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Integrating AI and Literature to Enhance Public Health Awareness on Fluoride: A Cultural Perspective

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ABSTRACT

Purpose: The study analyzes the role of AI-integrated literary content (AI-Lit) on the public's intentions regarding health awareness (PHA Int) with respect to fluoride exposure, exploring the mediating impacts of Health Awareness and Understanding (HAU), Engagement with AI-Literary Content (EngAIL), and Cultural Relevance Perception (CRP).

Design/Methodology/Approach: Researchers targeted Kaifeng high school and university students for data collection. For educational initiatives, this group is important and able to share information throughout their communities. In order to test the proposed relationships, Structural Equation Modeling (PLS-SEM) was utilized.

Findings: With CRP and EngAIL acting as mediators, AI-Net has a considerable impact on the production of PHA Int. The results suggest that cultural relevance and engagement have a greater effect on health awareness intentions when compared to HAU.

Practical Implications: The analysis demonstrates that AI has the capability to deliver both culturally relevant and engaging health education. AI Technology allows health campaigns to easily promote fluoride awareness to students attending high school and university, who are already at ease with this technology.

Theoretical Implications: This study expands the Elaboration Likelihood Model (ELM) by stressing the vital importance of cultural applicability and involvement in AI-integrated health communication.
Originality/Value: This body of research highlights the way AI technology can enrich public health messaging, placing importance on engagement and cultural adaptation in changing health behaviors.
Keywords: Content enhanced with AI, awareness around public health, fluoride, engagement, cultural relevance, as well as high school and university students.

INTRODUCTION

The introduction of fluoride into water, food, and oral health products has for many years provoked conversations about the possible consequences for both cognitive and physical wellbeing [1, 2]. In spite of widespread measures to improve understanding on fluoride, there is a continuing gap in refined insight about its health effects, especially from a cultural and literary viewpoint. Artificial Intelligence (AI) when merged with literature presents a groundbreaking way of delivering health information, which could transform society's understanding and engagement with messages regarding fluoride [3, 4]. As AI technologies have grown, the method by which information spreads has changed greatly, helping to construct persuasive narratives that take into account cultural nuances and can strongly shape public attitudes and behaviors [5]. For quite a while, storytelling in literature has performed an important function in representing social cultural values and beliefs. The integration of literary resources with AI forms unique experiences for different audiences, making health topics that are more involved, such as fluoride exposure, easier to connect with and understand. This research looks to examine the potential of AI-augmented literary materials in promoting public health behaviors related to fluoride, moving away from conventional educational techniques that commonly do not connect with a variety of cultural perspectives [6]. This investigation uses the Elaboration Likelihood Model (ELM) as a crucial theoretical framework that illustrates the processing of information via central and peripheral routes [7] . Participation in the central route is heavy and reflective, yet participation in the peripheral route is contingent upon superficial aspects such as cultural relevance or unique narratives generated by AI. The goal of this study is to understand how AI-literature can affect public health perception of fluoride through direct, cognitive interaction or indirectly via culturally mediated channels using the ELM. The research proposes, according to the ELM framework, that incorporating AI in literature focused on fluoride (the independent variable) has the potential to improve both public health awareness and behavioral intent (the dependent variable) across varying levels. The moderating variables consist of engagement with AI-literary content, how culturally relevant it seems, and understanding health awareness and health. This methodical approach gives us the ability to examine how AI-produced narratives can positively affect both the level of engagement and how culturally relevant information about fluoride influences public behavior and understanding. In spite of the crucial demand for public health education, particularly about the effects of fluoride, there have been very few studies that investigate the role of AI in literature to communicate health information [8]. The purpose of this study is to address that gap by analyzing ways in which AI-integrated literary content can augment public awareness and influence actions that enhance health from a cultural point of view. The objective is to establish whether AI can be an effective persuasive tool, adept at turning complex health messages into stories that connect with a variety of audiences, and hence, support informed decision-making and behavior modification. Thus, in this study, we address two primary research questions: At the outset, how does AI-infused literary material about fluoride influence public participation, health mindfulness, and behavioral preferences? To what degree does cultural relevance and the perceived interaction with AI-based narratives affect the relation between these narratives and public awareness on fluoride? Addressing these questions will contribute to both the academic literature exploring the impact of AI on public health education and to the development of practical insights into the use of technology to improve cultural and health literacy. The objective of this investigation is to integrate literature with AI in order to bridge the divide between scientific knowledge and the public’s comprehension of fluoride, providing a new perspective on health communication that might encourage behavior change. The results will carry important implications for educators, lawmakers, and health workers, offering a new engagement tactic for conversations about how fluoride affects health.

2. LITERATURE REVIEW

2.1 Elaboration Likelihood Model (ELM) Framework

In an effort to explain how those factors are worked out, Petty and Cacioppo (1986) developed the Elaboration Likelihood Model (ELM) which is a theory of attitude change. The ELM suggests that individuals engage with information through two primary routes: The two main pathways described in the phenomenon are the central route, and the peripheral route. The central route is used when consumers are attentive, interested and willing to put a lot of effort in information processing thus developing a critical opinion about the message content [9]. On the other hand, the peripheral route is used for those people who have low motivation, or low ability to process a received message, using instead the observable characteristics of the source of the message such as its physical appearance or credibility, or the message ad's being appealing or unique [10]. In the field of health communication, ELM offers a good account of how credible, persuasive and hostile sources of information affect attitudes and intended behaviours. For instance, if individuals are exposed to written material on fluoride done by the AI, they are most likely to engage the central processing angle in the event that they find the material personal, corrective and in line with their cultural intra-narratives Bond, Zawacki-Richter [11]. On the other hand, if the content does not belong to the relevant domain either or if the individual does not have prior knowledge about the material, for example, fluoride, the individual will use peripheral cues and make their attitudes based on the novelty of the AI technology used to complete the task or cultural references from the literary content provided [12]. Applying extant learning in this respect, the 'AI generated literary content about fluoride' can be categorized as a persuasive message to improve to heighten people's awareness on this subject. The public comprehending the health effects of fluorides through the central route of the elaborated content will possess well-intentioned behavioral intention [13, 14]. On the other hand, the processor through the peripheral route may be directed by cultural stories or utilization of content through generative AI, which may also change the perception and behavior of the users. The consideration of interaction with AI-literary materials, CPC, and health literacy as mediating variables is consistent with ELM. When people attend to the AI-literature, the elaboration of the information attendant on it through the central or peripheral route will be affected by such factors as culture and comprehension of the health consequences thus impacting on their public health change towards the fluorides. The use of ELM in this study shows that there is the need to adapt the health message to fit the cognitive and the cultural endogenieties that exist to ensure that the content and the way it is presented is-responsive to the public health awareness. Consequently, ELM is an appropriate theoretical framework to justify the influence of the AICLC on the awareness of the fluorides by the public through central and peripheral route to bear the message. This theoretical approach elucidates why incorporating both the technical aspect of AI in health communication in conjunction with cultural stories offer a fairly good approach to improve on the understanding of the public and consequently improve on proactive health literacy.

3. MODEL AND HYPOTHESES

3.1. The Impact of AI-Lit on CRP

Using AI in literature (AI-Lit) may greatly affect individual understanding of the cultural relevance of health information, including fluoride awareness. In the context of the ELM, it's claimed that those individuals who see content that matches their cultural background usually participate via the central route, which results in heightened understanding and impact [15]. The customized narratives of AI-Lit mirror cultural particularities, dialects, historical points of view, and societal beliefs, rendering fluoride-related content far more interesting and engaging for multiple target audiences. This technique customized for cultural preferences allows the content to respond to certain cultural beliefs and misconceptions linked to fluoride, increasing its relevance. In one case, AI can develop literary narratives that mesh metaphors from culture and folklore, resulting in information that is both educational and has a

greater personal relevance for the intended audience. As a result, this raises the chance of involvement with and appropriating the health information. The expectation is that utilization of AI technology for the purpose of creating culturally appropriate literary work will markedly improve the perceived relevance of fluoride information. Hence, we propose the following hypothesis: •

H1: AI-Lit has a big impact on individuals' cultural relevance perception (CRP).

3.2. Enhancing Engagement with AI-Lit

How AI-Lit is constructed has a major influence on audience interaction, especially in relation to health themes such as fluoride. Survey results from ELM show that engagement levels are greater among viewers who see the content as credible, engaging, and meaningful to their surrounding circumstances. AI helps present complex fluoride data in a manner that is stimulating, interactive, and easy to obtain [16, 17]. The outcomes include the potential for literature generated by AI to synchronize stories with audience reading skills, preferences, or their prevailing mood, enhancing the experience into something richer and more fascinating. As such, AI technology offers narratives or poets form, personalized and interactive, alongside a user feedback component that promotes engagement with the content. This interactive format supports learning reinforcement and better understanding of fluoride's health effects [18]. In addition, AI-generated literary material can deliver visual aids, sound effects, and interactive quizzes, which both enhance the fun of the experience and improve understanding and memory recall. As a result, it is expected that literary content enhanced by AI will drive higher participation in health conversations. Therefore, the following hypothesis is suggested: •

H2: There is a great impact of AI-Lit on the interaction with AI-literary content (EngAIL) experienced by individuals.

3.3. Improving Health Awareness through AI-Lit

Embracing AI in literary material may greatly help to improve health awareness and understanding about fluoride (HAU). The ELM model illustrates that the central route of processing shows that individuals can fully understand health concepts better when the information is both informative and relatable (Petty & Cacioppo, 1986). By means of a simplified, immersive, and culturally informed approach, AI-Lit communicates challenging fluoride information, leading to improved cognitive processing [19]. The literary efforts created by AI can provide explanations for fluoride's science in a way that is both engaging and easy to grasp, through either narrative, poetry, or stories linking information to readers' own lives, thus increasing their ability to both understand and remember it. Added to that, AI is capable of personalizing content delivery to suit multiple learning styles, which helps to guarantee that wide audiences can effectively learn and internalize the health messages [20]. The personalized strategy is likely to considerably bolster HAU, enabling people to achieve better understanding about fluoride consumption and health practices. Hence, the following hypothesis is proposed:

H3: AI-Lit greatly improves HAU related to fluoride.

3.4 Cultural Relevance's Role in Health Intentions

The important role played by CRP is in defining public health awareness and behavioral intentions related to fluoride usage (PHA Int). The ELM recommends that content which is culturally relevant prompts individuals to process information using the central route, consequently driving more lasting changes in both attitudes and behaviours [21]. Messages pertaining to fluoride for health will become significantly more customer and socially relevant and engaging when they consider personal beliefs, traditions, and values. Integrating cultural stories, historical teachings, or local sayings in the automated creation of content ties broadly available scientific data to the understanding of the commoners, rendering the message more authentic [22]. The result is a greater chance that individuals will take on positive health behaviors, including using

fluoridated toothpaste and pushing for safe water sources rich in fluoride. As a consequence, culturally significant content can foster health behavior modification by underlining the demand to link health messages with one's cultural roots. Therefore, we hypothesize:

H4: PHA Int is greatly affected by CRP in relation to fluoride.

3.5. Engagement with AI-Lit on PHA Int

The way people engage with literary content generated by AI has a deep effect on their PHA Int. The ELM promotes the conviction that increased engagement with content facilitates more profound processing, creating more successful behavioral intention [23]. With its appealing, interactive, and user customized health information provision, EngAIL stimulates active engagement from users. As an example, stories produced by artificial intelligence that enable readers to inform options or have conversations with characters might render health information about fluoride more powerful and effective. Such a high degree of participation assures that the information reaches its audience and receives a response, improving the possibilities of contributing to positive health behaviors. The outcome shows that people who are actively involved with AI-Lit are likely to demonstrate improved awareness and a greater intent to practice fluoride health behaviors. Therefore, we propose:

H5: Phosphate hunting communities are seriously affected by the fluoride situation.

3.6. HAU and Public Health Intentions

HAU is key in the formation of PHA Int. Those with increased comprehension and better awareness about a health issue, for instance fluoride, will usually follow the central route when processing information, resulting in stronger intentions for health behaviour [24]. As people become better informed about the pros and cons of fluoride via AI-Lit, they are more apt to practice behaviors such as using fluoride toothpaste or to endorse safer fluoride levels in the water of their own community. The relationship focuses on the importance of AI-Lit for improving understanding and motivating favorable health behaviors. Therefore, we hypothesize:

H6: PHA Int experiences a major effect from HAU related to fluoride.

3.7 HAU as a Mediator in AI-Lit and PHA Int

To effectively change behavioral intentions, the Elaboration Likelihood Model (ELM) requires that we understand and are aware (Petty & Cacioppo, 1986). Within this framework, literature that includes artificial intelligence (AI-Lit) plays an important role in refining Health Awareness and Understanding (HAU) for individuals. As AI-Lit grows in familiarity, users typically learn to identify the health dangers and the pluses of fluoride, which boosts their intention to implement preventive health practices (PHA Int) [25]. Consequently, HAU plays a key role as a way for AI-Lit to shape public health intentions. Persons who realize the health risks associated with fluoride exposure tend to participate in preventative measures and to make insightful health choices. As a result, content generated by AI proves to be an effective tool for communication important health messages, boosting understanding and encouraging altered patterns in behavior. Based on this reasoning, we hypothesize:

H7: Public Health Awareness Intention (PHA Int) is mediated by the relationship between AI-Integrated Literary Content (AI-Lit) and Health Awareness and Understanding (HAU).

3.8. EngAIL Mediating AI-Lit and PHA Int

Interaction with literary material containing artificial intelligence (EngAIL) strongly affects the intention to raise public health awareness (PHA Int). The researchers indicate that the Elaboration Likelihood Model (ELM) indicates that increasing content interactions elevates how people process information, making it more persuasive[26]. This research intends to engage

the audience, making fluoride information more interesting and easy to relate to. This interaction enhances a robust tie to the material, causing individuals to be more welcoming to health messages. People involved with AI-Lit tend to absorb health information more fully, resulting in a lift in their intention to participate in healthy behaviors. As a result, EngAIL is an important facilitator that enhances the effects of AI-Lit for PHA Int. This finding implies that limited engagement could constrain the role of AI-Lit in directing public health choices. Therefore, we propose:

H8: Engagement with AI-Literary Content (EngAIL) intermediates the connection between AI-Integrated Literary Content (AI-Lit) and Public Health Awareness Intention (PHA Int).

3.9. CRP as a Mediator in AI-Lit and PHA Int

Cultural Relevance Perception (CRP) is an important mediator that moderates the relationship between AI-integrated literary content (AI-Lit) and public health awareness intention (PHA Int). Messages that target health and are adapted to cultural preferences are considerably better received by the recipient, supporting the chance of behavior change based on the Elaboration Likelihood Model (ELM) [27]. Throughout this study, AI-Lit content is formulated to be culturally relevant, which guarantees that fluoride information corresponds with the core beliefs, practices, and cultural norms of the target audience. This cultural correspondence improves the perceived importance of the content, causing people to become more accepting of the recommended health behaviors. CRP serves as a link that connects AI-Lit with PHA Int, confirming that the health messages resonate with both the intent and understanding of the viewing audience. Therefore, we hypothesize:

H9: The contribution of Cultural Relevance Perception (CRP) mediates the interplay between AI-Integrated Literary Content (AI-Lit) and Public Health Awareness Intention (PHA Int).

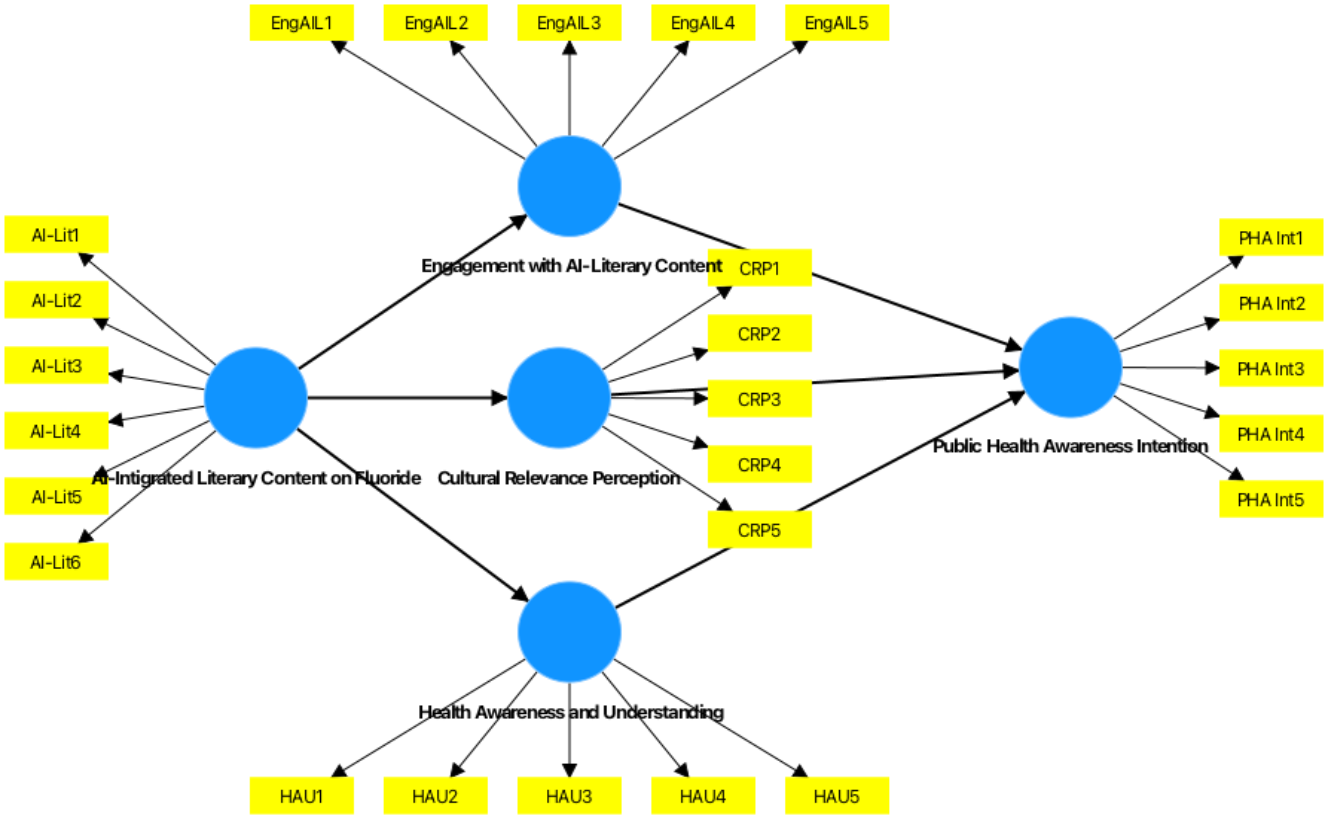

Figure 4: Path model

4. METHODOLOGY

4.1 Measures

To guarantee content validity and reliability, multiple-item scales from existing literature were used to measure the study's constructs. The variables included in this study were as follows: 1. *AI-Integrated Literary Content (AI-Lit):* The measurements for this construct used six items abstracted from former studies focused on technology-enhanced learning and health communication. The objects demonstrated the use of AI technology to deliver fluoride content in an entertaining and instructional way [28]. *2. Cultural Relevance Perception (CRP):* Five items measuring this construct evaluated the way participants understood the cultural relevance of AI-generated literary materials concerning fluoride. These items emerged from existing research related to health communication and cultural adaptation [29]. *3. Engagement with AI-Literary Content (EngAIL):* Using five items, this variable was assessed to evaluate the degree of participants' involvement and interaction with the AI-created literary materials related to fluoride. The scale has been modified from research into the interactions with educational technologies.[30] *4. Health Awareness and Understanding (HAU):* We used five items from existing health awareness studies to quantify this construct, concentrating on the knowledge and awareness levels gained about fluoride via AI-integrated contente [31]. *5. Public Health Awareness and Behavioral Intentions (PHA Int):* Five items from behavioral intention scales in public health research were adapted to measure the dependent variable related to the participants' intentions to engage in health-promoting behaviors linked to fluoride [32]. Each item on the list received a rating from the participants, measured on a 5-point Likert scale, through which 1 equated to 'Strongly Disagree' and 5 to 'Strongly Agree'. This technique permitted the documentation of detailed differences in views and perceptions, congruent with the methods employed in like studies (Kumar & Kumar, 2020).

Table 1: Constructs

Construct	Items	Sources
AI-Integrated Literary Content (AI-Lit)	AI-Lit1: The AI-generated content was informative about fluoride. AI-Lit2: The AI content made fluoride-related health information interesting. AI-Lit3: The AI technology made the literary content about fluoride more engaging. AI-Lit4: I found the AI-generated stories about fluoride easy to understand. AI-Lit5: The use of AI helped to simplify complex information about fluoride. AI-Lit6: The AI-enhanced content was appealing to read.	[28]

Table 1. Constructs . Continued.

Construct	Items	Sources
Cultural Relevance Perception (CRP)	CRP1: The fluoride-related content was culturally relevant to my background. CRP2: The AI-generated stories reflected my cultural beliefs about health. CRP3: The content felt tailored to my cultural understanding. CRP4: I could relate to the examples used in the fluoride information. CRP5: The cultural aspect made the fluoride information more meaningful.	[29]
Engagement with AI-Literary Content (EngAIL)	EngAIL1: I spent a significant amount of time engaging with the AI-generated content. EngAIL2: I found myself interacting more with the AI-literature on fluoride. EngAIL3: The content encouraged me to learn more about fluoride. EngAIL4: I actively participated in reading the AI-generated stories. EngAIL5: The AI-enhanced content kept me interested throughout.	[30]
Health Awareness and Understanding (HAU)	HAU1: I gained new knowledge about fluoride from the AI content. HAU2: The AI-literature improved my understanding of fluoride's health effects. HAU3: I feel more aware of fluoride's role in public health. HAU4: The content increased my awareness of the benefits and risks of fluoride. HAU5: I now understand how fluoride impacts overall health.	[31]

Table 1. Constructs . Continued.

Construct	Items	Sources
Public Health Awareness and Behavioral Intentions (PHA Int)	PHA Int1: I intend to use fluoride toothpaste regularly after reading the AI content. PHA Int2: I am more likely to seek fluoride-safe water sources. PHA Int3: I will share the information about fluoride with others. PHA Int4: I feel motivated to advocate for fluoride-safe practices in my community. PHA Int5: I plan to take measures to protect myself and my family from fluoride exposure.	[32]

4.2 Sample and Data Collection

A questionnaire designed for a survey collected information from both undergraduate and graduate students in Kaifeng, known for its unusually high fluoride levels. A pilot study assessing the clarity and relevance of the survey items was done at the outset, involving 20 students. After considering their input, small modifications were introduced to ensure the questions were unambiguous and correctly captured all constructs. The finalized questionnaire was translated into Chinese and administered online via the survey platform (https://www.wjx.cn/). Data collection happened across two weeks that began in June 2024. In order to increase survey participation, we engaged 30 seed investigators to share the survey link through social media, university contacts, and emails. In order to guarantee na unbiased role, these investigators took part outside of the study. All in all, 472 responses were obtained, but 65 were eliminated owing to missing data or characteristic response styles (such as responding identically to all questions). In turn, 407 responses were available for analysis. Representing a mixture of ages and academic levels, 47% of the participants were male, and 53% were female. Below you will find the demographic characteristics outlined in table 2.

Table 2: Demographic Characteristics of Respondents

Demographic Factor	Categories with Percentage
Age Group	18-24 (29.5%), 25-34 (36.9%), 35-44 (19.7%), 45 and above (13.9%)
Gender	Male (47%), Female (53%)
Education Level	Undergraduate (44.2%), Graduate (39.3%), Postgraduate (16.5%)

5. DATA ANALYSIS AND RESULTS

The impacts as statistical analysis by using Structural equation modeling (SEM) is effective for the reason of the accuracy, efficiency and convenient as compared to the customary statistical approaches [33]. Second, as distinct from other first-generation analysis techniques, SEM is free of their limitations and allows for the examination of several variables at once. This has made it easier for use in research since it performs a well on complex relationship[34]. There are two main SEM techniques: Structural equation modelling (SEM) is available in two forms using covariance: covariances based SEM (CB-SEM) and variance based SEM (VB-SEM) also called Partial Least Squares SEM (PLS-SEM). Since, data, in the social science studies are often faced with normality problems, PLS-SEM is applied not CB-SEM as the latter is more rigid with regards to such concerns[35]. PLS-SEM follows a two-stage approach: first, the measurement model analysis and, second, the structural model analysis. The analysis of this research employed SmartPLS 4.0.

5.1 Measurement Model; Reliability and Validity

The evaluation of the measurement model involved reliability and validity tests for all constructs presented in this study. The component of reliability evaluated included internal consistency reliability (Cronbach's α along with Composite Reliability, CR) as well as item reliability (outer loadings). To assess convergent validity, the Average Variance Extracted (AVE) was used. Table 3 illustrates that Cronbach's α values ranged from 0.836 to 0.954, and CR values ranged from 0.884 to 0.963, all exceeding the needed threshold of 0.7 [36]. This reflects that the constructs presented considerable internal consistency along with reliability. In order to evaluate convergent validity, an analysis was performed on the standardized loadings of each item along with the Average Variance Extracted (AVE). Table 3 suggests that all item loadings went above the threshold of 0.70, and the AVE (average variance extracted) values for all constructs were above the minimum of 0.50, ranging from 0.604 to 0.813. These results illustrate that the constructs demonstrate satisfactory convergent valid [37].

Table 3: Construct Reliability and Validity

Constructs	Items	Loading	Cronbach alpha	CR	AVE
AI-Intigrated Literary Content on Fluoride (AI-Lit)	AI-Lit1	0.912	0.954	0.963	0.813
	AI-Lit2	0.856			
	AI-Lit3	0.921			
	AI-Lit4	0.927			
	AI-Lit5	0.865			
	AI-Lit6	0.926			
Cultural Relevance Perception (CRP)	CRP1	0.739	0.836	0.884	0.604
	CRP2	0.794			
	CRP3	0.783			
	CRP4	0.829			
	CRP5	0.739			
Engagement with AI-Literary Content (EngAIL)	EngAIL1	0.815	0.836	0.900	0.646
	EngAIL2	0.870			
	EngAIL3	0.847			
	EngAIL4	0.607			
	EngAIL5	0.850			
Health Awareness and Understanding (HAU)	HAU1	0.808	0.846	0.890	0.621
	HAU2	0.845			
	HAU3	0.673			
	HAU4	0.835			
	HAU5	0.765			

Table 3: Construct Reliability and Validity. Continued.

Constructs	Items	Loading	Cronbach alpha	CR	AVE
Public Health Awareness Intention (PHA Int)	PHA Int1	0.803	0.839	0.884	0.605
	PHA Int2	0.812			
	PHA Int3	0.789			
	PHA Int4	0.725			
	PHA Int5	0.757			

5.2 Common Method Bias (CMB)

In order to confirm that common method bias (CMB) did not heavily influence the results, an evaluation of it was conducted due to the reliance on self-reported data. Two approaches were used: The one-factor test from Harman alongside the typical latent factor strategy. • Harman's One-Factor Test: A five-factor exploratory factor analysis showed that the variables; Common Latent Factor Approach: A comparison was made of the regression weights that have been standardized with and without considering a shared latent factor. The results proved there were no important differences, emphasizing that CMB was probably not a problem [38] .

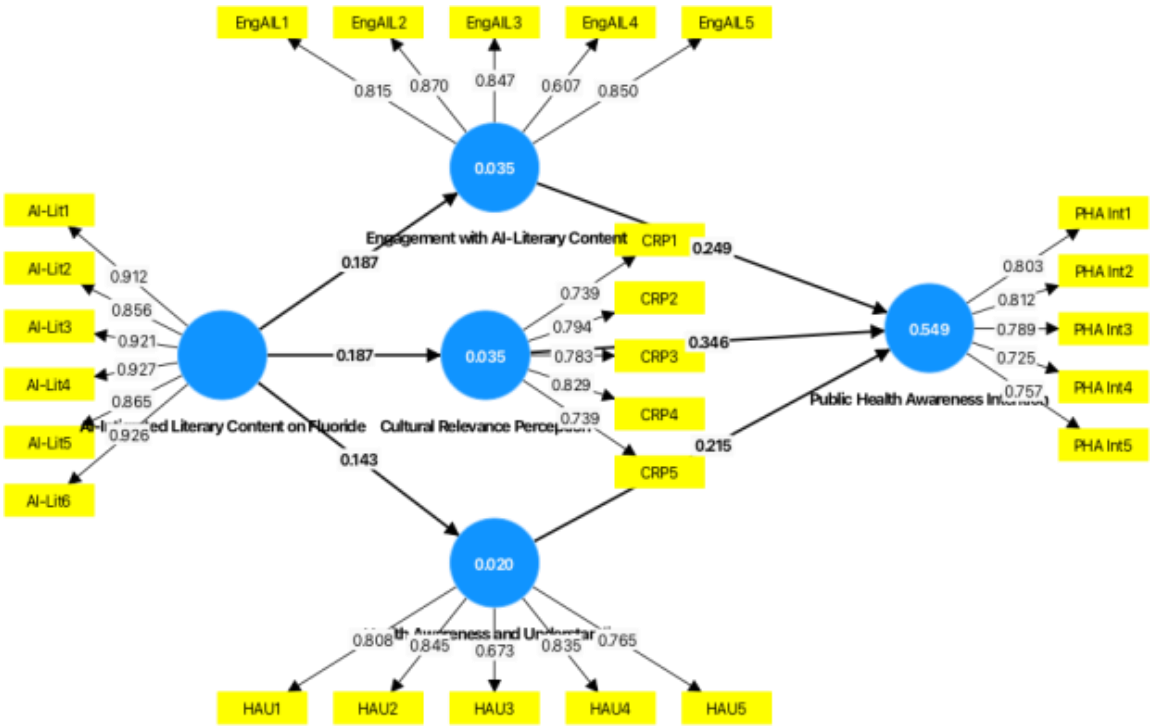

Figure 4: Measurement model

5.3 Discriminant Validity

Discriminant validity evaluation relied on the Heterotrait–Monotrait (HTMT) ratio, thought to be a more useful measure than the Fornell–Larcker criterion by a variety of scholars [35]. Discriminant validity is established when values of HTMT are under 0.90. As represented in Table 4, all figures were below the 0.90 threshold, proving discriminant validity. As displayed in Table 3, all HTMT values were less than the cut-off value of 0.90, which varied from 0.147 to 0.910, and confirmed discriminant validity [39]. The HTMT value at 0.202 indicated that AI-Lit and CRP are adequately distinct.

Table 4 :HTMT mattrix

	AI-Lit	CRP	EngAIL	HAU	PHAInt
AI-Lit					
CRP	0.202				
EngAIL	0.191	0.910			
HAU	0.147	0.886	0.831		
PHAInt	0.198	0.814	0.733	0.732	

Fornell and Larcker Criterion

Table 5 presented the findings of the Fornell-Larcker criterion. The square roots of each construct's AVE (diagonal elements) were larger than the correlations with other constructs, suggesting good discriminant validity [40]. For example, the square root of the AVE for AI-Lit is 0.902, which is larger than its relations with other constructs, proving that each construct differs from the others.

Table 5: Fornell-Larcker criterion

	AI-Lit	CRP	EngAIL	HAU	PHAInt
AI-Lit	0.902				
CRP	0.187	0.777			
EngAIL	0.187	0.779	0.804		
HAU	0.143	0.751	0.701	0.788	
PHAInt	0.180	0.702	0.670	0.650	0.778

5.4. Structural model

5.4.1 Model Fit Assessment

Several fit indices were computed in order to test the degree of assessment of the measurement model that was proposed. The goodness of fit was complimented by the Root Mean Square Error of Approximation (RMSEA) of 0.055 which was lower than 0.08 cut off standard. The Chi-Square to Degrees of Freedom Ratio (CMIN/DF) was 1.987, which was below the cut off value of 3 thus suggesting that the model was a good fitting one. More fit indices were in support of this model. CFI was 0.960, TLI was 0.935, and IFI was 0.958, all were above 0.90, thus indicated a reasonable fittings in the model. These indices support that the proposed model is compatible with the data and has high construct validity.

5.4.2 Hypotheses Testing Results

4.2 Structural Model Following the assessment of the measurement model, the structural model

was also tested in order to identify the links between the endogenous and exogenous constructs. In the evaluation of the structural model, these were path coefficients (β values, t values), with effect size (f^2), predictive relevance (Q^2) and the coefficient of determination (R^2). The importance of the hypotheses was tested using a bootstrapping procedure with 5,000 resamples at a 5% significance level (one-tailed). The studies also show that all proposed hypothesis one to six were supported. They established a positive path coefficient (β) of 0.187 significant at the 5% level with the t-value of 3.244 that exceeds the limit of 1.64 and p-value of 0.001 in favour of the null hypothesis that considers the positive relationship of AI-Integrated Literary Content on Fluoride (AI-Lit) and Cultural Relevance Perception (CRP). This means that AI-Lit successfully improves CRP of the participants and assures cultural adaptation of the AI produced content that can change the health intentions of people. Likewise, AI-Lit had a positive path coefficient ($\beta = 0.187$, $t > 1.64$), t-value of 3.236, and p-value of 0.001 on Engagement with AI-Literary Content (EngAIL). This reveals that, there is an important function of utilizing content that is associated with Artificial Intelligence and participation to improve intentions in public health awareness. Further, the positive association between AI-Lit and health awareness and understanding (HAU) with a path coefficient ($\beta = 0.143$, $t = 2.350$, and $p = 0.019$ underline that AI content enhancing individual's health awareness. The subsequent analysis indicated that CRP had a significant and positive effect on PHA Int ($\beta = 0.346$; $t = 3.787$; $p < 0.000$). This finding also suggests that the community's perception of culture plays a tremendous role in enhancing the awareness of public health. EngAIL also had a direct positive effect on the PHA Int with $\beta = 0.249$, $t = 2.892$, and $p = 0.004$, which indicate that the participants' engagement with AI integrated contents positively affected their health intentions. Finally, HAU had a positive impact on Automatic Intention to Purchase or PHA Int with the path coefficient (β) of 0.215, while possessing a t-statistic of 3.030 and a p-value of 0.002. The value of the R^2 of the established model was considered significant, which points to the fact that the totality of the independent variables under consideration: AI-Lit, CRP, EngAIL, and HAU explain a significant percentage of variance in PHA Int. However, it should not be forgotten that while applying the test, only the R^2 is considered. Therefore, the predictive relevance was computed as Q^2 greater than zero, indicating that the exogenous constructs have the ability to predict the model. Coefficient of determination (f^2) was also analyzed with values measuring r: 0.02, small; 0.15, medium; and 0.35, large. A comparison of the above findings show that the eta squared values ranged between.017 and.138 indicating that there exists differences in the degree of significance that AI-Lit, CRP, EngAIL, and HAU bear for the prediction of PHA Int (see table 6). In total, these findings corroborate the idea that the structural model is indeed valid and that the relationships postulated in this study are indeed significant.

Table 6: Path coefficient

	Original sample (O)	T statistics (|O/STDEV|)	P values
AI-Lit -> CRP	0.187	3.244	0.001
AI-Lit -> EngAIL	0.187	3.236	0.001
AI-Lit -> HAU	0.143	2.350	0.019
CRP -> PHA Int	0.346	3.787	0.000
EngLit -> PHA Int	0.249	2.892	0.004
HAU -> PHA Int	0.215	3.030	0.002

5.5 Results from Mediation and Serial Mediation Analysis

The mediation analysis was conducted to examine the indirect effects of AI-Integrated Literary Content on Fluoride (AI-Lit) on Public Health Awareness Intention (PHA Int) through

three mediators: Among them, Health Awareness and Understanding (HAU), Engagement with AI-Literary Content (EngAIL), Cultural Relevance Perception (CRP). The mediated effects were analyzed through the bootstrapping method with resamples of 5,000 and examined the path coefficients, t-values and p-values to ascertained its significance. The first mediation model examined was the indirect effect of AI-Lit on PHA Int was tested as mediated by HAU. A path coefficient (β) of 0.031, t-value of 1.827, and p-value of 0.068 were realized. Despite the positive and directly significant relationship with the path coefficient, the p value of the mediated direct residuals is equal to 0.06 thus rejecting HAU as significantly mediating the relationship between AI- Lit and PHA Int at 5% level. This implies that, though AI-Lit improves HAU, HAU does not substantially influence PHA Int sufficiently to meet statistical significance in this model. The second mediation pathway comprised of EngAIL as a mediator of the relationship between AI-Lit and PHA Int. The analysis significantly proved the direct mediation as the results shown the path coefficient value (β) is 0.047 along with t-value 2.056 and p-value 0.040. Based on this, it could be argued that AI Int fully mediates the relationship between AI-Lit and Int PHA. This means that, the more the people read AI-integrated literary content, the more their willingness to be informed on public health issues which validates the notion that engagement is key to boosting AI-Lit to effect change on public health consumers. The third mediation analysis considered CRP as the mediator of the relationship between AI-Lit and PHA Int. The analysis revealed meaningful mediation impact with path coefficients (β) equalling 0.065, t-ratio of 2.336 and p-value equals 0.020. This goes to show that CRP moderately controls for for the AI-Lit – PHA Int association. It means that when AI-Lit is considered culturally appropriate, it increases people's inclination to pay attention to public health concerns, which shows that cultural adaptation of AI productions drastically impacts health intentions see the table 7 which presented mediation results. Lastly, the mediation analysis confirmed that EngAIL and CRP are mediators between AI-Lit and PHA Int and that they have a vital role in increasing the awareness of the public. On the other hand, the results reflected that HAU was not significant and fully supporting the theoretical claim that it is not very influential in this case. These studies point to the need for interaction and culture incorporation in the use of AI created content on awareness intentions of public health.

Table 7:Indirect Effects

	Original sample (O)	T statistics (|O/STDEV|)	P values
AI-Lit -> HAU -> PHA Int	0.031	1.827	0.068
AI-Lit -> EngAIL -> PHA Int	0.047	2.056	0.040
AI-Lit -> CRP -> PHA Int	0.065	2.336	0.020

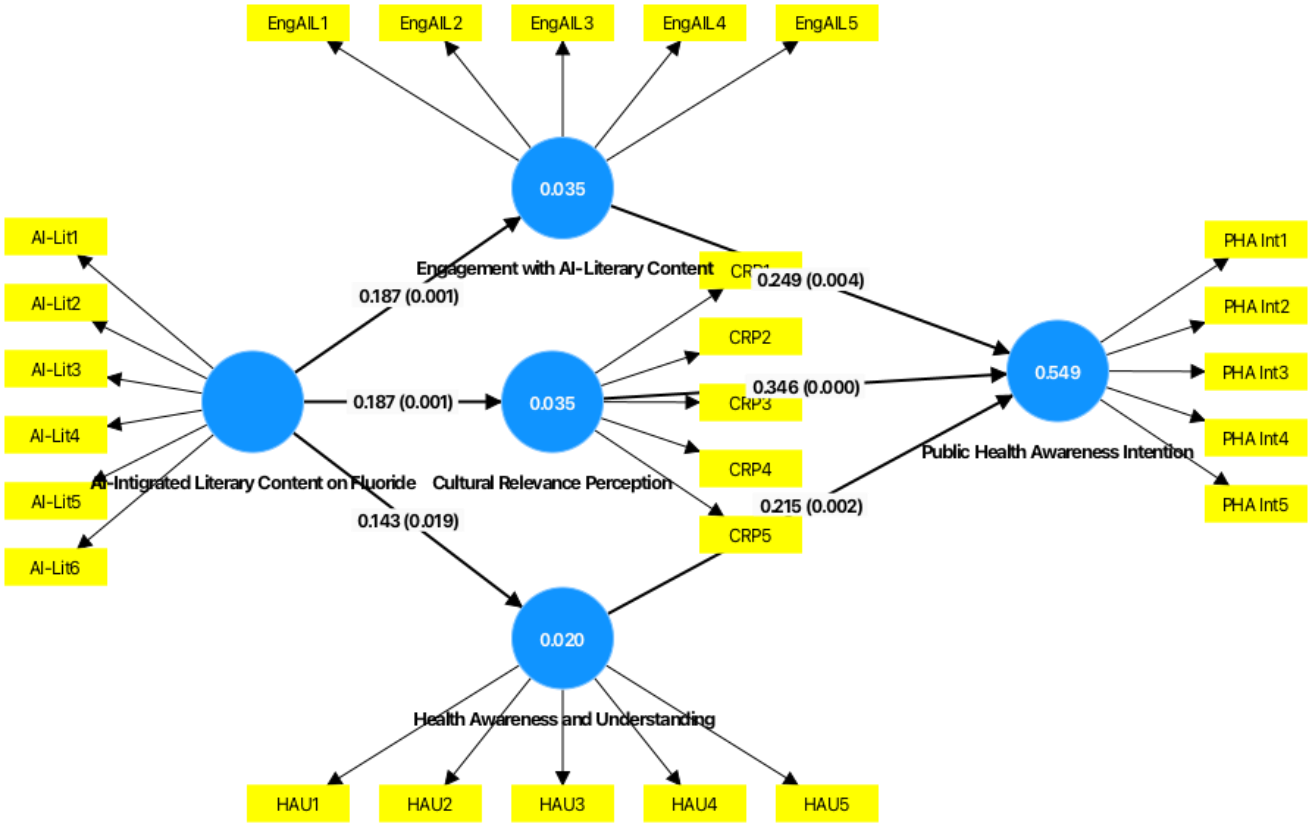

Figure 6: Structural Model

6. DISCUSSION AND CONCLUSIONS

This research identified the interaction between AI-integrated literary content (AI-Lit), Cultural Relevance Perception (CRP), Engagement with AI-Literary Content (EngAIL), Health Awareness and Understanding (HAU), and Public Health Awareness Intention (PHA Int). These findings confirm the current literature on how AI content influences public health behaviour [41, 42]. H7 was supported, as the connection between AI-Lit and CRP was confirmed to mean that AI can develop lit that is culturally relevant for target consumers, affecting their overall health intentions. This stated with current research that highlight the perception of culturally appropriate health communication for it increases message personalization and persuasiveness [43]. The significant support for the hypothesis H8 suggesting that AI-Lit would enhance engagement strengths the value of engaging content for affecting engagement in public health campaigns. With current advancements in the AI technology, theories, it is a highly engaging tool that enables learning anchored on attention and increasing the understanding, and in the process, the behavioural intentions [44, 45]. HAU was not found to be a mediator of the relationship between AI-Lit and PHA Int (H9), that is, knowledge transformation does not automatically lead to behavioural transformation. This result aligns with other research that posited that awareness should be accompanied by other factors like cultural appropriateness or activation to achieve best outcomes in the aspect of health behaviors[46]. The role of CRP is interpreted to confirm that AI-Lit provides awareness that when user-specific and culturally congruent, boosts health-promoting behaviour uptake, consistent with recent meta-analyses of culturally tailored health interventions[47]. Interaction emerged as another moderating factor showing that participation with AI produced material influenced intention toward the promulgation of public health. This is in accord with interventions considered essential to be more effective in health education since engagement prompts retention and understanding of imparted

information hence the attainment of more profound behavioral modifications [48]. In addition to the theoretical propositions offered by this study, there are practical or practical implications. They especially emphasize the significance of AI in the application of a health education model that considers culture. With an increasing number of public health campaigns utilizing uniquely generated content, the application of AI proves to be an effective approach to convey appropriate content that can become important in persuading groups of people in terms of their possible or desirable behaviors in the future. In sum, this investigation provides further evidence of the need to integrate AI-based content with cultural importance and interest to optimise public health messaging. Another way, future research should replicate these findings in other cultures to support and push these relationships ahead.

Implications

6.1. Theortical Implications

The investigation adds considerable value to the current body of knowledge in health communication by combining AI technology with public health awareness approaches. Using AI-integrated literary content (AI-Lit) for the distribution of information on fluoride health links with the latest enhancements in AI's function within health communication. The research shows that culturally relevant content (CRP) plays an important role in shaping health intentions, In line with the notion that customized cultural messaging could be more successful in enhancing health behavior changes. The study illustrates the expanded application of the Elaboration Likelihood Model (ELM) by showing how engagement functions as a central route in digesting health information, while confirming that involvement with AI-Lit (EngAIL) is what moderates the relationship between AI-generated content and health awareness intentions. The results illustrate the opportunities for AI to deliver customized health education, enhancing knowledge about AI's success in promoting public health.

6.2. Practical Implications

This study, examined from a functional point of view, proposes that public health campaigns could exploit AI technology to produce culturally adjusted and engaging content that resonates broadly with different populations. AI-based educational strategies designed by health care practitioners are more equipped to increase awareness and encourage healthful behaviors when they realize that engagement and cultural relevance are vital factors, particularly in locales facing high fluoride concentrations. Through this approach that generates content with AI to reach students, both their understanding of concepts and their motivation to take preventive steps can improve within educational spaces. People in charge of policy should recognize that using AI in health communication strategies offers a scalable and effective avenue to connect with a variety of demographics, improving public health literacy in general .

6.3. Limitation and Future studies

This study demands attention to the city of Kaifeng, China, which might undermine the relevance of the insights to substantial populations. To make the results more applicable, forthcoming studies should take into account a wider geographic scope that includes multiple fluoride-rich areas (Zhou & Zeng, 2023). Besides, the self-reported data involved might generate biases, because the participants could fail to accurately represent their intentions pertaining to health awareness. The combination of methods, including surveys and interviews or observational studies, may lead to a richer understanding of this phenomenon (Lin et al., 2021). Due to the cross-sectional design, the study can capture data at just one moment in time, which prevents the opportunity for making causal conclusions. Research that unfolds over time will allow for following changes in health awareness intentions and would deliver insights into the maintained impact of content that integrates AI (Huang et al., 2021). On top of that, the study showed the importance of cultural relevance and engagement as mediators, but

future exploration could examine other variables, including trust in AI technology or digital literacy, to understand their role in health communication results. Finally, the fast advancement of AI technology indicates that the content examined in this research might soon become obsolete. In order to continue to be useful and relevant throughout alterations in public health guidelines and cultural norms, researchers need to add dynamic AI models.

6.4 Conclusions

This research examined the role of AI-backed literary material in enhancing public health awareness intentions with respect to exposure to fluoride. The results reveal that AI-generated content greatly influences health awareness intentions as long as it is both culturally engaging and relevant. Although Health Awareness and Understanding (HAU) did not remarkably mediate the relationship, the role of Cultural Relevance Perception (CRP) and Engagement with AI-Literary Content (EngAIL) as mediators stresses the importance for personalized, engaging health communication approaches. The research results illustrate the prospects of AI technology in becoming a transformational asset for delivering public health messages that connect with a broad range of populations. The contributions of theory in this study embrace validating the part cultural relevance and engagement play within the Elaboration Likelihood Model (ELM) while extending its practicality to health communication involving artificial intelligence. This research delivers important insights to public health practitioners and policymakers on the strategy of using AI-driven content to enhance health awareness and effect behavior change. Research aimed at the future ought to examine these insights across a number of cultural environments and employ longitudinal designs to analyze the enduring effect of content fused with AI. Briefly, AI technology adopts a novel procedure to raise public health awareness, particularly in overcoming issues such as fluoride exposure. Interacting with many groups by combining cultural relevance, participation, and advanced AI functionalities helps health initiatives achieve remarkable public health results.

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