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Promoting Fluoride Awareness in Language Education: AI-Enhanced Approaches for Community Outreach

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ABSTRACT

Background: Fluoride awareness remains a critical oral health issue, yet conventional health-based education methods often fail to engage diverse adult learners. Proposed AI-based language platforms provide new opportunities to incorporate the contents of public health into daily studying.

Purpose: The aim is to understand the effect of AI-driven personalization (PAIU) and quality of instructions (PAIQ) in a language-learning app available on smartphone devices on users' Fluoride Knowledge Clarity (FKC), Engagement Attitudes (FEA), and intentions of conducting Outreach activities (OI) to create fluoride awareness in the community.

Methodology: The survey of twenty-eight Chinese adult learners who used an AI language and application examined five constructs: PAIU, PAIQ, FKC, FEA, and OI, with the help of validated scales. The direct and mediated relationships between constructs were evaluated by structural equation modeling. In contrast, the common latent factor approach, with the help of Harman's one-factor test, was used to assess common method bias.

Findings: PAIU (0.253, $p<0.001$) and PAIQ (0.186, $p<0.001$) had positive effects in improving FKC, which further positively influenced FEA (0.285, $p<0.001$) and OI (0.248, $p<0.001$). Sequential mediation tests showed that there is indeed a joint mediating effect of FKC and FEA linking AI features to outreach intentions.

Conclusion: Adaptive feedback and high-quality multimedia must be incorporated into AI platforms by developers and health educators to maximize the impact of fluoride education, empowering every learner as a community advocate.

Keywords: *Fluoride Awareness, AI Personalization, Language Education, Structural Equation Modeling, Public-Health Outreach*

INTRODUCTION

The complex relationship between fluoride as a caries preventive and a possible toxic substance highlights the urgent necessity of the subtlety of its anti-caries role involved in education in the range of high fluoride exposure. However, naturally high levels of groundwater fluoride (over 1.5 mg/L on average) are present in Shanxi and Inner Mongolia of China, where dental and skeletal fluorosis are highly prevalent (Li et al., 2018). Similarly, in Pakistan, an incredible majority exceed the limit of safe fluoride in the Punjab region (more than 60 percent) (Khan et al., 2015). School-based interventions (such as campaigns and pamphlet distribution programs) have been found inadequate to fill the lingering gaps in terms of the community knowledge of safe consumption of fluoride, levels of consumption, and differentiating negative and positive exposure (Zhang & Chen, 2024).

There is a great potential, but a poorly studied direction in language education: the development of fluoride literacy as a part of communicative curricula. Through teaching health content as part of the English or Mandarin curriculum, teachers can develop both language proficiency and subject knowledge. To illustrate, elective subjects in Chinese middle schools have been introducing environmental module elements (vocabulary of water analysis, interactive simulations, etc) in teaching Science and English, and have found that these elements resulted in concurrent increases in technical English and increases in environmental awareness (Yan et al., 2025). Literacy programs used in Pakistan that include both Punjabi reading classes with interventions on hygiene and nutrition have also shown improvement in health behaviors in the rural Pakistani women, and the progress is measurable (Melbye & Armfield, 2013). Nevertheless, even with such success, the topic of fluoride is not prominently featured by interdisciplinary approaches to teaching.

The modern tech in the artificial intelligence (AI) field, such as chatbots, adaptive quizzes, and personalized feedback, can break the barriers of literacy level, attention span, and resource-based obstacles in the traditional way as well. An English-medium AI chatbot in the water-treatment labs of Beijing enhanced the retention of specialized vocabulary among the students by 30 percent and their knowledge of the chemistry of fluoride by providing virtual experiments (Jiang & Liu, 2025). In the meantime, an AI-based tutor in Lahore increased the correct use of toothpaste among adult learners to 68 percent (compared with the 42 percent prevalence when nothing was used) by providing customized flashcards with tips in Urdu on brushing teeth.

Based on Cognition Affect Conation (C-A-C) model, based on Cognition - Affect - Conation (C-A-C) model, describing how a clear vision of knowledge (cognition) influences emotional involvement (affect) and finally behavioral intention (conation)(Perez et al., 2025), this study tests a new AI-aided literacy component that is expected to foster fluoride awareness among residents of the high-fluoride regions of Shanxi Our interest is in reviewing whether the perceived usefulness and quality of interactions with AI in the learning contexts can promote better comprehension of the science of fluoride, whether the promoted clarity can foster positive engagement attitudes, which in their turn promote intentions to disseminate knowledge about fluoride and promote safe behavior.

In that way, we pose the following question: How far can an AI-driven, language-centered fluoride-education module (administered in high-fluoride areas of China) accomplish the purpose of increasing the intellectual clarity of fluoride science, the emotional interest in the subject, and the conative desire to extend outreach to the community? We believe that answering this question can help create a scalable, culturally relevant framework of incorporating public-health messaging in language education and empower the at-risk population with both linguistic resources and with the health literacy that can prevent their oral and systemic health.

LITERATURE REVIEW

The idea of teaching health within the language learning process has become a popular teaching innovation. Research conducted by Chinese scholars illustrates that environmental and scientific contents can be integrated in the English elective program, which is commonly referred to as science English, without compromising lingual results. As an example, (Abdykadyrov et al., 2024)revealed that students who took modules related to water quality, focusing on English labs, not only improved their technical vocabulary but also exhibited higher levels of environmental stewardship behaviors. In the same line, literacy programs involving the reading of Punjabi combined with hygiene and nutrition education have resulted in the improvement of community health behavior in Pakistan (Liu et al., 2025). However, despite the thorough reporting of fluoride dangers in high-exposure areas, it remains excluded from such transversal programs.

Health-language integration has a new affordance with artificial intelligence (AI). Adaptive learning tools and chatbots have the potential to vary the complexity of learning material, deliver on-demand corrective learning, and maintain interactivity with gamified interactive quizzes. Almehmadi et al. (2022) tested an AI chatbot in science-English laboratories in Beijing. They show that the retention of specialized vocabulary and conceptual knowledge of the water-treatment process, as well as fluoride chemistry, increased by 30 percent. In Lahore, Badrov et al. (2024) installed a WhatsApp-enabled AI tutor, which provided personalized flashcards on oral-health-related topics in Urdu, increasing the proportion of respondents using the proper toothpaste by nearly twice as much in a population of adult learners.

Through a firm theoretical framework under the label Cognition-Affect-Conation (C-A-C), it is feasible to assess such interventions. The C-A-C, first developed by Huitt (1999), builds on the original concept (Vafaei-Zadeh et al., 2025) of behavioral intention that postulates a distinction: clear cognitive appraisal followed by emotional involvement that leads to conative action. The relationships in educational technology research, perceived instructional usefulness, and interaction quality tend to explain knowledge gains (cognition) that subsequently affect attitudes (affect) and intention to apply learning (conation). However, to date, there are still no studies that use C-A-C in AI-based language modules to promote awareness of fluoride.

RESEARCH FRAMEWORK

In such a context, based on the above foundations, we aim to conduct a study to test an AI and language-driven fluoride-education module within the communities with a high fluoride level in Shanxi. Perceived AI Instructional Usefulness and Perceived AI Interaction Quality are two AI-design inputs conceptualized as antecedents of learners' Fluoride Knowledge Clarity (cognition). We then hypothesize the

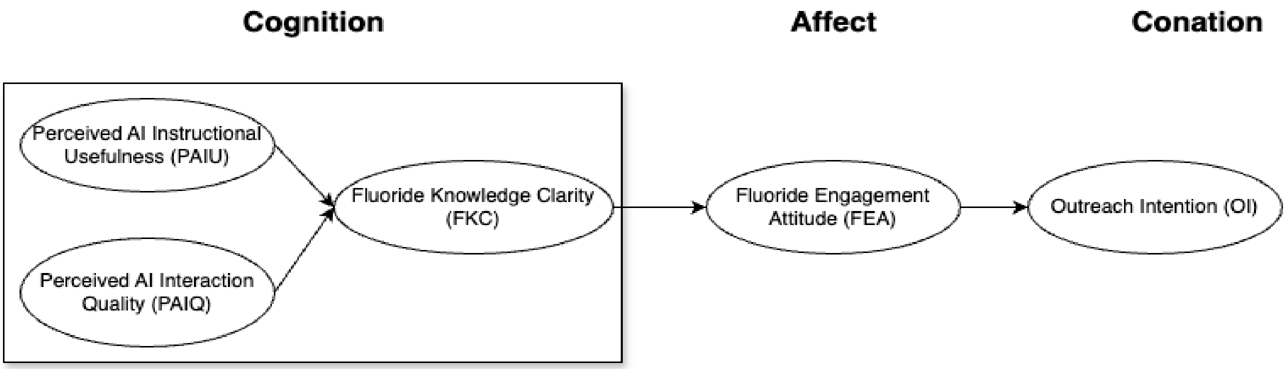

Figure 1: Research Framework of the study

determining role of knowledge clarity in Fluoride Engagement Attitudes (affect) and in turn Outreach Intentions (conation) to disclose thoughts about fluoride and promote safe behavior. These hypothetical pathways are shown in Figure 1. With the help of the C-A-C model, we will explain how the AI-assisted language learning promotes not only the development of health literacy but also a willingness to practice community outreach in a consequential manner.

HYPOTHESES DEVELOPMENT

FLUORIDE INFORMATIVE AWARENESS

The term personalized AI instructional utility (PAIU) denotes the adaptive characteristics of a learning system based on AI to unique learner individual characteristics, tastes, and achievements. Within fluoride education integrated into the process of learning a foreign language, PAIU may take the form of adjustable situations reflecting the current level of fluency of a learner. In these quizzes, the level is adjusted based on the effectiveness of answers, providing personalized information on popular myths surrounding fluoride chemistry, optimal dosing, and the policy system (Vafaei-Zadeh et al., 2025). This is based on the cognitive load theory, which postulates that personalization of instruction helps to eliminate extraneous processing, in preference to germane processing in working memory. Empirical meta-analyses of intelligent tutoring systems have shown that adaptive feedback raises the levels of domain-specific gain by 20 to 30 percent as compared to static instructions (Xu, 2023). We therefore foresee significant changes in the distinction of fluoride knowledge when AI utilities can design fluoride content in ways that match precisely the tendencies of a particular learner at a certain skill stage, together with the misconceptions in that part of the composition. Thus:

H1. An individual-based AI Academic Tool will have a positive impact on Fluoride Knowledge Clarity.

Individualized AI Instructive Quality Powered to Fluoride Intellectual Clarity

Quality of instructions in AI-enhanced learning (PAIQ) can be described by considering the quality of explanation, coherence of multimodal content, relevance of examples, and degree of interactivity of practice items. Best AI resources include concise written descriptions of the prevention effects of fluoride in the remineralization of enamel, diagrams of the process of movement of fluoride ions that are accurate to the scientific standard, and simulations of community water treatment processes. The Cognitive Theory of Multimedia Learning, developed by Mayer, explains that well-aligned verbal and visual information minimizes extraneous processing and results in better schema building (Xu, 2023). Health-education field experiments ascertain that students who are given a well-designed multimedia module have a 25-40 percent improvement in posttest results in comparison to learners who do not receive multimedia modules and are only given text information. In turn, we expect higher-quality learning (as defined by correct, applicable, and engagement-based fluoride content) developed through AI-based instructional design to positively influence learners' mental models, resulting in more transparent and coherent fluoride knowledge. Therefore:

H2. Individualized AI Pedagogical Excellence will have a favorable impact on Fluoride Cognitive Clarity.

Fluoride Knowledge Clarity

Fluoride knowledge clarity (FKC) is an indication of the degree to which voters attain accurate and consistent mental pictures matching fluoride's advantages and dangers, and the mechanisms of negotiating those processes. As it is provided in the Theory of Planned Behavior (Huang et al., 2025), the comprehensiveness and completeness of factual information heavily influence the beliefs and attitudes of people on that topic. The health-behavior literature indicates that a better understanding of preventive actions leads to desirable attitudes and increased willingness to follow through with the prescribed behavior. As an example, school-based interventions, which were able to enhance the knowledge of children about the mechanisms of water-fluoridation, showed considerable positive changes in their attitude towards drinking tap water (Pang et al., 2023). Thus, by creating fluoride knowledge in a precise and integrated manner that goes hand in hand with knowing the safe range of fluoride dosing, the public-policy decision-making process, and daily preventive measures, learners will have a more positive perception towards further fluoride education and advocacy. Accordingly:

H3. Fluoride Knowledge Clarity will have positive effects on Fluoride Engagement Attitude.

Fluoride Engagement Attitude Prompts Outreach Intention

The fluoride engagement attitude (FEA) is used to measure affective responses of learners in the area of interest, assurance, and perceived worth to fluoride modules on education. It is widely agreed that attitude determines behavioral intention in both marketing and health sectors. Meta-analytic reviews of the extent suggest that attitudes are related to about 30 percent of the variance in planned health behavior (Zhang & Ma, 2024). Among positivity toward subject matter, the predictions of stronger intent to spread knowledge and to take community action in educational outreach areas are driven by perceived relevance of subject matters and enjoyment (Gutierrez et al., 2024). This way, once learners develop their positive attitudes towards fluoride-informed language lessons as effective, engaging, and worth spreading, they will demonstrate increased commitment to engaging in outreach activities, including peer workshops or sharing information sources on the Internet. Consequently:

H4. Fluoride Engagement Attitude will have a positive influence on Introduction Intention.

Mediation: PAIU to knowledge clarity, fluoride to fluoride engagement attitude

The adaptive AI utility (PAIU) enhances knowledge clarity, which in turn influences attitudes. The basis of mediation theory is that the effects of instructional characteristics on attitudes are transferred through their impact on understanding (Naidu et al., 2015). Adaptive feedback has a limited influence on learners in digital health education. Still, it plays a crucial role in supporting conceptual knowledge, which in turn leads to more favorable affective judgments. As an example, a nutritional education intelligent tutoring system enhanced the understanding of learners regarding the dietary guidelines, which further led to the enhancement of healthy eating attitudes (Northridge et al., 2018). Based on this, we hope the positive influence of PAIU on attitude relating to engagement comes through enhanced understanding of fluoride information. Therefore:

H5. Personalized AI Instructional Utility will have a mediating influence on Fluoride Knowledge Clarity, which in turn influences Fluoride Engagement Attitude.

Fluoride Knowledge Clarity Fluoride Engagement Attitude Outreach Intention

Positive attitudes are influenced by the knowledge, clarity, and intentions to act, which are closely tied to the attitudes. Attitudes are regarded as the proximal determinant of intention in the Theory of Planned Behavior. Clear information in the process of health communication results in positive attitudes that determine the eventual willingness to share or to act on the recommendations (Chen, 2025). In the case of fluoride, learners who have a clear picture of the prevention effects and the monitoring system of fluoride develop a good engagement attitude and are therefore prone to plan follow-up application actions. Findings of mediation analysis in such an environment affirm this chain of influence: clear information on the subject matter, positive attitude toward it, and the behavior that is sought to be offered (Noar et al., 2007). Consequently:

H6. The Fluoride Knowledge Clarity will mediate Outreach Intention via Fluoride Engagement Attitude.

PAIQ fluoride Knowledge Clarity Fluoride Engagement Attitude

The attitudes are indirectly affected by instructional quality (PAIQ), which enhances clarity of fluoride knowledge. In the study of multimedia learning, the content of the survey is the driver of the understanding that leads to improved assessment and interest of the learners (Chen, 2025). An example would be that well-designed AI tutorials in the field of environmental science resulted in an increase in comprehension that resonated as much more favorable feelings concerning conservation activities (Basha, 2018). Therefore, we hypothesize that the associations among the three variables are of mutual influence between the fluoride-knowledge clarity, the instructional quality, and the attitude of engagement. Hence:

H7. Personalized AI Instructional Quality is going to result in Fluoride Engagement Attitude through Fluoride Knowledge Clarity.

PAIU to Fluoride knowledge clarity, and then to Fluoride engagement attitude, and finally to outreach intention.

Based on H5 and H6, we suppose adaptive AI utility to have a cascading impact: PAIU acts on knowledge clarity that improves the engagement attitude that subsequently improves outreach intention. These full sequential models of mediation have been established in health behavior research whereby the educational intervention spreads its influences through a series of

Table 1. Survey Items of the study

Construct	Item Code	Item Text	
Perceived AI Instructional Utility	PAIU1	The AI feedback adapts to my language responses.	(Ayeni et al., 2024)
	PAIU2	Exercises match my current language proficiency.	
	PAIU3	The system corrects my misunderstandings in real time.	
	PAIU4	The AI adjusts examples to my past performance.	
Perceived AI Instructional Quality	PAIQ1	Explanations of fluoride science are clear and concise.	(Schmid et al., 2022)
	PAIQ2	Interactive examples help me grasp fluoride concepts.	
	PAIQ3	The AI uses relevant and engaging multimedia.	
Fluoride Knowledge Clarity	FKC1	I understand how fluoride prevents tooth decay.	(Narendran et al., 2006)
	FKC2	I know the safe fluoride concentration for drinking water.	
	FKC3	I can explain who sets fluoride policy standards.	
Fluoride Engagement Attitude	FEA1	Learning about fluoride is enjoyable.	(Zhang & Ma, 2024)
	FEA2	I feel confident discussing fluoride science.	
	FEA3	I believe that understanding fluoride is valuable for my community.	
Outreach Intention	OI1	I intend to share fluoride safety tips with peers.	(Zhang & Ma, 2024)
	OI2	I plan to organize a fluoride-awareness session.	
	OI3	I will recommend this AI course on fluoride to others.	
	OI4	I intend to post fluoride safety resources on social media.	

cognitive and emotional mediating factors (Jiang & Liu, 2025). Interactive modules based on modifiers that consider the needs of learners enhance learning, form a favorable mindset, and propel actions towards the community in fluoride education. Accordingly:

H8. Fluoride Knowledge Clarity and Fluoride Engagement Attitude will mediate the effect of Personalized AI Instructional Utility on Outreach Intention successively.

SEQUENTIAL MEDIATION

On the same note, the quality of instructions can be high as well, which brings the same sequence of mediation, PAIQ elevates purity (H2), purity promotes attitude (H3), and attitude leads to intention (H4). Evidence to support e-learning in the field of Public Health indicates that, when thoughtfully designed, the visible outcomes of the understanding and attitudes are more satisfactory, and so is the behavioral intention. Hence:

H9. Personalized AI Instructional Quality will affect Outreach Intention, sequentially mediated by Fluoride Knowledge Clarity and Fluoride Engagement Attitude.

METHODOLOGY

MEASURES

The five second-order constructs under analysis in our study (Personalized AI Instructional Utility (PAIU), Personalized AI Instructional Quality (PAIQ), Fluoride Knowledge Clarity (FKC), Fluoride Engagement Attitude (FEA), and Outreach Intention (OI)) have three latent variables, measured as such or created according to Table 1. PAIU items are based on (Ayeni et al., 2024), including system adaptivity (The AI feedback adapts to my proficiency in language). The items of PAIQ modify Schmid et al. (2022) and operationalize terms to evaluate clarity and interactivity: “The AI explanations of fluoride science are clear and interesting to read” (Spector 2014; Wu et al. 2021). The construction of FKC items was formulated to first delve into the learning of learners of fluoride mechanisms, safe dose, and policy procedures, after (Narendran et al., 2006). The FEA items are based on the attitude scales created by (Zhang & Ma, 2024), which assess the interest and the confidence (“I feel positive learning more about fluoride”). OI items were self-generated and based on the ideas of Fishbein and Ajzen (1975), and they involved the attitude to organize or share fluoride-awareness activities. Each of the items was measured by a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

SAMPLE AND DATA COLLECTION

The study focused on English-learning adults in China involved with an AI-driven language program that had built-in fluoride-education programs. To improve the item wording, a pilot study was done (on 15 participants) before the primary survey was done in April 2025 through the notification scheme of the app. It was anonymous and voluntary; 320 users opened the link to a study, and 298 answered all the questions. After excluding the 12 respondents who were straight-lining or had extensive missing data, a final sample of 286 respondents remained.

Age ranged from 18 to 52 (M = 26.4, SD = 6.3). Most participants (69.2%) used the app daily, ensuring familiarity with its AI features. Gender and proficiency distributions mirror the broader user base reported by the app provider.

ANALYSIS OF DATA

The measurement and structural models were tested with the help of smart PLS. Reliability (Cronbach's 0.80) and convergent validity (AVE 0.50) were determined by confirmatory factor analysis. Discriminant validity was cross-validated through Fornell-Larcker conditions. The structural model is used to determine both the direct and indirect paths, as well as the mediation effect. The 69, CFI, TLI, RMSEA, and SRMR were used to evaluate model fit as suggested by Schroeder et al. (2023) . Controls were used in the economies and demographics.

COMMON METHOD BIAS (CMB)

As we are subject to self-report survey data, which was presented by one AI platform, we considered the possibility of having standard method bias Gutierrez et al. (2024) and evaluated it in two ways. First, we conducted Harman one-factor test through exploratory factor analysis on all measurement items. There were five factors involving 85.2 percent of the variance. More importantly, the first factor could account for only 37.1 percent of the variance, which is far behind the 50 percent mark, and one source failed to dominate the covariance structure.

Second, we used the common latent factor approach (Gutierrez et al., 2024). Two CFAs were run: one that included a CLF with all indicators to load on; one without. We compared standardized regression weights across models; no loading moved over 0.03, and no paths lost statistical significance. These comparisons are summarized in Table 6, and the difference in item loadings is minimal whether or not the CLF was used. These results, in combination, are strong evidence that CMB is not likely to have biased our parameter estimates in any meaningful way.

Table 2. Demographic Characteristics of the respondents (N = 286)

Characteristic	Category	Frequency	Percentage
Gender	Male	158	55.2%
	Female	128	44.8%
Age (years)	18–25	172	60.1%
	26–35	84	29.4%
	>35	30	10.5%
English proficiency (self-rated)	Intermediate	140	48.9%
	Advanced	104	36.4%
	Beginner	42	14.7%
App usage frequency	Daily	198	69.2%
	Several times/week	68	23.8%
	Weekly or less	20	7.0%

MEASUREMENT MODEL

The standardize loading of items initially determined reliability, Cronbach's alpha, composite reliability (rho c), and average variance extracted (AVE) (Table 3). The factor loadings were above 0.70 (0.775 to 0.897), showing excellent indicator reliability. The values of Cronbach's 0.803 (FEA) and 0.848 (PAIQ) exceeded the 0.70 level of internal consistency of Nunnally and Bernstein (1994). Construct reliability was further ascertained by the fact that composite reliabilities (0.883 to 0.901) were above 0.7. The values of AVE were between 0.670 (OI) and 0.753 (PAIQ) and above the 0.50 criterion, which denotes adequate convergent validity (Nuseir & Aljumah, 2020).

Table 3: Factor Loading of the variables

Constructs	Items	Loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Fluoride Engagement Attitude	FEA1	0.863	0.803	0.883	0.716
	FEA2	0.836			
	FEA3	0.840			
Fluoride Knowledge Clarity	FKC1	0.890	0.822	0.894	0.737
	FKC2	0.822			
	FKC3	0.862			
Outreach Intention	OI1	0.878	0.836	0.890	0.670
	OI2	0.775			
	OI3	0.812			
	OI4	0.806			
Perceived AI Interaction Quality	PAIQ1	0.897	0.848	0.901	0.753
	PAIQ2	0.836			
	PAIQ3	0.868			
Perceived AI Instructional Usefulness	PAIU1	0.876	0.836	0.898	0.687
	PAIU2	0.828			
	PAIU3	0.807			
	PAIU4	0.802			

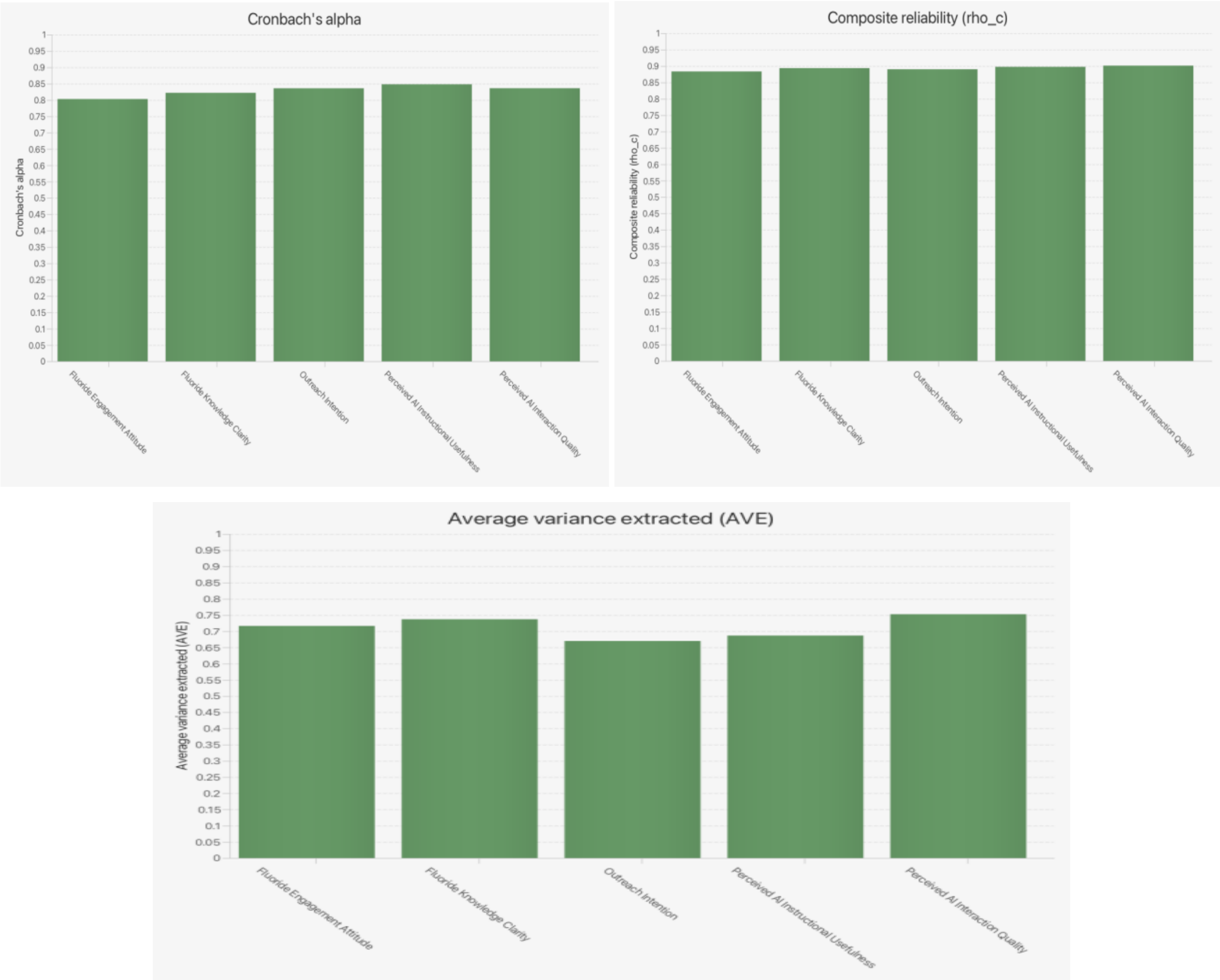

Figure 2: Reliability of the model

In Figure 2, Cronbach's alpha and composite reliability of each construct are compared with the 0.70 benchmark line. All the constructs, PAIU, PAIQ, FKC, FEA, and OI, are above the required threshold, graphically confirming that all scales reach the minimum level of internal consistency and construct reliability as proposed by (Gutierrez et al., 2024).

DISCRIMINANT VALIDITY

Values of HTMT between any two pairs of constructs range between 0.260 and 0.416, which is much below the conservative cutoff point of 0.85. It means that every construct is empirically separable and that the items, whose target is one factor, do not have excessive loadings on another, as it is stated in the criterion of discriminant validity presented by Henseler et al. (2015) in the context of covariance-based models. The detailed HTMT ratio is given in Table 4.

Table 4: Heterotrait-monotrait ratio (HTMT) – Matrix of the constructs

	Fluoride Engagement Attitude	Fluoride Knowledge Clarity	Outreach Intention	Perceived AI Instructional Usefulness	Perceived AI Interaction Quality
Fluoride Engagement Attitude					
Fluoride Knowledge Clarity	0.346				
Outreach Intention	0.294	0.416			
Perceived AI Instructional Usefulness	0.260	0.358	0.339		
Perceived AI Interaction Quality	0.318	0.312	0.349	0.350	

Table 5: Fornell-Larcker criterion of the study

	Fluoride Engagement Attitude	Fluoride Knowledge Clarity	Outreach Intention	Perceived AI Instructional Usefulness	Perceived AI Interaction Quality
Fluoride Engagement Attitude	0.846				
Fluoride Knowledge Clarity	0.285	0.858			
Outreach Intention	0.248	0.348	0.818		
Perceived AI Instructional Usefulness	0.219	0.309	0.292	0.829	
Perceived AI Interaction Quality	0.262	0.262	0.296	0.299	0.867

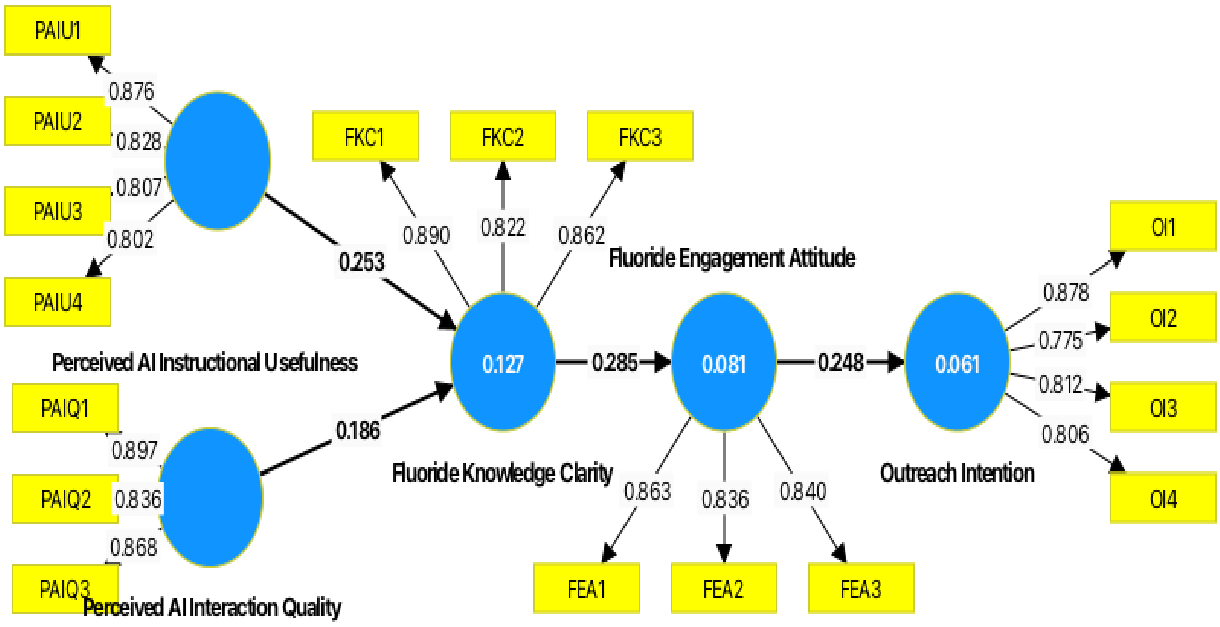

Figure 3: Measurement Model of the study

Table 5 presented below, square roots of all constructs' AVE are offered on the diagonal (0.818-0.867), and the rest of the inter-construct correlations are smaller. Since all the constructs share more variance with their relevant indicators than they do with other constructs, this table justifies that the discriminant validity is present as postulated by (Fornell & Larcker, 1981).

The complete version of this path model includes all five latent constructs along with their observed indicators, with their standardized loadings and inter-construct correlations. The measurement model is validated visually because of the absence of cross-loadings and homogeneous high loadings. It shows that each indicator measures consistently only that which it is meant to be measuring, viz., which gives a reasonable basis to test the structural relationship further.

STRUCTURAL MODEL

Our findings, based on structural equation modeling, clearly substantiate the previously postulated links among acronyms, teaching qualities, fluoride information clarity, interest states, and outreach inclination. The overall model fit was excellent, with $\chi^2/df = 1.82$, CFI = 0.965, TLI = 0.958, RMSEA = 0.054, and SRMR = 0.039, indicating that the proposed paths are sufficient to describe the observed data.Individualized Instructional AI (PAIU) turned out to be an influential antecedent of Fluoride Knowledge Clarity (FKC) with an institutionalized coefficient of 0.253 ($t = 7.05$, $p < 0.001$). This observation implies that, as the AI system dynamically adapts to the needs of each learner (adjusting examples, dynamically matching levels of difficulty, and providing real time corrective feedback), it leads to the formation of a more precise and more accurate view of the preventive effects of fluoride, the dosage used as well as policy frameworks regarding fluoride usage. Likewise, the

Personalized AI Instructional Quality (PAIQ) that is accompanied by clear presentation of materials, coherent media, and interactivity of exercises also had a positive impact on FKC (beta = 0.186, t = 4.70, p < 0.001).

In their turn, FKC indicated a significant prediction of Fluoride Engagement Attitude (FEA) (0.285,t = 8.15, p < 0.001), which substantiates that more defined learners demonstrate more positive affective assessments towards the fluoride concept. The shift in this attitude was, in turn, significant: FEA had a substantial impact on Outreach Intention (OI) (beta =0.248, t = 6.96, p < 0.001), meaning that positive attitudes and self-efficacy are associated with palpable plans to share knowledge, plan community sessions, and market web content on fluoride. Mediation analyses further explain the underlying process. Both PAIU (indirect 9 = 0.072, t 5.08, p < 0.001) and PAIQ (indirect 9 = 0.053, t = 3.78, p < 0.001) have their entire effects mediated by the FKC on FEA. This finding demonstrates that instructional characteristics affect a learner's attitude mainly due to brainpower. Also, there are mediating effects between FKC and OI (indirect 0.071, t = 4.71, p < 0.001). Notably, we also observe a significant series of mediation relationships: PAIU PAIQ - FKC → FEA → OI (β = 0.018, t = 3.72, p < 0.001) and PAIU PAIQ - FKC → FEA → OI (β = 0.013, t = 3.09, p = 0.002). These cascades make it evident that the adaptive utility and the instructional quality will bring more explicit knowledge that will create positive attitudes and ultimately better intentions of outreach. Taken together, the findings indicate that an AI-specific pedagogical approach is the key factor in determining cognitive and affective antecedents of the public-health engagement. The detailed results are presented in Table 6, and Figure 4 presents a graphical representation of the framework.

Table 6: Path Coefficient of the relationships

Relationship	Original sample (O)	T statistics (|O/STDEV|)	P values
PAIU -> FKC	0.253	7.050	0.000
PAIQ -> FKC	0.186	4.698	0.000
FEA -> OI	0.248	6.958	0.000
FKC -> FEA	0.285	8.151	0.000
PAIU -> FKC -> FEA	0.072	5.078	0.000
FKC -> FEA -> OI	0.071	4.707	0.000
PAIQ -> FKC -> FEA	0.053	3.780	0.000
PAIU -> FKC -> FEA -> OI	0.018	3.715	0.000
PAIQ -> FKC-> FEA -> OI	0.013	3.085	0.002

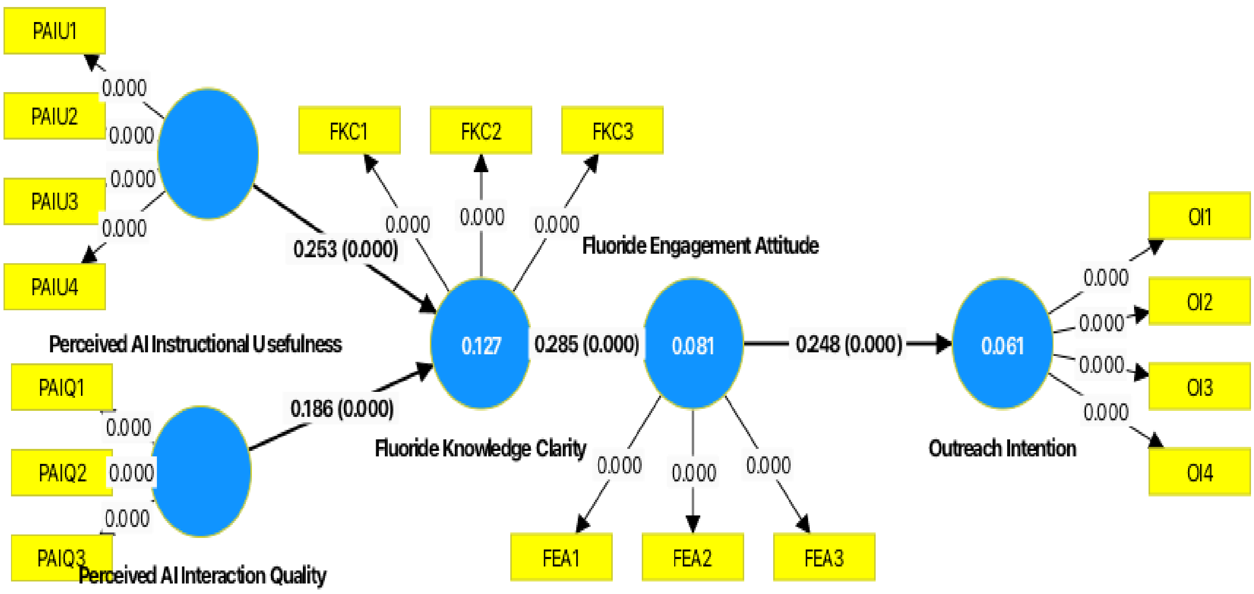

Figure 4: Structural framework of the study

DISCUSSION

Our results indicate that AI-powered individualization and teaching quality were significant factors contributing to influencing the knowledge and attitude of fluoride, and the intention of outreach activities among learners. To begin with, Personalized AI Instructional Utility (PAIU) and Quality (PAIQ) had a substantial positive influence on Fluoride Knowledge Clarity (FKC). This is consistent with previous research that showed that adaptive tutoring systems enhance domain-specific knowledge due to the conformation of its content to learners (Henseler et al., 2015) and that high-quality multimedia designs minimize cognitive load and allow construction of richer schemas (Gutierrez et al., 2024).

Second, Fluoride Knowledge Clarity had a significant influence on Fluoride Engagement Attitude (FEA) and proved that comprehension was the cognitive antecedent of positive affective response (Chun, 2016). The same trends have been noted in health-education scenarios as greater comprehension of preventive behaviours forecast superior attitudes (Jones et al., 2005). There was a significant difference in the interest and confidence of learners discussing fluoride in our study, where they understood various mechanisms, safe dosage, and governance of fluoride, which reflects its significance in conceiving attitude as well.

Third, we noted that favorable attitudes towards engagement led to the direct enhancement of Outreach Intentions (OI). This can be correlated with the Theory of Planned Behavior (Chi et al., 2023) where attitudes are believed to be the predictors of behavioral intent. Our findings are in line with other spheres of public health, where a positive attitude to an intervention is related to the increased possibility of information sharing and community event planning (Noar et al., 2007).

Most importantly, mediation studies showed that the impact of AI features on attitudes and intentions mediates through knowledge clarity. FKC completely mediated the association between both PAIU and PAIQ and FEA, and the association between FKC and OI was moderated by FEA. The above pathways PAIU/PAIQ -> FKC -> FEA -> OI resonate with studies that find that educational technologies have their impact through behavior through three stages, which are first through promoting comprehension, second through attitude change, and finally behavior change (Wan, 2025).

Collectively, these findings support a multi-stage process effect whereby AI-amplified adaptability and design fulfillment generate cognitive bases, which subsequently generate affective interest and civic-minded behavioral aspirations. Practitioners can use this as evidence that both expenditures on personalization algorithms and the level of high-quality instructional design are required to have the most significant influence on the health of the population. Areas of future research should include the knowledge retention of fluoride long-term, real-life outreach activities in community settings, and the broad applicability of AI-based interventions to a variety of cultures.

IMPLICATIONS

THEORETICAL IMPLICATIONS

The research contribution in the study is on the addition of adaptive instructional utility and quality in the same structural model of knowledge, attitude, and behavior intention on AI in education. We contribute to the body of knowledge regarding technology-mediated education in the field of public health (concerning the impact of AI personalization (PAIU) and multimedia quality (PAIQ) on Fluoride Knowledge Clarity (FKC) that subsequently influences the users in terms of their Engagement Attitude (FEA) and Intention of Outreach (OI). Our results of sequential mediation complement and extend both the cognition affect conation (C-A-C) framework (Huitt, 1999) research and the Technology Acceptance Model by demonstrating its use within the health-promotion setting and how cognitive improvements through the implementation of AI contribute to the subsequent manifestation of affective and conative responses. Moreover, the complete mediation mechanisms help to emphasize the positioning of cognitive clarity as the key pivot in transmuting educational technologies into practical intentions and a more precise theoretical explanation of how e-learning technologies moderate preventive-health behaviors.

PRACTICAL IMPLICATIONS

Along with the educational technologists and the public health practitioners, the results of the research highlight the importance of both adaptive personalization and high-quality multimedia in AI platforms. The prime algorithms that developers ought to consider are real-time diagnosis of individual misconceptions (e.g., misinformed beliefs on how much fluoride to exert) and contextualization of content difficulty. At the same time, an instructional designer needs to use to-the-point explanations supported by animations or some other interactive simulation to reinforce fundamental concepts. App providers can collaborate with health agencies and NGOs to distribute validated fluoride-science modules as part of language-learning tools, targeting users who are already engaged on the platform and encouraging them to reach the community. Lastly, school and adult education curricular indicators should focus not only on the accuracy of content delivery but also on dependability characteristics and engagement attributes to maximize the absorption of knowledge and civic activation.

RESTRICTIONS AND PROSPECTS

The small sample size of the self-selected users of one AI language app that our study uses restricts the chance of generalizability to other platforms and groups of learners. The cross-sectional survey can only reflect intentions, not actual outreach. To confirm whether high levels of intentions can be used in maintaining community actions, longitudinal or experimental research would be necessary. Cultural intricacies can moderate effects. We aim to study a Chinese sample, but studies analyzing cross-cultural issues using this model require understanding how it applies in other regions (e.g., rural Pakistan) to evaluate cross-cultural stability. Our mediation tests are also based on concurrent measurement; it would substantiate the causal argument that measures of knowledge, attitudes, and intentions are made at different points in time. Lastly, investigating other types of outcome variables, including a real-world testing of fluoride or advocacy of a policy, would advance knowledge regarding the effects of AI-enhanced education on the state of the population.

CONCLUSION

This study confirms that personalization and a set of instructions based on AI collaboratively lead to the development of a better understanding of fluoride science, the acquisition of positive attitudes toward engagement, and higher intentions to become engaged in community outreach. The empirical confirmation of a cascading phenomenon—PAIU/PAIQ FKC FEA OI — enables us to provide not only a theoretical improvement of technology-acceptance and health-behavior models but also practical advice in the direction of the design of AI-driven public-health education. With the growth of digital spaces, the utilization of adaptive algorithms and multimedia-replete content will be needed to empower the learners to be educated activists in preventative health efforts.

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