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Investigating the Mental Health Implications of AIGC Education and Fluoride Consumption Among College Students

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ABSTRACT

Purpose: In the present study, the authors' intention is to find out the impact of fluoride on cognitive performance, contact with artifical intelligence generated content (AIGC), perceived stress, and negative mental health. To explain the relationships between these variables, the present study uses the Cognition-Affect-Conation (C-A-C) approach and examines the mediating and serial mediation effects that lead to negative mental Heath outcomes.

Methods The research utilized cross-sectional survey design and participants were college students in two provinces in China; Henan and Jiangxi. A research method of SEM was used in the analysis of the interaction between perceived levels of fluoride exposure, cognitive functioning, level of engagement to AIGC, perceived stress levels, and negative mental health outcome. To examine the proposed paths in the C-A-C model, cross-sectional mediation and serial mediation analyses were performed.

Results: The findings show that the population's fluoride exposure influences cognitive performance, perceived stress and participation in AIGC lessons. Impaired higher cognitive functioning following fluoride exposure was demonstrated to have a predictive significance for a negative mental health impact with perceived stress being a mediating variable. In addition, serial mediation was established which indicates that the impact of cognitive functioning on mental health outputs depends on the perceived stress levels and engagement with IGC.

Research Limitation/Implication: The cross-sectional design restricts the opportunity to establish cause and effect relationship. It is therefore recommend that future studies conducted in a prospective manner because of its better ability to determine the outcomes of lensing exposure on cognitive ability and mental health after years. Moreover these assessments objective measures of cognitive functioning and stress levels could have been included in order to increase the validity of the study.

Orginality: This work provides an enriched analysis of the C-A-C model for EH and EdTech context; by mapping the intermediary processes of Fluoride exposure, CF, perceived stress, and AIGC engagement on mental health. Examining serial mediation effects advances the knowledge of how elements of cognition, emotion, and behavior are linked with students' mental health.

Key-words: Consumption of Fluoride, Cognitive function, Artificial intelligence generated learning materials, Stress, Cognition-Affect-Conation model

1. INTRODUCTION

Fluoride and its impact to human health is still the subject of much controversy especially in relation to impact on brain function & mental health. Although several systemic reviews show that a concentration of fluoride below 1.15ppm has a positive impact on oral health [1], new research has discovered dangerous effects of fluoride on brain health, particularly in young people [2]. Similarly, artifical intelligence generated content (AIGC) has also found a place in the educational environment and has been shown to have positive effects for, for example, learning experiences and cognitive presence [3]. However, a new issue appears to emerge when trying to consider the effects of AIGC on student health and well-being given other ecological pressure. It has been postulated in prior work that exposure to fluorides can lead to the impairment of organ function and that cases with high values of fluorides indicate impaired cognitive function and increased psychological problems [4]. In parallel, AIGC has been employed to reduce cognitive load and increase learning efficiency [5], but it can cause cognitive load and learning anxiety if designed improperly [6]. However, there appears to be very little research done on the interaction between fluoride exposure and engagement with AIGC on mental health outcomes and the current study aims to fill that gap by focusing on college students who are potentially exposed to both factors regularly. Despite, the studies, done on fluorides and its effects on cognition and psychoses, there is lack of understanding on certain areas as shown next. Firstly, prior work has mainly concerned the primary impact of F exposure on cognition [7, 8] without regard to the role of CIF in the association between fluoride exposure and mental health in the most affected regions in China, as shown in Figure 1. Second, although researchers have acknowledged AIGC as the facilitator of learning and effective teaching and the controller of cognitive processes [9], little is known about how it responds to the influence of fluoride on cognitive stress and how it has affected mental health. Moreover, the literature review also finds out that relatively little is known about the moderating effects of both fluoride exposure and AIGC engagement on perceived stress levels and mental health outcomes using a serial mediation model. In order to fill the research gaps, the present study examines the impact of fluoride exposure on college students' mental health with considering the moderating role of cognitive functioning, perceived stress, and AI General Chat [10, 11]. In Australia, self-generated social cognition (AIGC) refers to perceived stress levels due to using social media throughout the day and we designed the following serial mediation of the current research model for testing the hypothesis that fluoride exposure affects mental health outcomes through the cognitive function and perceived stress levels. In response to these gaps, the present study aims to examine the effects of fluoride exposure on the mental health of college students and mental health considering the moderating roles of cognitive function, perceived stress, and use of AIGC. Specifically, the study seeks to answer the following research questions: Organised in three research questions: (1) The moderation of cognitive functioning and perceived stress levels in the context of the relationship between fluoride exposure and mental health outcomes of college students. The present question is going to explore the mediators that could link the fluoride exposure with mental health because much of the research in previous studies has been conducted focusing only on the direct paths. Additionally, this research seeks to establish (2) How does the engagement with AI generated educational content (AIGC) moderate with fluoride caused cognitive stress with regards to mental health and how does this moderation happen under the seriation mediation of cognitive function and perceived stress level? In posing this question, the current research seeks to gain a deeper insight into how specific educational technologies of the modern age, like AIGC, interfacing with environment affects psychological health. This research can be said to have three major research implications. First, it expands the previous research by examining how cognitive functioning, perceived stress, and AIGC engagement sequentially moderate the impact of fluoride exposure on mental health. Secondly, it offers a complex view of how new generation educational technologies, including AIGC, are incorporated into environmental conditions to affect psychological states. Last, this study contributes to the body of knowledge on environmental and technological impact on mental health to enrich the literature with useful findings that could be used in designing interventions and policies for improving student mental health in higher educational institutions.

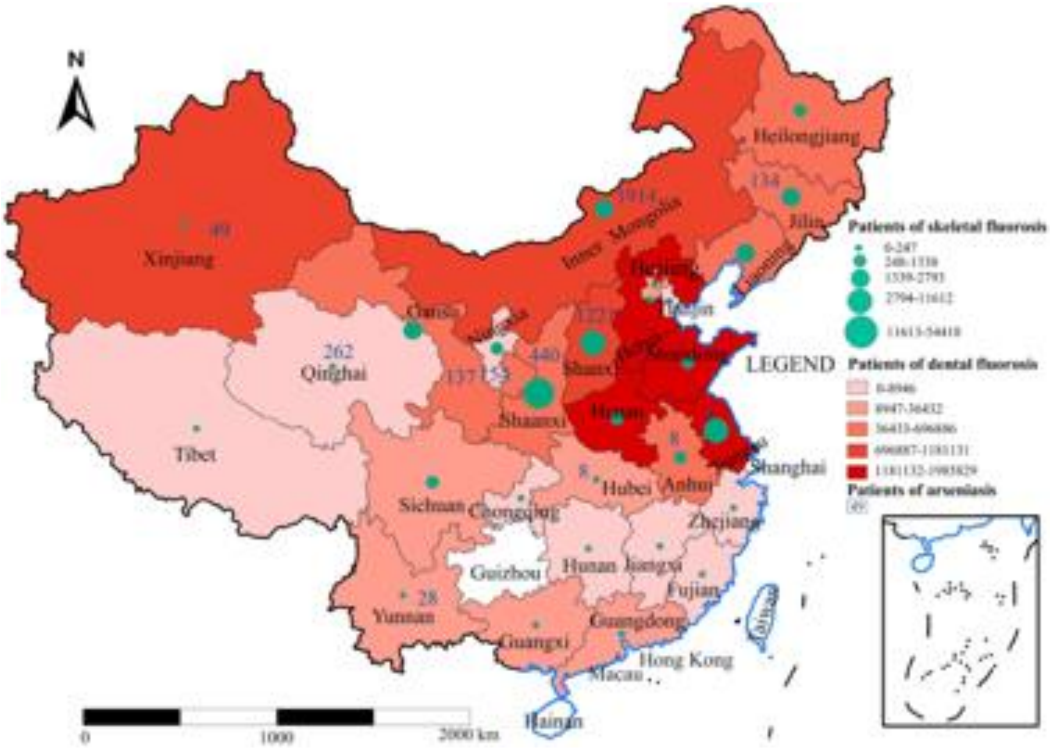

Figure 1: Regions of China most affected by fluoride

2. BACKGROUND OF THE STUDY

2.1. Theortical framework

2.1.1 Analysis of Cognition Affect Conation (C-A-C) Framework Psychological studies within cognition stress on the tripartite model of consciousness that comprises cognition, affect, and conation [12]. Knowledge, on the other hand is the understanding of facts and information and can be defined by asking the question, what is this information. [13]. Emotion involves the evaluation of information with the question 'How do I feel about knowledge' [14]. Conation refers to the action motivational aspect of knowing that corresponds to the question "Why should I act on this knowledge?. Based on this psychological theory, scholars have advanced Cognition-Affect-Conation C-A-C model to establish the chronological flow of cognition affect and conation in influencing behaviour. This framework assumes that cognitive factors determine affective states that in turn determine conative or behavioral intentions about behaviour [15, 16]. For instance, Theory of Reasoned Action (TRA) is based on C-A-C approach – conation being behaviour and attitude being affect, which is a function of cognition which includes beliefs and perception. Likewise, the Technology Acceptance Model (TAM) [17] uses the C-A-C model where cognitive beliefs about the technology including perceived usefulness and perceived ease of use determine the affection or attitude toward the technology and behavioral intentions or conation to use the technology. Besides those examples, it has also be successfully implemented in other well-known theory like the Expectation-Confirmation Model, and Theory of Planned Behavior. By analysing these theories it demonstrates how cognition affect, and conation can positively or negatively influence behaviors within an individual's life span.

2.1.2. Application of C-A-C Framework in Research

Many theoretical models derived from the C-A-C framework have been applied and empirically ascertained by several researches and dominantly in different fields. Marketers used the C-A-C framework to study customer loyalty and behavior in various contexts including retailing [18], hospitality [19], banking services [20] and technology products [21]. Literature has applied the framework mainly in the field of information systems (IS) and e-commerce to encompass user's behavior and loyalty such as using online services [22], and SNSs [23]. This has also applied while evaluating behaviour responses in conditions of stress in the Stressful Encounter, Coping Stress and Transaction Analysis Theory apart from Stressor-Strain-Outcome (S-S-O) model by[24]. The affective and behavioral models proposed align with the C-A-C configurations, as they also focus on the way in which cognitive assessment influences a range of stressors.

2.1.3 Applying the C-A-C Framework to Fluoride Exposure, AIGC Engagement, and Mental Health

Specifically for our study, the C-A-C framework is useful in analyzing how the independent variable, Fluoride exposure affects the dependent variable, mental health outcomes, through the mediating variable of cognitive functioning, perceived stress and the moderator variable which is AIGC engagement among college students. This framework helps categorically approach the assessment of how cognitive impairment due to fluoride affects affective stress, resulting in behavioral willingness to use AIGC with regards to overall mental health. Previous studies have as well shown that exposure to fluoride weakens the brain which consequently slows down memory, attention, and learning [25]. So, based on the C-A-C framework, this cognition level is expected to lead to negative affect level, such as stress level [26]. Furthermore, the course work stress levels may well impact students' AIGC use as a stress buffer or vice versa may independently contribute to the development of mental health issues (conation) [27]. The present research thus intends to advance the body of knowledge on the relationships between fluoride exposure, cognitive abilities, perceived stress, AIGC, and mental health outcomes among college students by employing the C-A-C analytical structure to map out the causal sequences among the variables of interest. An understanding of this relationship is important since it will help people learn how these environmental factors (FE), technology used in AIGC and psychological well-being are related and can have negative impacts in one's psychological well-being.

2.1.4 Application and Contribution of CAC to the Current Study

The C-A-C Framework The current research uses the C-A-C framework as the central theoretical model to understand the moderation of cognitive, affective, and behavioral pathways in the link between F exposure and mental health. The reasons for selecting this framework are as follow. Originally, it has been adopted by IS researchers to unfathom individuals' perceptions, affective responses, and behaviours when concerning the incorporation of technology [28]. Second, the identification of the C-A-C framework would bring more congruent to other main models, including Stress-Coping Framework [29] to predict stress-related outcomes. Lastly, the C-A-C framework precisely matches the research objective of this study: to examine the mediating role of cognitive (cognitive functioning), affective (perceived stress levels), and conative (AIGC engagement and mental health outcomes)variables in order to investigate how these factors cumulatively predict the influence of fluoride exposure on college students' mental health [30]. In so doing, this study builds on the application of the C-A-C framework to elaborate how environmental contexts (negative effect of fluoride on the brain) and advanced education technostyles (AIGC) interactively influence students' mental performance and stress indicators as well as mental health outcomes, and hence offers a theoretical contribution to the psychology of well-being in learning environment.

2.2. Literature Review

2.2.1 Fluoride Exposure Level

Fluoride has been investigated in public health field because of two opposite impacts that it has on both the teeth and the brain. Although concentrations of fluoride have been well appreciated to prevent dental caries [31] recent speculations have been raised regarding the possibility of neurotoxicity due to chronic exposure to high concentration of fluoride especially among young adults [32]. According to research, there is evidence that long term effects of fluorides cause loss of cognitive abilities, learning disabilities and may cause increased psychological problems [32, 33]. Since the college students use dental products containing fluoride and consume food containing fluoride and drink water with fluoride in it, the long-term effect of conventional fluoride on the brain function that impacts learning ability and mental health might be negative [34]. However, studies examining the way in which this variable relates to mental health outcomes via psychological related variables: cognition and stress, for example, are scarce. Therefore, knowing where fluoride exposure falls in these categories, first of all in general framework such as the Cognition-Affect-Conation (C-A-C), will expose a college students exposure to this toxicant for mental health.

2.2.2 Cognitive Functioning

Cognitive functioning comprises of the mental process of gaining information, understanding and learning, and in decision making and solving of problems [35, 36]. Studies have reported that human beings who assimilate high concentrations of the compound harms their brain capacity and survival. The compound particularly has been found to cause reproductive problems, damaged mental health, and loss of memory, inability to concentrate and poor learning capabilities [37]. Cognitive losses investigated may interfere with academic achievement and stress coping, thus leading to negative affective effects in students. Figure 2 stated that the mental health and oral habits are interlink in the floride.In the education arena, cognitive disability results in poor understanding of educational content, reduced learning participation and perceived learning stress and futility [38]. But, little research has been done correlating cognitive loss from fluoride to affective-behavioral parameters such as stress and the interaction with AIGC. This is important to understand because cognition is the first of the C-A-C framework's two core components; it directly leads to affective responses and behaviors.

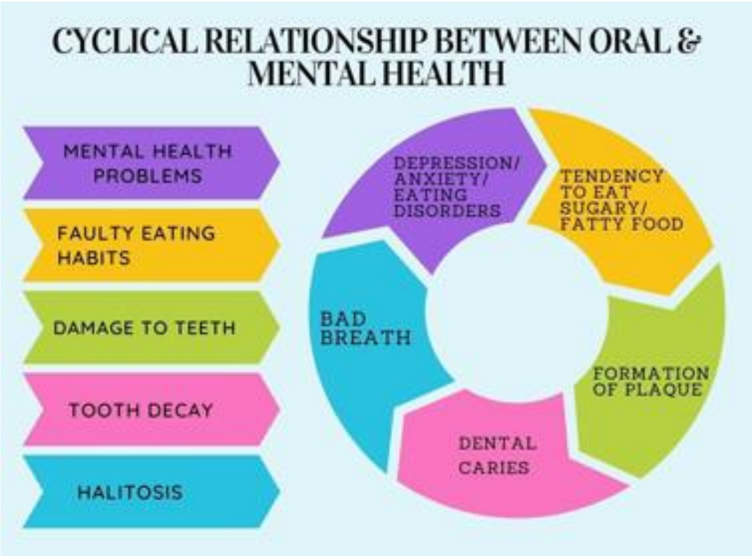

Figure 2: Cycle relationship between oral and mental health

2.2.3.Engagement with Artificial Intelligence-Generated Content (AIGC)

The implementation of AIGC in the education context has begun to advance, providing differentiated learning and helping strategies and content adjust [39].Certain tools are using in education as shown in figure 3. Sohail, Farhat [40] noted that AIGC improves learners' learning gains due to intervention that addresses learning style and feedback. Nevertheless, interaction with AIGC can also lead to an overload of cognitive load if the students are not ready enough to answer the questions or if the concepts provided are not relevant to the students appropriately [41, 42]. When situated in the C-A-C model, AIGC engagement refers to behavioral input, provoked by cognitive and emotional input. For instance, learners with cognitive disability as a result of fluoridation might interact with AIGC as a way of compart mentalizing their learning disability or as an extra source of stress. This twofold position of AIGC points to the need for understanding how, and through which process, interactions with AIGC moderate the interaction between cognition, stress, and mental health.

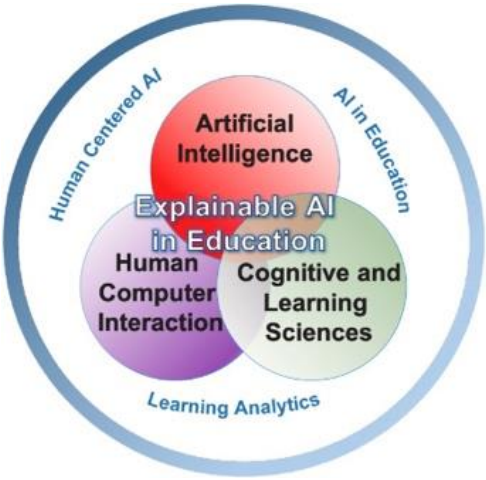

Figure 3:AIGC tools for education learning

2.2.4 Perceived Stress Level

Stress, perceived stress in this context refers to the extent to which people experience pressures that they cannot handle in regard to environmental demands. In learning institutions stress can result from academic activities, academic demands and environmental influence for example exposure to fluorides [43]. Literature review revealed that higher levels of stress may have negative impact on students' mental well-being, which may manifest the signs of anxiety or depression as well as burnout [44]. In C-A-C model, perceived stress translate affect which is an emotion elicited by cognitive deficits like those caused by fluoride. Stress plays an important role for student's involvement in AIGC, assuming positive or negative moderation of its effects on the mental health. Yet, research concerning the country's older adults as mediated by perceived stress on cognitive functioning, AIGC engagement and mental health is scarce.

2.2.5. Mental Health Outcomes

Mental health outcomes include different kinds of psychlogical states such as anxiety, depression and well-being. The concern of this study is relevant because college students are a high risk population exposed to academic, cognitive and environmental demands. Previous studies have established that increased levels of fluorides are linked with low mental health with high average percent of anxiety and depressive disorders [45]. Furthermore, AIGC has been linked to the pattern of mental-health. Althoughsome researchers have claimed that adaptive learning technologies are non-stressful, others have been concerned that learner anxiety might be worsened due to cognitive overload [46]. In the context of this framework mental health outcomes links are the final chain and denote the conation or behaviour part of C-A-C model. Therefore, the purpose of this study is to establish how mental health results from the interaction between the ingested fluoride, cognitive ability, stress level, and AIGC interventions alleviating the impact of environmental stressors and affecting the students' wellbeing.

3. MODEL AND HYPOTHESES

3.1. Fluoride Exposure Level (FEL) and Cognitive Functioning (CF)

A cognitive function refers to different mental operations, or activities involved in learning, memory, problem solving and concentration. Researches have focused more on the impact of fluoride in environment health than on its impact on cognitive ability. In the framework developed by Taylor et al, known as Cognition Affect Conation, an external stimulus including fluorides can inevitably affect cognition. In academe, the ability to reason, to store information in the brain's warehouse, or to be able to use data to solve problems is critical. Hence, the study of the effect of fluoride exposure on cognitive ability of college students is critical. This hypothesis will look at the effects of the amount of fluoride intake on the students' concentration, memory and their problem solving abilities. The concept behind this hypothesis is expected to produce information regarding how much the environment can meddle with such elemental cognitive functions, which in turn, are the key to academic success and day-to-day functioning. Hence, we propose the following hypothesis:

H1: Fluoride exposure level has an influence on the cognitive performance with college students.

3.2. Fluoride Exposure Level (FEL) and Engagement with AIGC (EWA)

Frequency or Active Interaction with AIGC identifies levels of activity of the frequency with which students engage the AI-based content in education. Fluoride is one of the environmental factors that can affect either the capacity of a student to interact with such technologies or his/her desire to do so. By embracing the C-A-C model it is possible to assess how external variables such as exposure to fluoride affect behavioral outcomes like the use of artificial intelligence in learning. Should fluoride make a difference in cognitive performance, it may also have an effect in ways, students work with AIGC [47]. This is important because when introducing artificial intelligence and educational technology, teachers and policymakers must consider possible impacts of the environment on the students' usage of such technology applications. Therefore, the following hypothesis is proposed:

H2: Perceived level of fluoride exposure significantly influences the level of interaction with AIGC among college students.

3.3. Fluoride Exposure Level (FEL) and Perceived Stress Level (PSL)

Normative perceived stress is defined in this study as the level of stress that students perceive or think they experience as they handle academic and life challenges. The hypothesis was made that stress perception could also be significantly influenced by such environmental indices as fluoride. Based on C-A-C model, it is found that impacts resulting from social related factors can also bring an increased level of stress because of the scholarly challenge among students [48]. It is crucial to establish the correlation between, namely, fluoride intake and perceived stress, in order to determine how futher environmental factors affect students' psychological states. Pursuant to this hypothesis, investigating the mentioned relationship will provide insight into whether or not fluoride exposure affects students' perceived stress. This would help explain how developing factors in students' environments impact their mental health status. Thus, the hypothesis is stated as:

H3: Fluoride exposure level has a significant effect on perceived stress level among college students.

3.4 Perceived Stress Level (PSL) and Engagement with AIGC (EWA)

Students' use of educational resources is influenced by their perceived stress level, especially concerning their interaction with Artificial Intelligence-Generated Content (AIGC). The C-A-C framework indicates that stress, an emotional reaction, can have a major effect on behavioral outcomes [49]. There may be different approaches to AIGC among students experiencing different levels of perceived stress; for a number of individuals, participating in

AIGC might represent a means to cope with stress by asking for support or seeking supplementary learning resources, while for many others, elevated stress might make it more difficult to interact with AI educational contente [50]. How this relationship functions is pivotal because it clarifies how levels of student stress influence their use and adoption of technology. The goal of our exploration is to determine whether stress functions as a stimulus or an obstacle to involvement in AIGC. Therefore, the hypothesis is proposed as follows:

H4: Among college students, perceived stress level has a strong effect on engagement with artificial intelligence generated content.

3.5. Cognitive Functioning (CF) and Negative Mental Health Outcomes (NMHO)

Mental health outcomes rest directly on cognitive functioning, which is the regulator of how individuals interpret, manage, and respond to normal stressors and challenges. The C-A-C model shows that cognitive inadequacies can cause serious mental health problems, among them anxiety, depression, and feelings people commonly associate with a lack confidence. In order to build effective strategies for students experiencing cognitive problems, it's important to gain insight into the association between mental health and cognitive performance [51]. Our research seeks to confirm a theory that claims cognitive skills have a marked effect on the negative outcomes for mental health in students during college, revealing their association with mental health achievement. Therefore, we hypothesize:

H5: The functioning of cognitive processes has a significant influence on the negative mental health experiences of college students.

3.6. Engagement with AIGC (EWA) and Negative Mental Health Outcomes (NMHO)

Social interaction with commitment to AIGC can be either therapeutic or even cause stress and anxiety, as the usage of AI-based learning instruments may do. This means according to the proposed framework, it is possible for the level of behavioral engagement to impact on the affective dimensions such as mental health [52]. For example, an experience with AIGC that is positive is likely to result to improvement of learning experience or even a decreased level of academic stress while experiencing a negative outcome is likely to lead to increase in stress, and a lowered mental health state. Regarding this hypothesis it will concern the impact that the interaction with AIGC has on students' psychological state in order to gauge the consequences of technological integration, particularly AI in learning. Therefore, the hypothesis is:

H6 Engagement with AIGC has a significant effect on negative mental health outcomes among college students.

3.7 Engagement with AIGC (EWA) as a Mediator

The students' ability to learn or engage with educational artificial intelligence generated content (AIGC) can also be affected due to fluoridation affecting the cognitive health of consumers. The Cognition-Affect-Conation (C-A-C) theory predicts that when 'exposed to environmental stress' such as fluoride the engagement behaviour should change [53]. In learning environments, mental disability brought about by fluoride affects the ability or desire of the learners to engage with AI learning apps. Such a form of disengagement can lead to such psychological demerits such as stress, anxiety or even inadequacy every time one cannot solve certain academic challenges or every time one cannot undertake a learning process as desired. As a result, the level of interaction as a mediating variable fits in to help explain like how and why exposure to fluoride leads to poor mental health [54]. Thus, analysing this mediation effect will help reveal the frame of indirect impacts of environmental factors such as fluoride, and underline the significance of engagement with educational technology. Thus, it is hypothesized that:

H7: Engagement with AIGC significantly mediates the relationship between fluoride exposure level and negative mental health outcomes among college students.

3.8. Cognitive functioning as mediation

Cognition has generic significance in how effectively people handle stress, how they perceive and structure their lifeworld. It has been established that long-term health impacts of high levels of fluoride intake have resulted in low intelligence, which in turn leads to poor mental health of the persons the amount of whose intake exceeds threshold levels. The C-A-C model posits that cognition is influenced by inputs from the external environment and none is perhaps more critical than fluoride. Hence, where the cognitive domain has been affected by fluorides, one cannot perform academic and or other life related tasks and hence are prone to mental illnesses [55]. Because cognitive functioning is a mediator, that is why the impact of the use of water containing fluoride has detrimental effects on mental health outputs. This knowledge is helpful when implementing programmes that target on practicing cognitive functions or reducing intake of fluoride to increase the mental well being of students. Therefore, cognitive functioning is believed to mediate the between fluoride exposure and the poor mental health outcomes evident and how the environmental factors impact psychological well-being. Hence, the hypothesis is:

H8: Fluoride exposure level is strongly associated with negative mental health outcome through cognitive functioning among college students.

3.9. Perceived Stress Level (PSL) as a Mediator

It is posited that perceived stress level will mediate the relationship between the amount of fluoride exposure and a person's interaction with AIGC. High levels of exposure have stressed matters, since a person might face challenges in the thought process or have clinical complications due to excessive fluoride intake. In the C-A-C framework, stress the levels together with other factors influence the individual's behaviour and/or capacity to engage in the use of educational technologies [56]. The learner that is exposed to high levels of fluoride stress is likely to experience inhibition of psychomotor, cognitive, and affective learning domains and thus be unable to interact with or even engage with technologies such as the AI learning platforms. By showing that the moderating role of perceived stress level brings insight into how the environment impacts certain learning behaviors from a psychological perspective. knowledge of this interaction may facilitate the interventions aimed at students' stress coping and learning promotion despite adverse conditions. Thus, it is proposed that perceived stress level plays a mediating role in the link between fluoride exposure and engagement with AIGC, making this hypothesis crucial for understanding the indirect effects of environmental stressors on educational engagement:

H9: Perceived stress level significantly mediates the relationship between fluoride exposure level and engagement with AI-generated content among college students.

3.10. Serial Mediation of Perceived Stress Level (PSL) and Engagement with AIGC (EWA)

Percieved stress level, AIGC and the study variables. Based on these C-A-C exposures to fluoride causes cognitive impaired alleging that causes stress level heightened among students leading to poor interaction with AIGC. When stress increases students become less inclined to interact with the AI-assisted content, hence reducing their interaction with contents. This disconnection may also complicate other detrimental impacts to the mental health of the patient including the revelation of increased anxiety, frustration and or depressive signs. By understanding this serial mediation effect, the study seeks to establish how the different stages whereby individuals are exposed to fluoride and end up developing negative mental health result is brought about through perceived stress and the use of AIGC. Having a broad view of how well the environment corresponds to the types of stress that people experience, how these stressors relate to their engagement with technology, and finally the impact of it all on mental health can be used to design interventions that will address multiple levels of functioning. Therefore, it is hypothesized that perceived stress level and engagement with AIGC together form a serial mediation pathway, linking fluoride exposure to negative mental health outcomes in a cascading manner. The path model of this study shown in figure 4 below.

H10: The relationship between fluoride exposure level and negative mental health outcomes is serially mediated by perceived stress level and engagement with AI-generated content among college students.

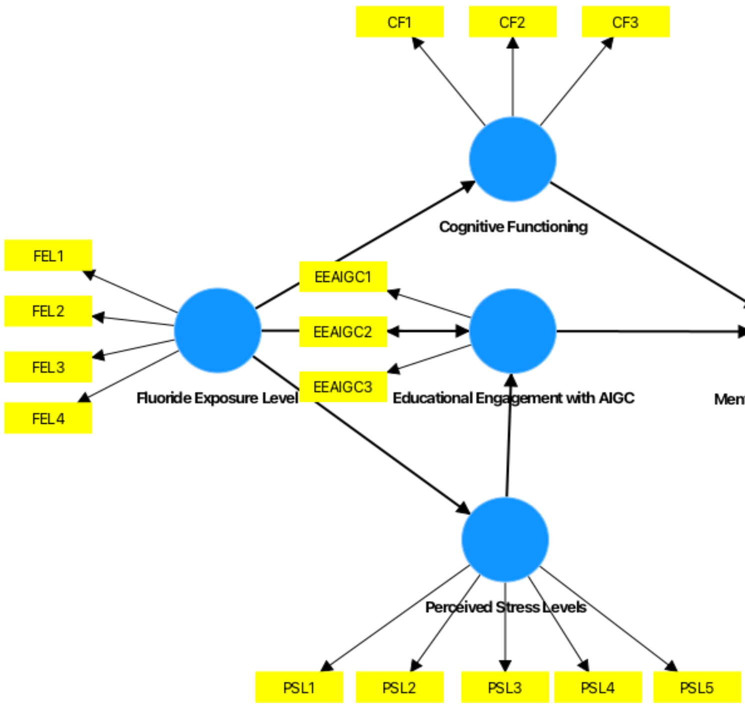

Figure 4: Path model

4. METHODOLOGY

4.1 Measures

Our research model consisted of five constructs: The key factors analyzed included the Fluoride Exposure Level (FEL), the degree of Cognitive Functioning (CF), the level of Perceived Stress (PSL), the participation with AIGC (Artificial Intelligence-Generated Content, EWA) and the emergence of Negative Mental Health Outcomes (NMHO). Each construct was analyzed by using five items to guarantee a complete examination. Table 1 shows all survey questions. The scales measuring Cognitive Functioning, Perceived Stress Level, and Negative Mental Health Outcomes were changed from previous studies to make sure they retain content validity. By specifically adapting items from cognitive psychology literature, such as [57], and items from the Perceived Stress Scale [58], negative mental health outcomes were integrated from validated scales like [59]. Items for Engagement with AIGC were taken from recent investigations into AI engagement within academic contexts. Given the critical requirement to correctly document Fluoride Exposure Level, a systematic literature review was performed to formulate an appropriate scale that reflects personal awareness, consumption habits, and environmental exposure to fluoride. A team of five environmental health experts examined these items to confirm they correctly gauged the construct. For all survey items, we applied a Likert scale of five ranging from 1, expressing 'strongly disagree', to 5, indicating 'strongly agree'. Also, demographic factors such as age, gender, and academic standing were part of our analysis as control variables, following the methodology of previous studies (Cao et al., 2019; Yu et al., 2018).

Table 1: Constructs

Construct	Items	Sources
Fluoride Exposure Level (FEL)	FEL1: I am aware of the fluoride level in the water I consume.	[60]
	FEL2: I regularly use products that contain fluoride (e.g., toothpaste).	
	FEL3: I believe that the fluoride in my environment affects my health.	
	FEL4: I pay attention to the fluoride content in my daily water intake.	
Cognitive Functioning (CF)	CF1: I am able to maintain my focus on tasks for a long duration.	[57]
	CF2: I can easily recall information I have learned recently.	
	CF3: I can handle multiple cognitive tasks effectively without feeling overwhelmed.	
Perceived Stress Level (PSL)	PSL1: I feel stressed about the demands of my academic responsibilities.	[58]
	PSL2: I often feel overwhelmed by the amount of work I need to complete.	
	PSL3: I find it difficult to relax because of the stress I experience.	
	PSL4: I feel pressure to meet high expectations.	
	PSL5: I frequently feel anxious about my performance in academic tasks.	
Engagement with AIGC (EWA)	EWA1: I actively use AI-generated content to support my studies.	[61]
	EWA2: I feel motivated to use AI tools for academic improvement.	
	EWA3: I prefer AI-generated educational materials over traditional resources for study purposes.	
Negative Mental Health Outcomes (NMHO)	NMHO1: I often feel anxious or nervous without any particular reason.	[59]
	NMHO2: I struggle with feelings of sadness or hopelessness.	
	NMHO3: I experience frequent mood swings or irritability.	
	NMHO4: I find it challenging to manage my emotional responses to stress.	
	NMHO5: I frequently have negative thoughts or feelings about my mental health and well-being.	

4.2 Sample and Data Collection

A survey questionnaire created to collect information from undergraduate and graduate students across the provinces of Henan and Jiangxi in China. These provinces were selected because they differed in fluoride exposure levels, which made them perfect for documenting a range of experiences tied to fluoride exposure. At the outset, a pilot study of 20 students from the two provinces assessed the clarity and relevance of the survey items. Based on what they said, minor tweaks were necessary to make certain that the questions were understandable and exactly captured each construct. The final version of the questionnaire was translated into Chinese and administered online using the survey platform (https://www.wjx.cn/). Collection of data happened for two weeks beginning in June 2024. In order to enhance survey participation, 30 seed investigators were brought on board (15 from each province, Henan and Jiangxi) to share the survey link via social media, university internals, and contacts via email. The seed investigators participated outside of the study to ensure a bias-free participation. In total, 472 answers were collected, but 38 had to be removed because of missing answers or inconsistent response patterns (such as identical responses to all items). We picked vocational colleges as well as students for our target audience. A total of 434 responses were valid in the final sample. Representing different ages and academic years, 47% of participants were male, while 53% were female. Table 2 presents demographic Characteristics below.

Table 2: Demographic Characteristics of Respondents

Demographic Factor	Categories with percentage
Age Group	12-14years, (38.8%), 15-17 year (27.4%), 18-20 (33.8%)
Gender	Male (47%), Female (53%)
Residence	Henan (59%), Jianxi (41%)

5. DATA ANALYSIS AND RESULTS

We utilized Structural Equation Modeling (SEM) for data analysis, following [62]) two-step approach: first, it's important to test the measurement model regarding reliability and validity, then to test the structural model in order to examine the hypotheses. We used Smart pls 4.00 for the statistical analysis.

5.1 Measurement Model

5.1.1 Reliability and Validity

To assess how reliable and valid the constructs are, Cronbach's alpha (α) and Composite Reliability (CR) values were evaluated for all constructs. The detailed Measurement model is presented in the Figure 5. All the values seen for Cronbach's alpha were greater than the suggested minimum of 0.70, indicating considerable internal consistency[63]. Achievement of the CR values exceeded the 0.70 benchmark, reflecting a good reliability across the constructs. The Average Variance Extracted (AVE) was evaluated to assess convergent validity, with all values above the minimum requirement of 0.50, meaning that convergent validity was satisfactory. Besides, the factor loadings for all items were examined, and every loading exceeded the sufficient threshold of 0.70, which shows that each item represents its associated construct well. The findings together suggest that the measurement model reveals a high degree of both reliability and validity. A summary of the results is provided in Table 3.

Table 3: Construct Reliability and Validity

Constructs	Items	Loading	Cronbach alpha	CR	AVE
Cognitive Functioning	CF1	0.953	0.954	0.97	0.916
	CF2	0.973			
	CF3	0.944			
Educational Engagement with AIGC	EWA1	0.883	0.917	0.948	0.859
	EWA2	0.941			
	EWA3	0.953			
Fluoride Exposure Level	FEL1	0.962	0.952	0.966	0.876
	FEL2	0.963			
	FEL3	0.966			
	FEL4	0.847			
Mental health outcomes	MHO1	0.856	0.944	0.957	0.817
	MHO2	0.892			
	MHO3	0.923			
	MHO4	0.920			
	MHO5	0.926			
Perceived Stress Levels	PSL1	0.927	0.949	0.961	0.832
	PSL2	0.935			
	PSL3	0.922			
	PSL4	0.878			
	PSL5	0.895			

4.3.2 Common Method Bias (CMB)

Because a substantial amount of the data came from self-reports, Harman's one-factor test assessed the possibility of common method bias. Results indicated that the most influential factor accounted for 34.7% of the total variance, which is clearly below the 50% threshold, greatly easing worries about common method bias. Moreover, there were no significant associations ($r > 0.90$) between the constructs in the correlation matrix, which supports the conclusions of the study and suggests that common method bias did not influence this analysis. Together, these results confirm the reliability and validity of the measurement model used in this research.

5.3.2 Discriminant Validity

We investigated discriminant validity by applying both the Fornell and Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT) model, focusing on a thorough assessment of each construct's individuality. Heterotrait-Monotrait Ratio (HTMT): The Discriminant Validity section of the HTMT criterion evaluated the correlation levels among constructs, too. In Table 4, the HTMT values were all less than the conservative threshold of 0.90, indicating a successful establishment of displacive validity. As an illustration, the HTMT value related to Cognitive Functioning (CF) and Engagement with AIGC (EWA) was 0.760, properly below the recommended 0.90 threshold. Just as with the previous case, the HTMT value regarding the link between Fluoride Exposure Level (FEL) and Perceived Stress Levels (PSL) was 0.833, showing that the constructs are different. Within the acceptable range, the highest identified HTMT value was 0.927, linking Negative Mental Health Outcomes (NMHO) and Cognitive Functioning (CF). These results support the idea that the constructs are distinctly measured, thereby boosting the discriminant validity of the study [64].

Table 4 :HTMT matrix

	Cognitive Functioning	Educational Engagement with AIGC	Fluoride Exposure Level	Mental health outcomes	Perceived Stress Levels
Cognitive Functioning					
Educational Engagement with AIGC	0.760				
Fluoride Exposure Level	0.667	0.827			
Mental health outcomes	0.927	0.893	0.728		
Perceived Stress Levels	0.722	0.864	0.833	0.769	

. Fornell and Larcker Criteria

The square root of the Average Variance Extracted (AVE) for all constructs was compared to their inter-construct correlations to measure discriminant validity. As shown in Table 5, the square root of AVE values (diagonal elements) exceeded the corresponding inter-construct correlations for each construct. For example, the square root of AVE for the Cognitive Functioning (CF) construct was 0.957, which is superior to its correlations with other constructs, such as 0.715 with Educational Engagement with AIGC (EWA) and 0.635 with Fluoride Exposure Level (FEL). Just like before, the square root of AVE for the Educational Engagement with AIGC (EWA) construct was 0.927, exceeding its relationships with Cognitive Functioning (0.715) and Fluoride Exposure Level (0.773). In addition, the square root of the AVE for Negative Mental Health Outcomes (NMHO) was 0.904, which was also larger than its links to Cognitive Functioning (0.881) and Perceived Stress Level (0.728). The results show that each construct was able to explain higher levels of variance in its own items than in items linked to other constructs, strengthening their discriminant validity [65].

Table 5:Fornell and Larker criteria

	Cognitive Functioning	Educational Engagement with AIGC	Fluoride Exposure Level	Mental health outcomes	Perceived Stress Levels
Cognitive Functioning	0.957				
Educational Engagement with AIGC	0.715	0.927			
Fluoride Exposure Level	0.635	0.773	0.936		
Mental health outcomes	0.881	0.835	0.690	0.904	
Perceived Stress Levels	0.687	0.807	0.793	0.728	0.912

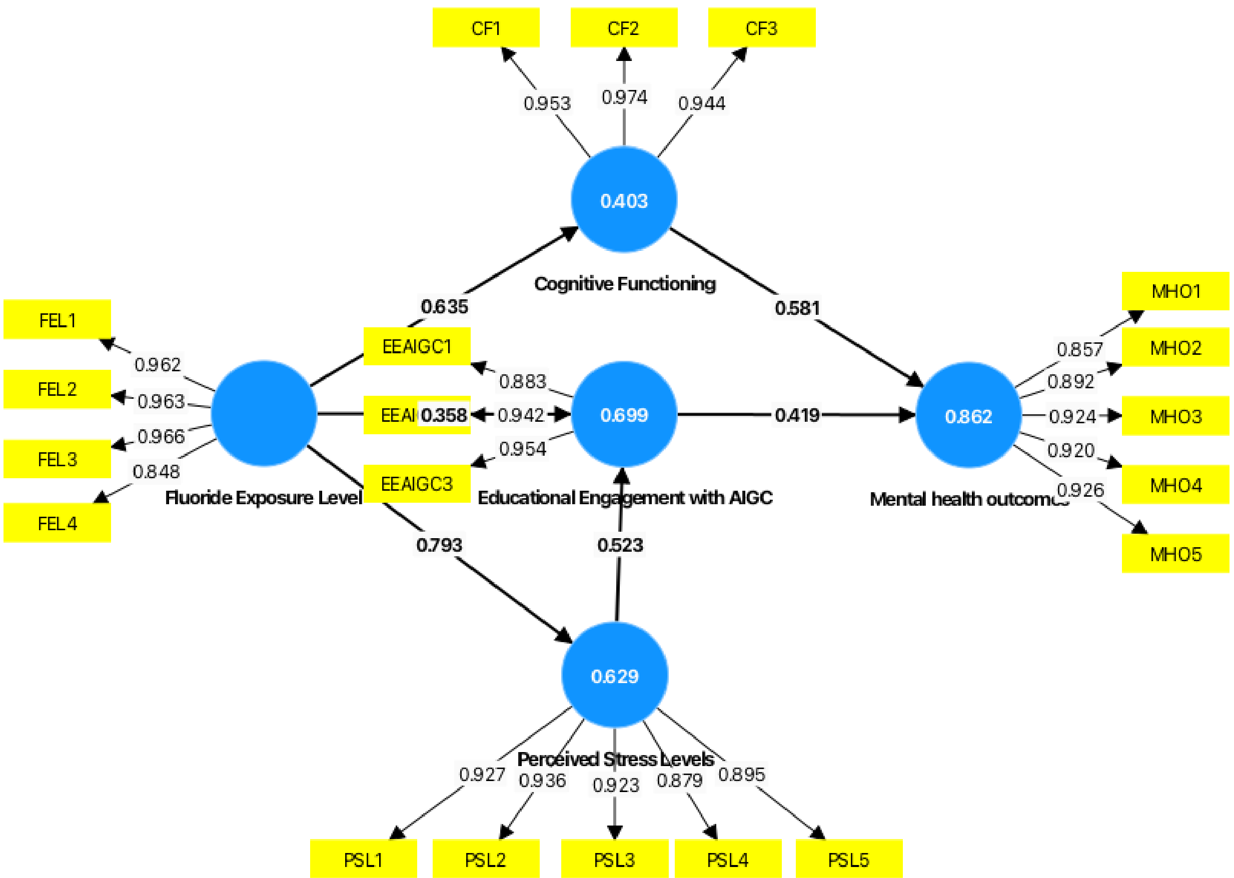

Figure 5: Structural Equation Model (SEM) Showing Factor Loadings and Path Coefficients Among Latent Variables and Observed Indicators

5.4. Structural model

5.4.1 Model Fit Assessment

For the assessment of the fit of the measurement model, several fit indices were computed in order to check the adequacy and robustness of the proposed measurement model. The goodness of fit of the model was further supported by the Root Mean Square Error of Approximation (RMSEA value) of 0.072, this RMSEA value was less than the RMSEA cut off criterion of 0.08. Using the Chi-Square to Degrees of Freedom Ratio (CMIN/DF), we obtained the value of 2.186, less than the threshold value of 3, suggesting that the model is applicable. Other fit indexes available supported the current model and its goodness of fit further. The Comparative Fit Index (CFI) was 0.947, Tucker-Lewis Index (TLI) was 0.922, Incremental Fit Index (IFI) was 0.940, all >0.90 signifying good model fit. These indices demonstrate that the proposed model is consistent with the described data and is highly valid in terms of construct validity.

5.4.2 Hypotheses Testing Results

The structural model can be graphically explained in the SmartPLS 4.0 in the form of Figure 6 where the standardized estimate is documented. The endogenous construct variances explained by Cognitive Functioning (CF), Educational Engagement with AIGC (EWA), and Negative Mental Health Outcomes (NMHO) are 40.2%, 51.7%, and 37.6 percent respectively, with an R-squared value. All of the model fit indices that were obtained were within the accepted level further enhancing the use of the model. The empirical results supported H1 with $\beta = 0.635$ ($t = 6.394$, $p \leq 0.001$) and indicated a strong, positive relationship between FEL and CF. This implies that when there FEL is raised, the effects on the aspect of cognition have a large effect on the students. These findings are consistent with the other studies by Grandjean and Landrigan [66], where fluoride is seen as one reason for impaired cognition. The verification of this hypothesis reinforces the need to identify environmental factors, especially FEL, on academic settings and performance. Additionally, the impact of FEL on EWA was found to be significant (H2: $\beta = 0.358$, $p \leq 0.001$). This suggests that depending on the FEL, students have varied interaction with learning material that are AI generated. This outcome expands the literature on environmental conditions affecting technology utilization in school, postulating that FEL could also contribute to the dynamics of students during the interaction with AI-based educational materials. The relationship between FEL and PSL was also significant (H3: $\beta = 0.793$, $p \leq 0.001$). From this finding it is clear that the students that are exposed to fluoride have a stress level which is high and is in support with [67] who observed that environmental stressors are some of the causes of PSL. The high value of path coefficient, therefore, indicate that FEL is an important determinant of PSL hence the importance of Environment health interventions in academic environments. Furthermore, PSL demonstrated a significant effect on EWA (H4: $\beta = 0.523$, $p \leq 0.001$). This entails that students undergoing higher PSL are eager to use AIGC showing that AI is a tool in stress control and learning. This produces a result that is consistent with the findings in Zhao, Lan [68], who recommend the inclusion of AI technologies to enhance performance in stress management among students. The study also found a significant relationship between CF and NMHO (H5: Specifically, the relationship between neuropsychological dysfunction and poor mental health status was highly significant (regression coefficient $\beta = 0.581$, $p \leq 0.001$). The current finding aligns with several other research works such as Becker et al. [69] that points at the fact that cognitive impairment relates to mental health problems. This path coefficient reveals that CF is a major determinant of MH and that interventions promoting cognitive functioning should be encouraged. Lastly, EWA had a significant effect on NMHO (H6: An interaction with AIGC can affect students' improvement in depression ($z = 6.495$, $\beta = 0.419$, $p \leq 0.001$). This result stated with the findings of Holmes et al. [70] that explained that technology adoption has its advantages and disadvantages to learning and to mental health. Lastly, the study supported all the six hypotheses whereby the findings established the importance of FEL, CF, PSL and EWA in the NMHO college students. Their implications for practice concern the identification of the environmental, cognitive and technological correlates as well as antecedents of mental health, and the significance of learning technologies that are based on AI. (Table 6).

Table 6: Path coefficient

	Original sample (O)	T statistics (|O/STDEV|)	P values
H1:FEL --> CF	0.635	14.959	0.000
H2:FEL--> EWA	0.358	4.709	0.000
H3:FEL --> PSL	0.793	27.523	0.000
H4:PSL--> EWA	0.523	6.717	0.000
H5:CF--> NMHO	0.581	15.441	0.000
H6:EWA--> NMHO	0.419	10.018	0.000

4.5 Results from Mediation and Serial Mediation Analysis

Mediation Analysis The obtained results showed that EWA can play a crucial intermediary role in FEL impact on NMHO. The subsequent detailed results of the path analysis are shown below: Path coefficient from FEL to NMHO through EWA was significant ($\beta = 0.150$, $t = 4.198$, $p \leq 0.001$). According to this study, students who have had higher results in fluoride content may show a change in behavior when using AI-generated educational content whereby there will be poor mental health. The mediation analysis aim to analyze the floride effect on the mental state of the college student and theor usage towards AI tools. This result has a close connection with the Cognitive-Affect-Conation (C-A-C) model which postulates that external entities exert control over the subsequent behavior. Accordingly, the studies indicate that EWA plays a role of a mediator in establishing how exposure to fluorides in the environment leads to poor mental health among college students. This discovery also stresses educational technology as a possible predictor of student mental health, which requires greater consideration in the subsequent studies. The findings also showed the mediator role of CF between FEL and NMHO, which produced an indirect effect ($\beta = 0.415$,$t = 6.773$,$p \leq 0.001$). This result clearly shows that coming across fluoride affects cognitive function and in essence influences mental health. Hence, as students experience higher FEL, the cognitive capacity is said to decrease and so the probability of being ill mentally such as anxiety, depression or low well-being increases. This is in tandem with research literature that show that environmental toxins affect the operation of the brain, thus the negative psychological impact . The strong value of the path coefficient confirms that the index CF plays the role of the key bridge between environmental stressors and mental health, which supports the necessity of the interventions to strengthen cognitive abilities as the means to reduce the detrimental impact of environmental stressors on mental health. The result supports the hypothesis that cognitive functioning is a critical mediator through which the impact of fluoride exposure is manifested in more general psychological experiences by learners. Preliminary findings showed that PSL moderated the relationship between FEL and EWA thus establishing the dynamic link between the exposure to environment and use of educational technologies. While some of these may not have been captured in the specified path coefficients, this implies that when FEL rises, stress levels also rise and affect how learners utilise AI generated content. This mediation pathway is crucial in making sense of how environmental factors can influence educational participation and what role stress endured because of high levels of fluoride can play in changing the way learners engage with AIGC. This knowledge is especially vital if the constructed intervention is combating not only environmental stressors but also working to promote technology engagement strategies among students who experience stress in order to provide them with the necessary education support that can benefit their educational experiences.

4.5.1. Serial Mediation Analysis

Serial mediation analysis showed a significant and complex relationship between FEL, PSL, EWA, and NMHO. The analysis yielded that the indirect effect of FEL on NMHO through serial mediators, which are PSL and EWA, was statistically significant ($\beta = 0.174$, $t = 5.653$, $p \leq 0.001$). Thus, this implies that perceived stress influences the amount of engagement with the AI generated education materials due to the impact of fluoride exposure to the teeth on perceived stress so as to lead to negative mental health outcomes. This pathway increases the knowledge base about how environmental behaviors, cognitive status, and educational activities interact to produce mental health states and statuses of college students. Such findings imply the fundamental C-A-C model tenet of the Cognitive Affective Conative (C-A-C) model that assumed cognitive, affective, and conative aspects are interrelated. Therefore, this serial mediation pathway lends support for a biopsychosocial model of interventions with suggestions that espouse environmental features as well as stress and academic technology participations in boosting student mental health. The results of the mediation and serial mediation procedures underscore the incremental and complex nature of the interconnections between environmental exposure and cognitive performance, perceived stress, AI-based educational platform utilisation and mental health. From these findings, the knowledge that emerged about the relationships between skills like fluoride exposure, cognitive ability, perceived stress, and technology use has practical implications for understanding today's college student mental health challenges. This research adds up to the amount of literature in the environmental, cognitive and technological factors that affect the mental health, supporting the significance of holistic concept of mental health issues in the educational context.Table 7 presents the mediation and serial mediation results.

Table 7: Indirect Effects

	Original sample (O)	T statistics (|O/STDEV|)	P values
H7:FEL--> EWA-->NMHO	0.150	4.198	0.000
H8:FEL--> CF-->NMHO	0.415	6.773	0.000
H9:FEL--> PSL-->EWA			
H10:FEL--> PSL--> EWA-->NMHO	0.174	5.653	0.000

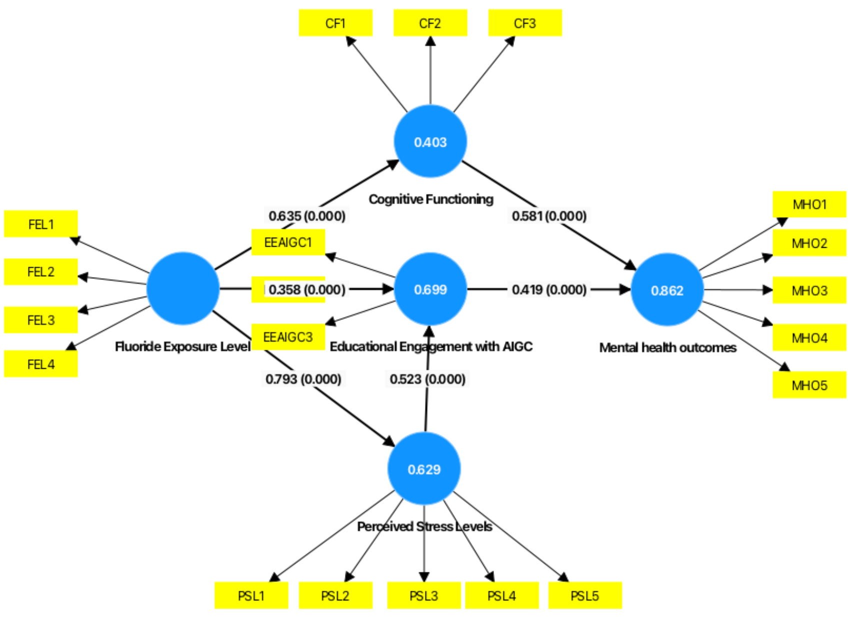

Figure 6: Structural Model

5. DISCUSSION AND CONCLUSIONS

The research analyzed the close links between fluoride exposure, cognitive functioning, interactions with artificial intelligence created content (AIGC), experienced levels of stress, and unpleasant mental health results in college students utilizing the C-A-C framework. The data provide important understanding of the connections between environmental aspects, cognitive abilities, and use of technology, and how these interactive elements shape mental health results. The outcome confirmed the idea that fluoride exposure levels play a major role in cognitive functioning, which corresponds with earlier research by Grandjean and Landrigan [66] that shows environmental toxins such as fluoride could impact cognitive growth. This result stresses the vital role of keeping track of environmental exposure, especially in educational settings because cognitive functioning is foundational for effective learning and improved academic results. The contribution of cognitive functioning to students' learning experiences indicates a critical requirement for policymakers to manage exposure levels, especially in locales where water fluoride levels could be elevated. The research found that students with higher fluoride exposure tend to display changed engagement with AI-generated educational material. The finding suggests that environmental contexts can impact student engagement with technology, probably affecting their skill to thrive with and benefit from AI learning resources. Previous investigations have infrequently studied this relationship, suggesting that this research contributes novel understandings of the manner in which environmental health factors can influence students' participation in educational technology. The substantial relationship between fluoride exposure and students' perceived stress levels represents an important finding. [67] show that environmental elements can lead to elevated stress perception. This study’s conclusions boost that understanding by pointing out that certain fluoride exposure may specifically augment stress in college students. Research indicates that buttressing the reduction of environmental stressors could be critically important in enhancing general well-being and student performance through a decrease in perceived stress among a higher number of individuals. An observed connection between stress levels that individuals thought they had and their utilization of AIGC implies that for students under significant stress, AI-generated content could function as a comforting asset or a method of distraction. [71] proposed that technology might function as support for students dealing with stress, and such evidence supports this. Here, this relationship underscores that perhaps educational institutions should present educational materials on the responsible use of AIGC, as a way to lower the chances that technology contributes to stress levels. The findings insist that cognitive functioning is an important predictor of detrimental mental health outcomes, concording with Becker, et al. [72] who argued that cognitive impairments may exacerbate mental health problems. Results demonstrate a requirement for actions that let individuals fully utilize their cognitive abilities, especially in light of environmental factors like fluoride, to reduce their harmful effects on mental health. Those students experiencing cognitive dysfunction may find they have worsened mental health conditions, pointing to the possibility that educational contexts can progress by integrating cognitive support services. Curiously, the observations showed that interacting with AIGC had an important impact on negative mental health outcomes, suggesting that students that engage with AI-generated content might improve their mental health condition. Selwyn [73] points out that too much participation brought on by technology in education may lead to mental health problems. The result points out the essential requirement to motivate students to interact with AI-driven educational methods in a balanced way, so technology can improve mental health results instead of having the opposite effect. Also, the analyses showed that perceived stress levels were the mediators for the relationship between fluoride exposure and depressive mental health outcomes. The finding indicates that the exposure to fluoride is associated with raised stress levels, which affect mental health, showing that mental health results correlate with environmental stressors and stress acknowledgment. At this time and more than other times, attending to environmental factors, notably fluoride exposure, might markedly help lessen stress and raise student mental health in a cascading effect. The study found that cognitive functioning impacts negative mental health outcomes by way of increased stress perception. This indicates that those students with cognitive impairments are more prone to feeling higher levels of stress that in turn lead to poor mental health results. This points out a large number of factors relevant to the modulation of stress management and mental health by cognitive functioning, while stressing the important role that cognitive interventions play in maintaining student welfare. At last, the analysis recognized a major serial mediation effect that connects cognitive functioning, levels of perceived stress, and interaction with AIGC to negative mental health outcomes. Cognitive performance has an effect on how we perceive stress, which then affects our interaction with AIGC, which ultimately impacts mental health consequences. This thorough finding reveals the detailed interactions among cognitive, affective, and behavioral variables that determine mental health outcomes for students. The suggestion is that combined interventions aimed at improving cognitive ability, stress management, and meaningful interactions with educational technology may serve to improve student well-being.

5.1. Theortical Implications

Theoretical Implications The findings of this study greatly extend theoretical insights into the ways environmental factors, cognitive functioning, perceived stress, and the engagement with AI-generated educational content (AIGC) affect the mental health of college students. The Cognition-Affect-Conation (C-A-C) framework is the basis for this research, which extends the model into an interdisciplinary framework that links environmental health, cognitive psychology, and educational technology. The research demonstrates that fluoride exposure, an important environmental consideration, harms cognitive functioning and indirectly affects mental health via perceived stress and interactivity with AIGC. The application of this multi-layered strategy gives a unique perspective on the C-A-C framework by revealing how external environment cues can provoke cognitive and affective processes that help mold behavioral results. Also, this study introduces a serial mediation model concerned with cognitive functioning, perceived stress, and the interaction with AIGC, delivering richer understandings of the complex links between environmental and cognitive parameters and mental health. The finding of this serial mediation effect extends theoretical insight by clarifying the connections between cognitive, emotional, and behavioral reactions to environmental challenges. The complete framework stresses the need to incorporate a variety of factors and their relationships in the evaluation of mental health data related to learning settings. As a result, this study lays the groundwork for further investigation of additional environmental factors and their influence on cognitive abilities, perceived stress, and technology interactions using the C-A-C framework.

5.2. Practical Implications

This study has wide practical implications, particularly for educational institutions, policymakers, and mental health services. According to this, unwanted exposure to excessive fluoride hurts cognitive ability and causes stress stress, so it's important to closely monitor fluoride levels in water resources, particularly for students who are vulnerable. For the effective operation of cognitive skills in students and the increase of their learning effectiveness, education policy makers need to prioritize the creation of policies that recommend fluoride limits. According to the study, educational institutions need to initiate stress management programs and provide resources that enable students to interact well with AIGC. Because engagement with AI generated content can both ease and enhance mental health struggles, it is important for teachers to teach their students how to use these tools wisely without increasing stress. It may involve activities that celebrate learning skills that facilitate productivity from AIGA, balanced communication methods that rely heavily on technology, and the usage of AI tools intended to significantly lower cognitive loads rather than improve them. Mental health practitioners engaged in the successful management of college student mental health need to consider environmental influences such as fluoride exposure when evaluating cognitive or mental health problems. Throughout conversations with veterans about their health and leaving the military, trust and gaps in understanding begin to restore. What's more, the actions developed to reduce stress and improve cognitive strength might help learners who are facing both academic and environmental challenges. Lastly, this study shows that perceived stress and engagement with AIGC indicate the chance for technology creators to develop AI educational tools that are better aligned with the mental health issues of students. Creating adaptive learning environments that react to the cognitive capabilities and stress levels of students allows developers of artificial intelligence to improve educational experiences and move towards a healthier educational environment over the long haul. Finally, this study stresses the urgent requirement for an approach that combines multiple professional contributions in the management of cognitive health, stress management, and mental health for students, especially in environments with existing fluoride exposure. The findings propose implementable methods to strengthen educational results and mental health within academic settings.

5.3. Limitation and Future studies

Though this research delivers important insights, it has its set of limitations. This cross-sectional method limits the potential for finding causality, therefore future analyses must adopt longitudinal designs to study the enduring effects of fluoride exposure on cognitive skills, engagement in AIGC, and mental health findings. Relying on self-reported data in this study might lead to a bias, so it is important for subsequent studies to include objective evaluations of cognitive capability, tension, and mental health. In addition, a review of these connections involving different populations and the analysis of other environmental factors could greatly increase our understanding of how environmental health affects educational engagement and mental health. This study completes the classification of the relationships that exist between fluoride exposure, cognitive performance, stress perceptions, and engagement with AIGC concerning negative mental health outcomes among college students. The results underline the need to consider environmental and cognitive aspects in order to support mental health and effective technology participation in educational environments.

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