with health policies. Finally, this new understanding of the relationship between regulatory focus and the ELM offers investigators a promising avenue through which the relationship between individual characteristics and how health content is processed and how public policy is supported can be analyzed.

5.2. Implications for Practice

This research provides useful practical insights for policy makers, organizations, and technology developers engaged with a Generative Ai Content in health communication. The first thing to take away from these findings is that Generative AI Content should be carefully used strategically to prevent those on the receiving end of it from being overwhelmed by too much information, which in turn leads to emotional exhaustion and stifling of creativity. AI content can have positive effect on health literacy and the public knowledge, but its overuse can create an emotional response that may decrease engagement with the policy conversation. It's critical for practitioners to create balance in AI driven content by ensuring it evokes cognitive engagement through the central processing instead of letting content overload activate peripheral processing in emotional fatigue.

Second, the study stresses the necessity of protocolizing in terms of how organizational norms should be employed in dealing with AI content. As the use of Generative AI Content could be a very good lever to improve health literacy, organizations should establish rules to prevent Generative AI Content from being used in a way that stimulates cognitive involvement and saturates employees with so much peripheral content that it overwhelms. Through moderate engagement with AI for health content, employees can be encouraged to get involved at certain times, and continue that effort long enough to lower the risk of emotional exhaustion without leaching away at the helpful beneficial effects on policy support and health literacy of that content.

Thirdly, the technology developers can integrate features that aid at the manage interruptions and reduce cognitive overload by the users. One way examples of this is platforms could implement filtering systems to filter more relevant content, enabling the user to control the information they receive – reducing peripheral processing. Furthermore, 'Do Not Disturb' modes and tools that help people pause interactions would let them digest and interact with Generative AI Content with a bit more cognitive focus.

So, understanding individual's regulator focus can aid organizations with the development of their communication strategies. More engaging and emotionally stimulating content may better promote but more structured and risk averse content may better prevent employees focused on promotion and prevention respectively. When these differences are understood, organizations can tailor AI-driven health communication to meet their respective processing styles and improve not only the engagement with them, but the health communication's effectiveness as well.

5.3. Limitations and Future Research Directions

The findings of the present study offer some important insights, yet a number of limitations need to be taken care of in the future research. Taking the Elaboration Likelihood Model (ELM) as a background, the study reduces the model by omitting other factors that could affect persuasion. As an example, extroversion may affect how people might cope with AI driven material from the emotional engagement counter, up to and including its processing. Future studies should look into the interplay between other personality traits and cognitive and emotional reactions to AI driven health content.

The study then goes on to cover traditional ESM platforms like smartphones and computers. From this, however, smart glassesand wearable devices are becoming important mediums of interaction with AI content. Future research should explore how these newer technologies combined with Generative AI Content impact person's cognitive and emotional responses.

Finally, the research utilized a cross sectional design making causal claims not possible. Better evidence of causality, and clarifying the relationships between Generative AI Content and its psychological and behavioral impacts would result from longitudinal studies or experimental designs.

The results of this study were based on a given specific cultural context. There may be differences in how people process AI driven health content and, therefore, future research should study how cultural variables interact with regulatory focus to impact the impact of AI on health literacy and policy support.

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