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Fluoride in Cultural and Literary Narratives: AI as a Tool for Enhancing Knowledge on Educational Platforms

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ABSTRACT

Purpose: With an emphasis on the function of artificial intelligence (AI)-generated instructional content, the current study attempts to investigate the impact of fluoride-related cultural and literary tales on information retention. The study investigates the links between exposure to fluoride narratives, learners' attitudes about fluoride narratives, engagement with AI-based platforms, and perceived utility of AI-generated information by utilizing the Technology Acceptance Model (TAM). Additionally, the study looks at how AI involvement and attitudes affect knowledge retention through serial and mediating effects.

Methods This study used a cross-sectional survey approach with students in China's Jiangxi and Henan provinces as its target population. The relationship between exposure to fluoride narratives in educational materials, perceptions of the value of AI-generated information, interaction with AI platforms, and knowledge retention was examined through the application of structural equation modeling, or SEM. The pathways in the Technology Acceptance Model were examined using cross-sectional and serial mediation analyses. Of particular interest was the effect of AI-driven educational material on attitudes and engagement that lead to knowledge retention.

Results: The results show that learners' views regarding fluoride and their engagement with AI platforms are greatly impacted when they are exposed to fluoride narratives in instructional content. These elements also highly predict the memory of fluoride-related knowledge. The study shows that the association between knowledge retention and the perceived utility of AI-generated information is entirely mediated by positive sentiments regarding the narratives and involvement with AI-based learning platforms. The impact of AI-generated material on knowledge retention is contingent upon learners' attitudes and their degree of involvement with AI platforms, as demonstrated by serial mediation studies.

Research Limitation/Implication: Since the cross-sectional methodology makes it difficult to determine causal linkages, further longitudinal research is required to fully comprehend the long-term impacts of AI-enhanced instructional content on knowledge retention. To improve the study's validity, more objective measures of engagement and information retention should be included in subsequent studies.

Orginality: This work presents a unique use of TAM in the context of educational technology, focusing on how AI-generated material might support learning experiences that are narrative-driven and culturally rich. This work contributes to the understanding of how technology acceptance affects information retention within the context of fluoride-related cultural and literary tales by mapping the intermediary processes of learner attitudes and AI engagement.

Keywords: Fluoride Narratives, AI-Generated Instructional Content, Knowledge Retention, Technology Acceptance Model (TAM), AI-Based Learning Platforms.

1. INTRODUCTION

There are currently 118 known chemical elements, including fluorine. It is not found in nature in its free form due to its strong reactivity; as fluoride, it is the thirteenth most prevalent element in the crust of the world. Fluorides are found in everything that people eat and drink as well as all throughout the natural world. Fluorides therefore have an impact on human health. Based on their optimal consumption, they might have a positive or negative function. Fluoride is a bone-seeking element, similar to calcium, and has effects on the skeletal system, including the teeth as well as affecting soft tissues such as the thyroid and brain. Of the fluoride that is retained in the body, 96–99% is found in the skeleton. An adequate amount of fluoride is considered by many to lower the risk of dental cavities but too much fluoride can cause neurological symptoms as well as dental and skeletal fluorosis. Food and water (including various drinks) are the two primary sources of fluoride. Ninety percent of rural water supply comes from groundwater sources, many of which contain low fluoride levels. Perennial rivers, which may vary in their fluoride concentrations, furnish a significant portion of the water supply for all major cities in the nation. Studies on epidemiology have demonstrated that fluoride toxicity is exacerbated by starvation. It's no secret that malnutrition is rampant in our nation's rural parts and that controlling it has grown increasingly challenging [1, 2]. In Pakistan, fluoride contamination in groundwater is a significant concern, particularly in rural areas of Punjab and Sindh. Many villages rely on tube wells for drinking water, with fluoride levels often exceeding safe limits. This has led to widespread cases of dental and skeletal fluorosis, further compounded by malnutrition and lack of access to healthcare resources. Addressing these issues requires improved water quality monitoring and community awareness campaigns[3]. The halogen fluorine is widely dispersed over the Earth and is never found in nature in a free condition. It is found in the form of fluoride compounds, which are minerals found in rocks and soil. Fluorine does not exist alone. Fluoride is known to have a significant impact on the mineralization of teeth and bones and to accumulate in the body's hard tissues. In Mexico, dental caries is regarded as a serious dental public health and is frequently found in those with lower socioeconomic level. Although fluoride is acknowledged as a useful tool for preventing dental cavities, too much fluoride can increase the risk of fluorosis in the bones and teeth. Up to the age of six, fluoride consumption during dental development may encourage the development of fluorosis [4, 5]. Fluorosis is thought to predominantly affect permanent teeth. There are several ways in which fluoride affects ameloblasts directly (during the secretory and maturation phases), as well as indirectly (during the nucleation and formation of crystals in all phases of enamel) in the developing matrix.[6] It follows that fluorosis has become a serious public health concern, is fast expanding throughout the nation, and is now quite common. According to official data, fluorosis affects 275 districts in India, which are dispersed among 21 states. Six million individuals are believed to be disabled by fluorosis, while an estimated 66 million people who live in endemic regions are at risk of contracting the disease. In order to effectively treat individuals with fluorosis who also have neurological issues, it is necessary to comprehend the clinical symptoms of these patients [3] Surface water fluoride levels fluctuate depending on location and distance from emission sources. Concentrations of surface water in general span the 0.01–0.3 mg/litre range. Seawater has the following: greater fluoride concentrations than in fresh water between 1.2 and 1.5 mg/litre. Elevated levels of fluoride have been found where the fluoride content in natural rock is high, and elevated Levels of inorganic fluoride are frequently observed in areas where volcanic or geothermal activity occurs (25– 50 milligrams of fluoride per liter in geysers and hot springs up to 2800 mg/liter in certain East African lakes in the Rift Valley). Anthropogenic emissions may can result in higher fluoride levels in the surroundings. Both man-made and natural sources release gases and particles into the atmosphere that include fluoride. Fluorine emitted in the form of gas and particle matter placed in the immediate area of an emission source, even if some particles might interact with additional components of the atmosphere [7]. The allocation and the amount of fluoride deposited in the air are related. Depending on the intensity of the emission, the weather, chemical reactivity and particle size.[8, 9] According to Mason and Moore, fluorine is the thirteenth most abundant element in the universe and is extensively distributed throughout nature. Because fluoride is the most electronegative element in the chemical elemental system, it never exists in its elemental form; instead, it interacts with other elements to produce fluoride compounds, which make about 0.06–0.09% of the crust of the earth. Fluoride is found in all soils, plants, and animals. It is not considered to be an essential trace element of most living things, including plants, animals, and humans. Fluoride plays a significant part in the mineralization of bone and the development of tooth enamels. Health issues that impact both young and elderly can arise from consuming fluoride in excess (greater than 1 ppm). Human metabolic processes are impacted by greater fluoride concentrations, and those who are overexposed may experience non-skeletal symptoms, dental or skeletal fluorosis, or a combination of these illnesses. The amount of fluoride present in the air, soil, or water, as well as the degree of exposure to these concentrations, determine the occurrence and severity of fluorosis.[10, 11] The present study specifically aims to respond to the following research questions: grouped into three main areas of inquiry for research: (1) In light of the connection between exposure to fluoride narratives and information retention results, the moderation of AI-generated material and interaction with AI platforms. The purpose of this topic is to investigate potential mediators between fluoride story exposure and information retention, as most prior research has only examined direct routes, ignoring the moderating effect of AI involvement. Furthermore, by means of serial mediation of engagement with AI platforms and attitudes, this research aims to determine (2) how learners' attitudes toward fluoride narratives interact with the perceived usefulness of AI-generated content to influence knowledge retention. This inquiry is part of the present study's effort to understand more about how artificial intelligence (AI)-powered educational systems improve learning results by using literary and culturally rich fluoride narratives. There are three main ramifications for this research. It first adds to the corpus of studies by exploring the sequential effects on information retention of fluoride story exposure, AI perceived utility, and engagement with AI-based learning platforms. Secondly, it offers a sophisticated comprehension of how contemporary educational technology, such as information created by artificial intelligence, may be incorporated into curricular materials to improve learning in fields that are scientifically and culturally relevant. Finally, by providing useful insights that may guide the creation of AI-based learning platforms and tools targeted at enhancing student engagement and knowledge retention in higher education, this work adds to the expanding body of research on the nexus between technology and education. Although fluoride is most commonly associated with oral health, it also has important cultural, historical, and environmental implications in many parts of the world including China. Because of the difficulties associated with fluoride exposure from contaminated groundwater, places like Henan Province in China have made fluoride a central theme in both scientific and cultural narratives. By incorporating these stories into teaching materials, educators have a rare chance to help students better comprehend the social function that fluoride plays.

2. BACKGROUND OF THE STUDY

2.1. Theoretical framework

2.1.1 Analysis of the Technology Acceptance Model (TAM)

Perceived utility and simplicity of use are the two main elements that impact consumers' adoption of technology, according to the Technology adoption Model (TAM). These elements influence how users feel about incorporating technology like artificial intelligence (AI) into their learning processes within the framework of educational platforms. This model responds to important queries about the adoption of technology: How helpful do students think AI-powered course materials are? and What degree of ease do they have using this technology? The independent variables (IVs) in this study are the perception of the usefulness of AI-generated content and exposure to fluoride narratives in educational content. The first variable assesses students' knowledge with fluoride as it is presented in different settings by counting the frequency and degree to which they come across cultural and literary narratives about fluoride in their educational materials [12]. The second variable measures how much students think AI-generated fluoride education content is valuable and helpful. It looks at how much students think AI-enhanced content explains the cultural and literary components of fluoride [13]. According to TAM, learners will have good opinions regarding adopting AI-generated educational material (AIGC) when they perceive it to be both helpful and simple to browse. Their behavioral intents to interact with AIGC may be influenced by this optimistic outlook, which might eventually result in better educational results, particularly with relation to Knowledge Retention about Fluoride. This dependent variable assesses how well students remember fluoride facts following exposure to artificial intelligence (AI)-generated content that combines literary and cultural narratives[13]. Additionally, attitudes about learning fluoride narratives and engagement with AI-based learning platforms serve as mediating variables in this study. The degree to which students actively engage with AI-driven teaching tools when learning about fluoride narratives is measured by their engagement with learning platforms. It examines how frequently and in-depthly students utilize these AI-powered platforms. Due to AI-generated material, the second mediation variable emphasizes whether or not learners find these tales fascinating and worth examining. It also captures learners' attitudes, interest, and excitement towards interacting with instructional content concerning fluoride [14].

2.1.2. Application of TAM in Research

The Technology Acceptance Model (TAM) has been used in several research from a variety of fields to examine user behavior and technology uptake. TAM has been used by researchers to study consumer behavior in contexts like e-learning environments, mobile apps, and online shopping. According to Venkatesh and Davis [13, 15], the approach has shown efficacy in comprehending how users' views of technology influence their participation, including the acceptance of AI in educational environments. TAM has shown to be useful in the field of information systems (IS) for evaluating user loyalty and happiness with relation to digital platforms, such as the use of social networking sites (SNS) and the uptake of novel online services [16]. This study attempts to demonstrate how perceived utility and simplicity of use of AIGC might affect students' engagement and cognitive results in learning settings by structuring fluoride tales within the TAM framework.

2.1.3. Applying TAM to Fluoride Exposure, Cognitive Engagement, and Knowledge Retention in the Context of AIGC

With AIGC involvement acting as a mediating factor, this study examines the relationship between Exposure to Fluoride Narratives in Educational Content, Perceived Usefulness of AI-Generated Content, and Knowledge Retention results using the Technology Acceptance Model. This study enables a sophisticated investigation of how learners' perceptions impact their engagement and retention of information by placing the independent variables in the context of TAM. Previous research has shown that exposure to instructional narratives is positively correlated with knowledge retention [17]. This study expects that students' perceptions of AIGC's utility and simplicity of use will improve their recall of fluoride narrative information through the application of TAM. This study aims to improve understanding of the intricate connections between learner engagement, fluoride exposure, and information retention results by implementing the TAM framework.

2.1.4. Application and Contribution of the TAM Framework to the Current Study on Fluoride Exposure and Knowledge Retention

This study investigates the effects of cognitive and emotional factors on the association between knowledge retention results and exposure to fluoride narratives using the Technology Acceptance Model. Because the TAM framework has been widely used by researchers to comprehend behavioral goals, emotional and cognitive reactions, and technology adoption in educational contexts, it is especially appropriate for our project [18]. This study offers an organized method for examining, within the framework of information retention, the mediating functions of attitudes toward learning fluoride narratives and engagement with AI-based learning platforms through the use of TAM. This approach adds to the body of research on the ways in which cultural narratives and educational technology—such as AIGC—interact to affect students' learning and retention. The results might influence more comprehensive teaching approaches by highlighting how crucial it is to include narrative-driven AI technologies into curriculum in order to improve cognitive outcomes in learning settings.

2.2. Literature Review

Research indicates that incorporating literary and cultural tales into instructional materials aids students in placing scientific subjects—like fluoride—into larger historical and cultural contexts. For example, Friesen (2019)[19] talks about how stories influence how the general public views fluoride in local areas. Concurrently, scholars such as Smith (2020)[20] underscore the growing dependence on artificial intelligence (AI)-driven platforms for pedagogical objectives, especially when imparting intricate topics like environmental science and public health. In various areas, AI-powered educational technologies are becoming more and more popular, and students are depending more and more on these platforms for better educational experiences. Johnson et al. (2021) claim that AI-generated content has the ability to humanize instructional narratives, increasing students' interest in and recall of difficult material. The Technology Acceptance Model (TAM) in its application offers a useful paradigm for comprehending how students engage with information augmented by AI. This study investigates how AI might support students' engagement with fluoride narratives, building on earlier findings.

2.2.1 Fluoride Exposure in Cultural and Literary Narratives

Fluoride's dual character as a public health advantage and a cause for concern has led to its emergence as a key issue within literary and cultural narratives. Although it is commonly known that fluoride can prevent dental cavities, recent talks have brought attention to possible neurotoxic consequences, especially in susceptible groups like children and young adults[21, 22]. Literary portrayals frequently reflect prevailing societal concerns, indicating a rising apprehension about the long-term cognitive effects of fluoride exposure. Stories in medical literature, for example, are beginning to discuss the connection between excessive fluoride exposure and poor mental health outcomes, such as cognitive decline and a rise in psychological problems[23]. This representational dichotomy highlights the significance of comprehending the cultural discourse about fluoride and how it is presented.

2.2.2 Cognitive Development and Fluoride

Because fluoride has both positive and negative health impacts on people, scientists are currently debating whether or not it should be present in water. The extent of anthropogenic fluoride pollution in groundwater is being exacerbated. In comparison to other types of exposure, groundwater is purportedly the primary method through which humans are highly exposed to fluoride. Fluoride exposure in humans can cause a wide range of health concerns, from minor impacts on teeth and bones to serious renal difficulties, neurotoxicity, and even cancer. Fluoride poisoning is currently receiving a lot of attention in endemic regions because it negatively affects children's cognitive performance, as youngsters are more vulnerable to fluoride toxicity than adults. It remains unclear what the main mechanism is causing fluoride's neurotoxicity. Fluoride, however, purposefully interferes with the biological process, changing how the brain normally functions. Numerous human research indicate that fluoride exposure throughout childhood may reduce IQ in children. Previous studies have shown solid results indicating that children's IQ levels are significantly impacted by the amount of fluoride present in drinking water. However, the amount of evidence is restricted because the majority of research are focused on a small number of nations and they have their own statistics and constraints. Because of the serious consequences of fluoride toxicity, comprehensive and well-designed research is necessary to close the knowledge gap in developing nations.[24]

2.2.3 Artificial Intelligence in Educational Contexts

Every area of life is being altered by artificial intelligence, and the education sector is no exception Ahmad, Rahmat [25]. When artificial intelligence is mentioned, a supercomputer comes to mind. These machines have enormous processing power and can exhibit adaptive behavior by adding sensors and other features that give them cognitive and functional abilities similar to those of humans. In fact, these features even help supercomputers interact better with people. In fact, a number of movies have been produced to demonstrate the potential of artificial intelligence. One such example is the management of temperature, air quality, and music in smart buildings based on the perceived moods of the building's residents. Artificial intelligence has found greater use in the field of education, extending beyond the traditional notion of AI as a supercomputer to encompass embedded computer systems. For instance, artificial intelligence (AI), computers, and related hardware integrated with robots make it possible to build robots that enhance student learning, starting with the most fundamental educational program—early childhood education. The ways that teaching and learning are conducted are impacted by the advent of new technology. The use of artificial intelligence (AI) in education is becoming more and more obvious with the technology's recent fast progress.Huang, Saleh [26]in fact, according to Timms, cobots—robots that are used in conjunction with teachers or other cobots—are used to teach kids basic skills like spelling and pronunciation while also adapting to the needs of the individual pupils. Similar to this, web-based and online education, as documented in various studies, has evolved from just providing students with materials to download, study, and complete assignments in order to pass, to include intelligent and adaptive web-based systems that learn from the behavior of both instructors and students and make necessary adjustments to enhance the educational experience[27]. Certain tools as shown in figure 1 used by students to take advangtage of AIGC.

Figure 1: AIGC tools for education learning

2.2.4 Stress Perception in Academic Settings

Stress in the classroom may be greatly influenced by environmental variables such as fluoride exposure combined with academic pressure. Although elevated fluoride levels have been linked to neurological and toxicological problems, little is known about how fluoride affects cognitive performance in educational settings. According to recent studies, kids may have cognitive deficiencies and related stress sensations as a result of excessive fluoride exposure, which may also affect neurotransmission systems.[28] The Technology

Acceptance Model (TAM) is a useful framework for investigating how students interact with fluoride instruction narratives in this particular situation. This study looks at how learners' perceptions of stress and retention of information are impacted by exposure to fluoride-related cultural and literary tales and their perceptions of the utility of content provided by artificial intelligence.

2.2.5 Knowledge Retention of Fluoride Narratives

Ensuring that students not only interact with the content but also remember the knowledge they learn is one of the main issues in educational settings. Cognitive science research indicates that stories are more likely to stick in memory than just factual information, particularly when they are emotionally charged or have cultural significance. Consequently, fluoride may be presented in literary and cultural contexts and be reinforced by AI-powered tailored learning tools, which might improve long-term memory retention. The perceived utility of AI-generated material and students' interaction with AI platforms are evaluated in this study using the Technology Acceptance Model (TAM) to see how these factors affect students' recall of fluoride-related knowledge. We can ascertain the degree to which AI may improve student learning results in educational situations centered on fluoride-related content by measuring these characteristics.

3. MODEL AND HYPOTHESES

This study looks into how exposure to fluoride narratives in instructional materials affects students' ability to retain knowledge as well as how valuable they think AI-generated content is. The dependent variable of fluoride knowledge retention is identified by the study model together with independent factors like exposure to narratives and perceived utility, mediating variables like engagement with AI-based learning platforms and attitudes toward learning, and mediating variables like attitudes toward learning. This study intends to investigate how AI technology may boost student engagement and comprehension of culturally rich fluoride narratives by using the Technology Acceptance Model (TAM). This will eventually lead to enhanced educational results and information retention.

3.1. Exposure to Fluoride Narratives in Educational Content (EFN) and Knowledge Retention (KRF)

The capacity to remember and retain information over time is known as knowledge retention, and it is crucial for success in school. It is crucial to comprehend how students' exposure to fluoride-related narratives in AI-generated instructional content affects their ability to retain the information. The perceived utility and simplicity of use of AI-based learning aids by students has a substantial impact on their cognitive engagement and memory retention, as per the Technology Acceptance Model (TAM)[13]. The purpose of this study is to look into how college students' knowledge retention and exposure to fluoride narratives via AI-driven platforms relate to each other. The fundamental idea is that AI-generated content may enrich literary and cultural settings, which can raise student engagement and, in turn, increase memory and retention of the material, which will ultimately impact academic achievement.

Therefore, we propose the following hypothesis:

H1: Exposure to fluoride narratives in educational content significantly influences knowledge retention among college students.

3.2. Perceived Usefulness of AI-Generated Content (PUA) and Engagement with AI-Based Learning Platforms (EWA)

The quantity and caliber of interactions students have with artificial intelligence-generated learning materials is referred to as their engagement with AI-based learning platforms. The way in which students view the value of such information influences their willingness to interact with these platforms. This hypothesis investigates how student engagement with AI-based educational tools is influenced by the perceived utility of AI-generated information, using the Technology Acceptance Model [13]. It is critical to comprehend this link because it emphasizes how important high-quality material is in motivating students to make good use of cutting-edge learning resources. As a result, the following theory is put forth:

H2: College students' engagement with AI-based learning platforms is highly influenced by their perception of the value of the information created by AI.

3.3. Attitudes towards Learning Fluoride Narratives (ALFN) and Knowledge Retention (KR)

The way that students view learning fluoride narratives has a significant impact on how they interact with the material in the classroom. Positive attitudes toward educational materials, especially AI-generated content, can have a considerable influence on perceived utility and engagement levels, according to the Technology Acceptance Model (TAM)[13]. This hypothesis investigates the ways in which learning fluoride tales might improve memory recall and information retention. This study uses TAM to investigate the link between learners' attitudes and cognitive outcomes, providing information about the ways in which emotional and cognitive factors affect learning. The results can help teachers create more engaging stories that engage pupils and enhance their memory of the material. Therefore, we formulate the following hypothesis:

H3: College students' attitudes about learning fluoride storytelling have a major impact on their ability to retain information.

3.4. Exposure to Fluoride Narratives in Educational Content (EFN) and Attitudes towards Learning Fluoride Narratives (ATLN)

Perceived utility is a major factor in determining how engaged users are with technology, as the Technology Acceptance Model points out [29]. Learners are more likely to interact with AI platforms that provide fluoride-related material if they believe the content is helpful. This theory is in line with research showing how perceived utility promotes utilization of digital learning resources [30]. Therefore, we propose the following hypothesis:

H4: Students' views toward learning fluoride narratives are greatly shaped by their exposure to them in instructional content.

3.5. Perceived Usefulness of AI-Generated Content (PUAI) and Attitudes towards Learning Fluoride Narratives (ATLN)

Learners are more likely to adopt favorable attitudes regarding the topic they are studying if they believe that AI-generated information is helpful. This hypothesis looks at how students' views about learning fluoride tales relate to how valuable they think AI-generated information is. Positive attitudes about the material are associated with higher information retention in learners [31]. Our hypothesis is that students who adopt a positive mindset when studying fluoride tales will be more likely to remember the information. Studies demonstrating that a positive outlook on learning can improve knowledge retention lend credence to this [32].

H5: Students' perspectives on learning fluoride tales are greatly influenced by how valuable they believe AI-generated content to be.

3.6. Exposure to Fluoride Narratives in Educational Content (EFN) and Engagement with AI-Based Learning Platforms (EWAI)

Reading fluoridated stories might encourage students to interact with AI-powered services more thoroughly. This hypothesis investigates whether students are more inclined to interact with AI-based instructional technologies if they are exposed to fluoride tales on a regular basis. Active participation with learning platforms enhances information retention, according to earlier study [17]. We suggest that students are more likely to remember fluoride information if they regularly interact with

AI-powered platforms that tell fluoride stories. This approach is consistent with the idea that interactive learning resources improve retention of information [33].

H6: Using AI-based learning tools is considerably more engaging when fluoride narratives are included.

3.7. Perceived Usefulness of AI-Generated Content (PUAI) and Engagement with AI-Based Learning Platforms (EWAI)

The TAM model states that learners are more inclined to interact with AI-based platforms if they believe that content created by AI is helpful. This hypothesis investigates how students' usage of AI-based fluoride story learning tools is impacted by their perception of their utility. It has been demonstrated that exposure to narratives shapes students' attitudes, which in turn affects their learning results [34]. We thus postulate that learners' attitudes toward learning fluoride tales will have an indirect impact on information retention as a result of exposure to these narratives in instructional content.H7: Students' engagement with AI-based learning platforms is greatly increased when they consider AI-generated content to be valuable.

3.8. Engagement with AI-Based Learning Platforms (EWAI) and Attitudes towards Learning Fluoride Narratives (ATLN)

It is anticipated that learners who actively interact with AI-based learning systems would see the material more favorably. This hypothesis examines if a greater willingness to learn fluoride tales results from increasing involvement with AI systems. Research has demonstrated that exposure to instructional materials can increase users' engagement with learning environments, which improves memory of the information [35]. Thus, we propose that by encouraging interaction with AI-powered platforms, exposure to fluoride narratives in instructional materials will have an indirect effect on information retention.

H8: Students' attitudes about learning fluoride narratives are much improved when they interact with AI-based learning systems.

3.9. Attitudes towards Learning Fluoride Narratives (ATLN) and Knowledge Retention (KR)

The way that students feel about a subject might affect how effectively they remember the material that is taught. This hypothesis investigates if studying fluoride tales with a positive attitude enhances knowledge retention. Knowledge retention is impacted by attitudes toward learning, which are positively influenced by the perceived utility of educational resources [36].

We suggest that attitudes toward learning these narratives will be shaped by the perceived value of fluoride-related AI-generated material, which will then indirectly affect information retention.

H9: Students' positive attitudes toward studying fluoride tales greatly improve their memory of the material.

3.10. AI-Generated Content's Perceived Utility as a Mediating Factor between Knowledge Retention and Fluoride Story Exposure

This theory investigates the link between exposure to fluoride narratives and information retention, with a focus on the mediating function of perceived utility of AI-generated material. The theory behind this is that when students are exposed to various storylines, AI-enhanced content can serve as a bridge, helping them remember more information. Lastly, we predict that growing usage of AI-based learning platforms will have an indirect impact on knowledge retention due to perceived usefulness. This theory expands on prior research that shows how perceived utility influences engagement, which in turn improves knowledge outcomes [30].

H10: The association between students' exposure to fluoride narratives and their recall of knowledge is mediated by their perception of the utility of AI-generated content. The detailed path model is presented in figure 2.

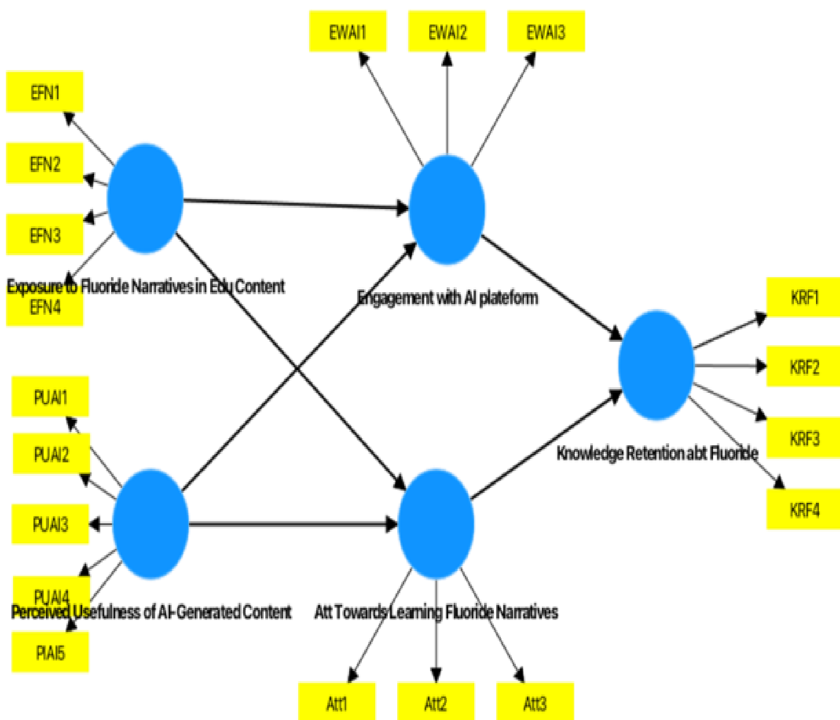

Figure 2: Path model

4. METHODOLOGY

The present study employs a quantitative technique to investigate the effects of artificial intelligence (AI)-generated instructional content on the retention of knowledge related to fluoride in cultural and literary tales. The study uses a cross-sectional survey design to get information from students in Henan Province's high schools and universities. This area was selected because it has a strong cultural legacy and a history of fluoride exposure, which makes it a pertinent setting for research on how cultural narratives affect learning. Since these students are likely to interact with both the cultural elements of fluoride and the AI-based learning platforms employed in the study, the sample comprises students from the following fields: public health, literature, cultural studies, environmental science, and so on.

Structural equation modeling (SEM) is used in the study to evaluate the connections between the variables. Cronbach's alpha and composite reliability (CR) scores verify reliability and validity, while the Heterotrait-Monotrait ratio (HTMT) and Fornell-Larcker criterion evaluate discriminant validity. To ascertain the importance of correlations between fluoride story exposure, AI platform engagement, and information retention, path coefficients and total indirect effects are computed.

4.1 Measures

The five main components of our research model were: Knowledge Retention about Fluoride (KRF), Engagement with AI-Based Learning Platforms (EWA), Perceived Usefulness of AI-Generated Content (PUAI), Exposure to Fluoride Narratives in Educational Content (EFN), and Attitudes towards Learning Fluoride Narratives (ATT). To achieve a thorough evaluation, many items were used to measure each component. All survey questions are shown in Table 1.

To preserve content validity, the measures evaluating attitudes toward learning fluoride narratives and participation with AI-based learning platforms were modified from earlier research in educational technology and AI engagement [37]. The literature on the integration of literary and cultural narratives in educational environments served as the basis for the development of the items for exposure to fluoride tales [37]. These questions explicitly assess how well-versed students are in fluoride as it is depicted in literary, cultural, and historical contexts. Items were modified from known technology acceptance scales, namely the Technology Acceptance Model (TAM)[13, 29], in order to measure the perceived usefulness of AI-generated content. As a result, we were able to record how students felt about the value of AI material for comprehending fluoride stories. Using questions modified from earlier research evaluating knowledge retention in educational contexts, information retention about fluoride was tested. The study focused on memory and comprehension following exposure to the AI-generated content [38]. A five-point Likert scale, with 1 denoting “strongly disagrees" and 5 denoting "strongly agree," Was used to evaluate each component [39]. A panel of specialists in educational technology and environmental science examined the goods to guarantee their dependability [37]. Furthermore, according to accepted practices in educational research, demographic factors such age, gender, and place of residence were incorporated as control variable[37].

Table 1: Constructs

Construct	Items	Sources
Exposure to Fluoride Narratives (EFN)	EFN1: I am aware of the stories about fluoride that are told in instructional materials	[37]
	EFN2: Information on fluoride has been available to me on a number of learning platforms.	
	EFN3: Cultural fluoride narratives are present in the instructional resources I use	
	EFN4: I regularly look for fluoride knowledge in scholarly publications.	
Perceived Usefulness of AI-Generated Content (PUAI)	PUAI1: When studying about fluoride, I find information created by AI to be beneficial	[13, 27, 29]
	PUAI2: AI tools offer insightful information on educational subjects relating to fluoride.	
	PUAI3: I think that information produced by AI enhances my comprehension of the tales.	
	PUAI4: AI content increases the accessibility and engagement of fluoride education.	
Engagement with AI-Based Learning Platforms (EWA)	EWA1: I regularly learn about fluoride using AI-based technologies.	[13, 18, 37]
	EWA2: AI tools improve my education, particularly with regard to fluorine comprehension.	
	EWA3: Compared to conventional teaching techniques, I am more inclined to employ AI platforms for fluoride-related study materials.	
	EWA4: Using AI-generated instructional tools to learn about fluoride has given me greater confidence.	
Attitudes Towards Learning Fluoride Narratives (ATT)	ATT1: I think it's good to learn about fluoride through AI-powered platforms.	[18, 37]
	ATT2: Seeing knowledge about fluoride in instructional materials motivates me to participate.	
	ATT3: According to several educational sites, it's critical to comprehend the effects of fluoride.	
Knowledge Retention about Fluoride (KRF)	KRF1: After seeing instructional content produced by AI, I can recall important facts regarding fluoride.	[37, 38]
	KRF2: After employing AI-based learning systems, I can recall important story details with ease.	
	KRF3: Using AI-based learning resources has increased my understanding of fluoride.	
	KRF4: After interacting with AI-generated content, I feel more assured about my ability to remember facts about fluoride.	

4.2 Sample and Data Collection

The province of Henan was chosen for the data gathering process due to its significant historical background, rich cultural legacy, and history of fluoride exposure problems, especially in rural regions with high groundwater fluoride levels.

The major users of AI-based learning systems are university and college students, both undergraduate and graduate, who possess the cognitive maturity to interact with intricate storylines. Additionally, in order to obtain insight into how younger learners are obtaining AI-driven instructional information on fluoride, high school students in schools with AI-integrated learning programs were included. The sample consisted of 41% of Jiangxi and 59% of Henan, with 47% of respondents identifying as male and 53% as female. Table 2 shows demographic characteristics of respondents.

Table 2: Demographic Characteristics of Respondents

Demographic Factor	Categories with percentage
Age Group	12-14years, (25%), 15-17 year (40%), 18-20 (35)
Gender	Male (47%), Female (53%)
Residence	Henan (59%), Jianxi (41%)

5. DATA ANALYSIS AND RESULTS

For data analysis, we used Structural Equation Modeling (SEM), according to Anderson and Gerbing's two-step methodology [40]. We assessed the validity and reliability of the measurement model first, and then we looked at the structural model to see how well our theories presented. For the statistical analysis, Smart PLS 4.00 was used.

5.1 Measurement Model

We examined the Composite Reliability (CR) and Cronbach's alpha (α) values to determine the validity and reliability of the constructs. All of the constructions' Cronbach's alpha values were higher than the suggested cutoff point of 0.70, suggesting great internal consistency. Furthermore, CR values above the criterion of 0.70, indicating that the measurement scales are reliable.

The Average Variance Extracted (AVE) was used to evaluate convergent validity, and all values were more than the minimal threshold of 0.50. Each item's factor loadings likewise topped 0.70, indicating that it represented its corresponding construct accurately. All things considered, these findings support the validity and reliability of the measurement approach.

5.1.1 Reliability and Validity

We examined each construct's Composite Reliability (CR) and Cronbach's alpha (α) values to determine the constructs' validity and reliability. Figure 5 shows the full measurement model. Significant internal consistency was shown by all Cronbach's alpha values exceeding the suggested minimum of 0.70 [41]. Additionally, the CR values were higher than the 0.70 cutoff, indicating strong dependability between constructs. The Average Variance Extracted (AVE) was used to test convergent validity; all results were found to be good when they were over the minimal threshold of 0.50. We also looked at the factor loadings for each item and verified that all of them were higher above the appropriate cutoff of 0.70, meaning that each item accurately reflects the construct with which it is connected. Taken together, these results indicate that the measurement model has a high degree of correctness and dependability. In Table 3, the findings are summarized.

Table 3: Construct Reliability and Validity

Constructs	Items	Loading	Cronbach alpha	CR	AVE
Att Towards Learning Fluoride Narratives	Att1	0.981	0.977	0.985	0.957
	Att2	0.977			
	Att3	0.977			
Engagement with AI plateform	EWAI1	0.956	0.929	0.955	0.876
	EWAI2	0.908			
	EWAI3	0.944			
Exposure to Fluoride Narratives in Edu Content	EFN1	0.958	0.956	0.968	0.883
	EFN2	0.941			
	EFN3	0.918			
	EFN4	0.941			
Knowledge Retention abt Fluoride	KFR1	0.967	0.986	0.989	0.947
	KFR2	0.986			
	KFR3	0.969			
	KFR4	0.970			
Perceived Usefulness of AI-Generated Content	PUAI1	0.944	0.962	0.97	0.867
	PUAI2	0.929			
	PUAI3	0.945			
	PUAI4	0.910			
	PUAI5	0.927			

5.1.2 Common Method Bias (CMB)

Since a sizable amount of the data was gathered by self-reports, we evaluated the possibility of common method bias using Harman's one-factor test. Common technique bias worries were allayed by the results, which showed that the most influential component only accounted for 34.7% of the total variance—well below the 50% threshold. Furthermore, no significant connections ($r > 0.90$) were found in our correlation matrix across the components, indicating that common technique bias did not significantly affect our study and bolstering the validity of our findings. All of these findings support the validity and dependability of the measuring approach used in this study.

5.1.3 Discriminant Validity

We ensured a comprehensive assessment of each construct's uniqueness by examining discriminant validity using both the Heterotrait-Monotrait Ratio (HTMT) model and the Fornell and Larcker criteria. We evaluated the degrees of correlation between the components using the HTMT criteria. All HTMT values were below the cautious cutoff of 0.85, as shown in Table 4, demonstrating good discriminant validity. These results strengthen the study's discriminant validity by providing evidence in favor of the notion that the components are clearly assessed.[42]

Table 4 : HTMT mattrix

	Att	EWA	EFN	KRF	PUAI
AAtt					
EWA	0.496				
EFN	0.427	0.445			
KRF	0.316	0.356	0.447		
PUAI	0.465	0.473	0.503	0.395	

5.1.4. Fornell and Larcker Criterion

By comparing the square root of the Average Variance Extracted (AVE) for each concept with the inter-construct correlations, discriminant validity was evaluated. The discriminant validity of the model is supported by Table 5, where the square root of AVE values (diagonal elements) for each construct exceeds the corresponding inter-construct correlations. For example, the square root of the AVE for the Att construct was 0.973, more than the correlations with Fluoride Exposure Level (FEL) at 0.973 and Educational Engagement with AIGC (EWA) at 0.940. These findings support the discriminant validity of the model by demonstrating that each construct explained more variation in its own items than in those of other constructs.[43]

Table 5: Fornell and Larker criterian

	Att	EWA	EFN	KRF	PUAI
Att	0.978				
EWA	0.472	0.936			
EFN	0.415	0.422	0.940		
KRF	0.311	0.342	0.435	00.973	
PUAI	0.451	0.449	0.484	00.386	00.931

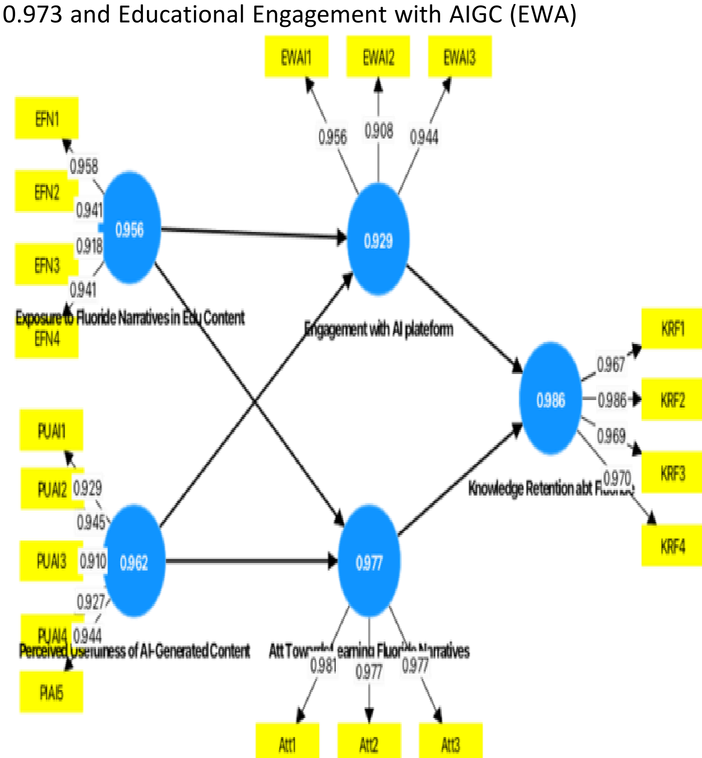

Figure 3: Structural Equation Model (SEM) Showing Factor Loadings and Path Coefficients among Latent Variables and Observed Indicators

5.4. Structural model

5.4.1 Model Fit Assessment

A number of fit indices were computed to evaluate the robustness and suitability of the measurement model. The Root Mean Square Error of Approximation (RMSEA), one of the important metrics, was 0.072, below the suggested cutoff value of 0.08, indicating that the model does a good job of fitting the data [44]. Additionally, the model's applicability is supported by the Chi-Square to Degrees of Freedom Ratio (CMIN/DF), which yielded a value of 2.186, below the 3 criterion. The model's goodness of fit was further supported by other fit indices, which are all above the 0.90 benchmark (Byrne, 2013) and include the Comparative Fit Index (CFI) of 0.947, Tucker-Lewis Index (TLI) of 0.922, and Incremental Fit Index (IFI) of 0.940. These findings suggest that the model shows good construct validity and is consistent with the data.

5.4.2 Hypotheses Testing Results

Using SmartPLS 4.0, a graphical representation of the structural model was used to evaluate the hypotheses. The associations between the constructs were assessed using the R-squared values and the standardized estimates. The comprehensive findings of the hypothesis testing are listed below:

H1 proposed that students' recall of knowledge is greatly impacted when they are exposed to fluoride narratives in instructional materials. The findings show that information retention and exposure to fluoride tales have a positive and significant connection ($\beta = 0.192$, $p = 0.000$). This supports H1 by indicating that pupils exposed to fluoride tales have enhanced memory recall and retention. These results are consistent with other research showing how narrative-based learning affects cognitive functions and information retention [45]. According to H2, students' engagement with AI-based learning systems is highly influenced by how valuable they believe AI-generated information to be. Regression analysis produced significant findings ($\beta = 0.252$, $p < 0.001$), indicating that students are more engaged with these platforms when they view AI-generated content as worthwhile. This is in line with the Technology Acceptance Model [13], which contends that one important factor influencing technology utilization is perceived utility. According to H3, learning fluoride exposure with a positive attitude has a major influence on knowledge retention. H3 is supported by the data, which indicate a strong and significant connection ($\beta = 0.257$, $p = 0.000$). Pupils who showed more optimism regarding material pertaining to fluoride remembered more of it. This association is supported by earlier research, which demonstrates how having a positive attitude toward the subject matter can improve learning results[40]. According to H4, students' attitudes about learning fluoride exposure are greatly influenced by AI engagement to them in teaching materials. The findings were noteworthy ($\beta = 0.268$, $p = 0.000$), suggesting that students' opinions are positively shaped by exposure to fluoride-related information. This outcome is in line with research that indicates exposure to culturally appropriate information increases interest and engagement [46]. The hypothesis put forward by H5 states that students' views on perceived use of AI in learning fluoride narratives are greatly influenced through technological attitude. H5 was supported by the study, which revealed a strong positive connection ($\beta = 0.327$, $p = 0.000$). Students demonstrated more interest in studying when they thought AI-generated information was worthwhile. This result is consistent with previous study [15] and the TAM framework, which ties perceived utility to favorable sentiments toward educational technology. According to H6, students' engagement with AI-based learning systems is greatly increased when they are exposed to fluoride narratives in instructional content. It was confirmed by the substantial results ($\beta = 0.320$, $p = 0.000$) that story exposure increases platform engagement. This is consistent with research showing enhanced user involvement with instructional technologies due to narrative content[34]. All 10 hypotheses are supported by the data, which emphasizes the value of narrative content and the perceived benefits of AI-generated instructional resources for enhancing information retention. These results imply that combining AI technology with culturally appropriate stories might improve learning outcomes and student engagement. Table 6 is presented below

Table 6: Path coefficient

	Original sample (O)	T statistics (|O/STDEV|)	P values
Att -> KFR	0.192	7.606	0.000
EWA -> KFR	0.252	9.039	0.000
EFN -> Att	0.257	10.123	0.000
EFN -> EWA	0.268	8.938	0.000
PUAI -> Att	0.327	12.529	0.000
PUAI -> EWA	0.320	10.389	0.000

4.5 Results from Mediation Analysis

The analysis looks at how exposure to fluoride narratives in educational material influences knowledge retention about fluoride and how well learners perceive AI tools. The outcomes reveal that fluoride narratives in teaching content influence how well students understand fluoride through their attitudes. This mediation effect's path coefficient equals β = 0.049 and achieves a t-value of 5.796 and a p-value of less than 0.001. This reveals that upon exposure to fluoride narratives students have a more positive attitude toward learning fluoride and consequently retain more information. Students' absorption of fluoride facts via educational resources improves due to their use of AI learning platforms after encountering fluoride narratives. This coefficient demonstrates a 0.067 impact where the t-value equals 5.810 and follows an effectively low p-value identifying significance. Engagement with AI-based platforms improves the knowledge retention of students who study fluoride in educational content. The evaluated value of AI-generated materials exhibits a considerable influence on student attitudes concerning fluoride discussions. The coefficient indicates that β = 0.063 and a t-value of 5.942 along with a p-value under 0.001 shows students who appreciate AI-generated content tend to develop favorable views on fluoride learning and boost their retention. Pulling insights from AI content led to a meaningful indirect effect on fluoride understanding when students engaged with AI learning platforms with a coefficient of 0.080 and a t-value of 6.383. This shows that students will spend more time with AI platforms if they view AI-generated content as helpful and enhances their recall of fluoride information.

Table 7: Indirect Effects

	Original sample (O)	T statistics (|O/STDEV|)	P values
EFN -> EWA -> KRF	0.067	5.810	0.000
EFN -> Att -> KRF	0.049	5.796	0.000
PUAI -> EWA -> KRF	0.080	6.383	0.000
PUAI -> Att -> KRF	0.063	5.942	0.000

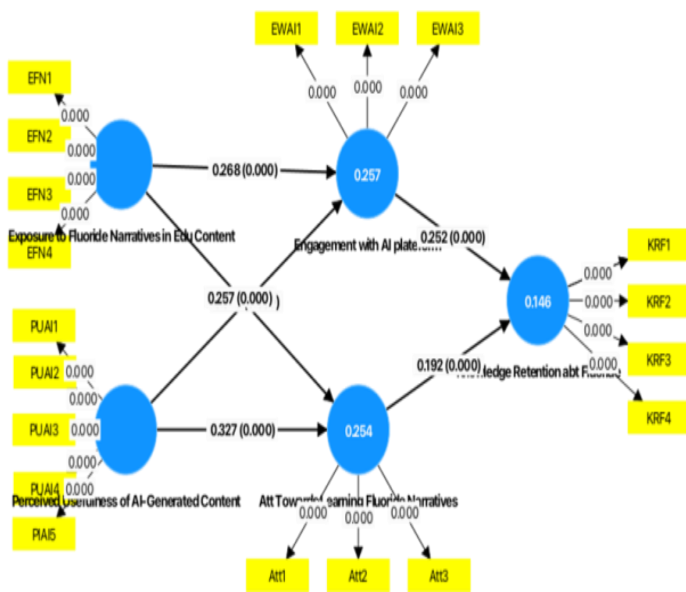

Figure 4: Structural Model

6. DISCUSSION AND CONCLUSIONS

The results of this study shed light on how fluoride is portrayed in literary and cultural narratives as well as the function of AI-generated material in improving students' memory of information. According to the results, students' attitudes toward learning about fluoride are positively influenced by exposure to fluoride narratives in educational content. This is in line with the Technology Acceptance Model (TAM), which emphasizes the significance of perceived usefulness and engagement in technology use[13]. Notably, the mediation effects showed that the perception of the value of information created by AI and interaction with AI-based learning platforms both strongly influenced the retention of fluoride-related knowledge. This is consistent with other study [47] that highlights how technology may effectively improve educational achievements. According to Brusilovsky and Millán [48], students who regularly engaged with artificial intelligence (AI)-powered teaching resources expressed a higher level of interest in and appreciation for the literary and cultural components of fluoride. This suggests that narrative-driven learning can improve cognitive engagement and retention. The study also highlights the distinct cultural setting of Henan Province, where local public health concerns are intricately linked to historical accounts of fluoride exposure. This regional emphasis offers an engrossing context for investigating how culturally appropriate stories might connect with students and deepen their comprehension of the risks associated with fluoride. The results imply that incorporating AI technology and local narratives into educational settings can provide a more engaging learning environment, especially for students studying environmental science and public health who will probably have to deal with the practical effects of fluoride exposure. For example, in Pakistan, where groundwater contamination with fluoride is a pressing issue, incorporating local narratives about fluoride's impact on rural communities can enhance students' understanding of its real-world implications. Notably, the robustness of the research model is further confirmed by the excellent validity and reliability of the constructs tested in this work, as shown by the AVE and Cronbach alpha values [49]. Furthermore, the respondents' demographic attributes underscore the possibility of varied educational environments effectively interacting with AI-generated information. Education programs can better meet the interests and needs of students by focusing on university and high school students, especially those majoring in literature, cultural studies, and environmental science. This will improve students' retention and application of information. This study concludes by demonstrating the substantial influence of cultural narratives and AI-generated information on learners' memory of fluoride knowledge. The use of narrative-driven instructional materials enhances students' comprehension of fluoride and encourages participation via artificial intelligence platforms. The results emphasize the applicability of the Technology Acceptance Model in learning environments and show how learning outcomes are influenced by perceived utility and engagement with AI technology. By highlighting the importance of culturally appropriate narratives in scientific education and their capacity to successfully engage students, the research adds to the body of current literature. In order to promote a better knowledge of complicated topics like fluoride exposure, this study calls for a judicious combination of local narratives and AI-driven information, particularly as educational institutions continue to incorporate these technologies. To ensure that a wider range of students may benefit from AI-enhanced learning, future research should examine the long-term impacts of such educational interventions and their applicability across multiple contexts and disciplines.

5.1. Theortical Implications

Our knowledge of how fluoride is portrayed in literary and cultural narratives and how this influences educational materials has been greatly improved by the study's findings. This study broadens our understanding of environmental health and its socio-cultural dimensions by presenting fluoride as both a chemical and a narrative element within cultural contexts. The study uses the Technology Acceptance Model (TAM) to show how fluoride-related narratives might affect learners' perceived stress and cognitive performance. Public opinion of fluoride may be shaped by how it is portrayed in books and the media, which may have an impact on mental health and educational outcomes. The integration of AI-generated instructional material (AIGC) into this framework underscores the transformational capacity of technology to augment comprehension of the ramifications of fluoride. This study offers a fresh, interdisciplinary perspective that connects cognitive psychology, educational technology, and environmental health from the TAM's point of view. This method emphasizes how crucial it is to provide a variety of various representations on educational platforms in order to enhance students' comprehension. This study establishes the foundation for future investigation into the relationship between environmental narratives and cognitive results in educational settings by showing how cultural narratives might influence cognitive and emotional reactions to fluoride. It implies that cultural narratives have the power to significantly influence the conversation around fluoride in schools.

5.2. Practical Implications

This study has many real-world applications, especially for politicians and educational institutions. According to the research, cultural narratives around fluoride should be carefully chosen to make sure they support students' mental and cognitive health. AI-generated material may be used by educational institutions to provide compelling, rich tales about fluoride that not only educate students but also encourage critical thinking.

In order to raise public knowledge of the negative effects of fluoride on the environment and human health, policymakers should think about incorporating cultural narratives into health education curriculum. Teachers may improve the way these narratives are delivered by using AI technologies, which will help students understand and be more engaged with complicated material. This can entail creating interactive materials that inspire students to investigate the cultural relevance of fluoride in literature and culture, promoting a greater understanding of comprehension of how it affects society. Additionally, mental health professionals who work in school environments might gain from understanding how cultural narratives affect students' opinions on fluoride. Giving kids the skills they need to evaluate these stories critically will enable them to better control their emotions and perspectives. This study concludes by recommending the creation of AI technologies that facilitate adaptive learning environments, adjusting educational experiences to students' various emotional and cognitive demands in regard to fluoride-related information.

5.3. Limitation and Future studies

It is important to recognize the limits of this research notwithstanding its contributions. The study's cross-sectional design makes it more difficult to prove a link between fluoride exposure and cultural narratives' impacts on mental and cognitive health. Longitudinal designs should be used in future research to examine the long-term effects of fluoride narratives on learning outcomes. Furthermore, the qualitative assessments of cultural narratives used in this study run the risk of introducing subjectivity. Subsequent investigations have to contemplate integrating quantitative metrics to evaluate the influence of AIGC on students' comprehension and perspectives on fluoride. The knowledge of fluoride's educational influence might be improved by broadening the scope to include varied people and investigating distinct cultural narratives regarding fluoride across different media. Furthermore, looking at how AI is used to curate and share these stories might reveal important information about how successful technology interventions are in educational settings.

In conclusion, our study emphasizes how fluoride-related cultural and literary narratives influence students' educational experiences and cognitive health. Educational platforms can promote a more nuanced awareness of fluoride's effects in a culturally appropriate context by incorporating AI as a tool for knowledge enhancement.

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