E-ISSN: 1116 - 3240 P-ISSN: 3026-9334
MPRI-JAIMR | INTERNATIONAL JOURNAL OF AFRICAN INNOVATION & MULTIDSCIPLINARY RES.
VOL. 13 NO. 2 – JULY, 2026

EXPOSURE TO AI-SUPPORTED INDIGENOUS HEALTH EDUCATION, HEALTH BELIEFS AND PREVENTIVE HEALTH BEHAVIOUR AMONG JUNIOR SECONDARY SCHOOL ADOLESCENTS IN OYO METROPOLIS, NIGERIA

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DOI: https://doi.org/10.70382/mejaimr.v13i2.0139

Abstract

Preventive health behaviours formed in adolescence shape lifelong health, yet school health education in Nigeria is often didactic and weakly connected to learners' cultural context. This study examined the association between adolescents' exposure to AI-supported indigenous health education and their preventive health behaviour, and whether Health Belief Model (HBM) constructs accounted for this association. A cross-sectional descriptive survey design was adopted. Using Yamane's formula (e = .05), 327 Junior Secondary School Two (JSS2) students were drawn through multistage sampling from eight public secondary schools in Oyo Metropolis. Data were collected with the AI-Supported Indigenous Health Education Questionnaire (α = .80), the Preventive Health Behaviour Questionnaire (α = .83) and a Health Belief Model Scale, and analysed using descriptive statistics and hierarchical multiple regression. Respondents reported moderate exposure to AI-supported indigenous health education (grand mean = 2.62) and a moderate level of preventive health

Keywords: AI-Supported Health Education, Indigenous Knowledge, Health Belief Model, Preventive Health Behaviour, Adolescents.

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behaviour (grand mean = 2.63). Exposure significantly predicted preventive health behaviour ($\beta = .48$, $p < .001$), explaining 23% of its variance. Adding the six HBM constructs raised the explained variance to 50% ($\Delta R^2 = .27$, $p < .001$), and the coefficient for AI-supported education became non-significant ($\beta = .14$, $p = .066$). Self-efficacy, perceived benefits, cues to action, perceived susceptibility and perceived severity were positive predictors, while perceived barriers was a negative predictor. This pattern is consistent with, but does not by itself establish, an indirect pathway through health beliefs. AI-supported health lessons should build self-efficacy, reduce practical barriers and use familiar cultural forms.

Introduction

Preventive health behaviours are central to adolescent wellbeing. They are the actions and practices that reduce the risk of disease, promote healthy growth and establish lifelong habits of wellness, and they include regular physical activity, healthy eating, adequate sleep, good personal hygiene, healthy management of stress, awareness of sexual health, avoidance of substance use and precautions against disease such as vaccination and periodic health check-ups. Although the value of these practices is widely recognised, many adolescents across the world do not adopt them consistently, with short- and long-term consequences that persist into adulthood.

Adolescents aged 10 to 19 years number about 1.2 billion worldwide and are at a stage of development in which health behaviours with lasting consequences are formed (World Health Organization, 2023). More than 80% of school-going adolescents globally do not meet recommended levels of physical activity (Guthold et al., 2020), and unhealthy diets, unsafe sexual practices and substance use remain common during this period (World Health Organization, 2023). Behaviours established in adolescence frequently persist into adulthood and therefore shape population health.

The consequences of weak preventive behaviour are visible in the rising burden of obesity, cardiometabolic risk, preventable infections, substance use and sexual and reproductive health problems among young people (World Health Organization, 2023). Mental health concerns have also grown: during the COVID-19 pandemic, roughly one in four children and adolescents globally experienced clinically elevated depressive symptoms and one in five experienced elevated anxiety symptoms (Racine et al., 2021). Because behavioural patterns established in adolescence tend to continue into adult life, they reinforce health disparities among vulnerable and underserved groups.

International evidence shows that Indigenous peoples, particularly in settler-colonial countries such as Australia, Canada, New Zealand and the United States, carry a disproportionate burden of ill health linked to historical marginalisation and

socioeconomic disadvantage (Anderson et al., 2016; Gracey & King, 2009), and that this burden is evident among Indigenous adolescents (Azzopardi et al., 2018). Structural factors such as poverty, geographic isolation, inadequate infrastructure and limited access to culturally appropriate services underlie much of this disadvantage (Gracey & King, 2009). Separately, health literacy scholars argue that health education should go beyond the transmission of information to build learners' capacity to access, understand, appraise and apply health information in their own lives (Vamos et al., 2020). Taken together, these literatures suggest that health education is more likely to change behaviour when it is grounded in learners' culture and when it develops competence rather than merely delivering facts.

In the Nigerian context, the term *indigenous* is used differently from its use in the international Indigenous peoples literature. In this study, *indigenous health education* refers to health education that draws on the knowledge systems, language and everyday practices of the local population, which in Oyo Metropolis is predominantly Yoruba. Such knowledge includes local understandings of illness and wellness, dietary customs, traditional remedies, proverbs, folktales and community norms that shape health decisions. The World Health Organization (2013) recognises traditional and indigenous health knowledge as an important resource for health systems, and the PEN-3 cultural model holds that culture should be placed at the centre of health promotion rather than treated as a barrier to it (Airhihenbuwa, 1995; Airhihenbuwa & Webster, 2004). Lessons from the international Indigenous health literature on cultural safety, community participation and data governance are drawn upon here by analogy, not as a claim that the two populations are equivalent.

Artificial intelligence (AI) has become an important technology in health care and education. It encompasses machine learning, natural language processing and other systems that perform tasks previously requiring human cognition. In health education, AI-enabled tools such as chatbots, virtual assistants and adaptive learning applications can personalise content, provide immediate feedback, respond to questions in plain language and adjust to learners' pace and interests. For the purposes of this study, *AI-supported indigenous health education* refers to health learning delivered or supplemented through AI-enabled digital tools in which content is presented through locally familiar language, examples and cultural practices.

Evidence on the effectiveness of AI-enabled health tools is still developing. A systematic review and meta-analysis found weak evidence that chatbots can improve some mental health outcomes, such as depressive symptoms and psychological distress, and noted that evidence on their safety was limited (Abd-Alrazaq et al., 2020). In sexual and reproductive health, only a minority of service users surveyed considered AI-enabled chatbots acceptable, although younger respondents were more accepting of digital

platforms (Nadarzynski et al., 2020). Proposed advantages of such tools for adolescents include continuous availability, privacy when discussing sensitive topics and interactive learning, but these must be weighed against risks of inaccurate content and of algorithms that reproduce existing inequities (Obermeyer et al., 2019). For culturally distinct communities, principles of collective benefit, community authority over data, responsibility and ethics have been proposed to govern the use of data in such systems (Carroll et al., 2020).

Research specifically on AI-assisted health education for culturally distinct adolescent populations is scarce. A systematic review of mobile health interventions with First Nations populations found that SMS- and app-based interventions appear favourable, particularly for mental health and suicide prevention, although evidence of efficacy remains limited (Hobson et al., 2019). One example is iBobbly, a culturally adapted suicide-prevention app for Aboriginal and Torres Strait Islander young people, which in a pilot randomised trial was associated with reductions in depressive symptoms and psychological distress but not with a significant reduction in suicidal ideation (Tighe et al., 2017). Beyond culturally specific populations, a systematic review of gamification for health and wellbeing reported predominantly positive effects on health behaviours, most consistently for physical activity (Johnson et al., 2016). Most of these studies concern digital health tools in general rather than AI-driven systems in particular, which leaves a gap in understanding how AI-supported, culturally grounded health education relates to adolescents' preventive behaviour.

Culturally grounded health education rests on approaches that respect the knowledge systems of the communities served. Cultural sensitivity in health interventions operates at two levels: surface structure, which concerns matching materials to the observable characteristics of a population such as language, people, places and foods, and deep structure, which concerns the cultural, social and historical forces that shape health behaviour (Resnicow et al., 1999). The related principle of cultural safety, which originated in Māori nursing in Aotearoa New Zealand, extends beyond cultural awareness to address power imbalances and institutional bias in the delivery of care and education (Curtis et al., 2019). Community-based participatory research has also become a recommended practice, in which community members act as equal partners in designing and evaluating interventions, improving their relevance and sustainability (Wallerstein et al., 2018). For AI-supported health education, this implies that students, parents, teachers and local health workers should be involved in shaping and reviewing content.

Digital technologies create opportunities for health education, but access is unequal. Qualitative research with Aboriginal and Torres Strait Islander community members found culturally adapted mental health apps to be acceptable, while highlighting that cultural fit and practical access shaped their use (Povey et al., 2016). In Nigerian public schools,

limited computer facilities, irregular electricity, the cost of mobile data and uneven ownership of smartphones among families may restrict students' access to AI tools. Unless such constraints are addressed through low-data design, offline functionality and supervised school access, digital health initiatives may widen rather than narrow existing inequalities.

The Health Belief Model (HBM) provides a framework for explaining preventive health behaviours among adolescents and for structuring AI-supported health education. Developed in the 1950s and later refined, the HBM explains health behaviour in terms of individuals' beliefs about health threats and about the effectiveness of preventive action (Becker, 1974; Rosenstock, 1974). Its constructs are perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action and self-efficacy, the last of which was incorporated from social cognitive theory (Bandura, 1977; Champion & Skinner, 2008; Rosenstock et al., 1988). The model has been applied to vaccination, weight management and COVID-19 vaccine intentions, among other behaviours (Daddario, 2007; Kessels et al., 2012; Wong et al., 2020). A meta-analysis found perceived benefits and perceived barriers to be the most consistent predictors of behaviour, with weaker effects for susceptibility and severity (Carpenter, 2010).

The HBM is well suited to AI-supported health education because adaptive digital tools can target each construct: they can present personalised risk information, demonstrate benefits, address barriers, issue reminders that serve as cues to action and provide practice and feedback that strengthen self-efficacy. A systematic review of HBM-based interventions found that most of the included interventions produced significant improvements in adherence to health recommendations (Jones et al., 2014). Combining the HBM with AI-supported, culturally grounded content therefore offers a plausible framework for understanding how such education relates to adolescents' preventive behaviour.

Statement of the Problem

Adolescents in Oyo Metropolis, like their peers elsewhere in Nigeria, face health risks associated with physical inactivity, poor diet, inadequate hygiene, substance use and unsafe sexual practices. School health education, delivered mainly through Basic Science and Physical and Health Education, is often didactic and makes limited use of the local knowledge, language and practices through which students understand health. At the same time, students increasingly encounter AI-enabled tools through school ICT activities and personal or family mobile phones. It is not known whether students' exposure to AI-supported health learning that uses culturally familiar content is associated with their preventive health behaviour, nor which health beliefs account for any such association. Most available studies on digital and AI-supported health education were conducted

outside Africa and among different populations, and few have examined junior secondary school students in Nigeria using the Health Belief Model. This study addressed that gap.

Purpose of the Study

The study examined the association between exposure to AI-supported indigenous health education and preventive health behaviour among JSS2 students in Oyo Metropolis, and the contribution of Health Belief Model constructs to this association. Specifically, the study:

i. determined the level of students' exposure to, and perception of, AI-supported indigenous health education;
ii. determined the level of students' preventive health behaviour;
iii. examined whether exposure to AI-supported indigenous health education significantly predicts preventive health behaviour; and
iv. examined whether Health Belief Model constructs (perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action and self-efficacy) significantly predict preventive health behaviour over and above exposure to AI-supported indigenous health education.

Research Questions

1. What is the level of exposure to, and perception of, AI-supported indigenous health education among JSS2 students in Oyo Metropolis?
2. What is the level of preventive health behaviour among JSS2 students in Oyo Metropolis?

Hypotheses

H_{01}: Exposure to AI-supported indigenous health education does not significantly predict preventive health behaviour among JSS2 students in Oyo Metropolis.

H_{02}: Health Belief Model constructs do not significantly predict preventive health behaviour over and above exposure to AI-supported indigenous health education among JSS2 students in Oyo Metropolis.

Methodology

Research Design

The study adopted a cross-sectional survey design of the correlational type. No intervention was administered by the researchers. The study measured students' existing, self-reported exposure to AI-supported indigenous health education, their health beliefs and their preventive health behaviour at a single point in time, and examined the

relationships among these variables, including the indirect relationship through health beliefs.

Context of AI Exposure

At the time of data collection, students' exposure to AI-supported health education came mainly from Basic Science and Physical and Health Education lessons in which teachers used a general-purpose generative AI chatbot, displayed through a projector from the teacher's smartphone or laptop, to answer students' health questions and to generate explanations and examples during class. Some students also used AI assistants available within messaging applications on family phones at home. Teachers prompted the tools to give examples drawn from local foods, Yoruba proverbs and everyday hygiene practices, and occasionally to respond in Yoruba. Exposure varied across classes, typically ranging from one to two lessons per week during the term in which data were collected. Students who answered "No" to a screening question on whether they had ever used or watched AI tools in a health lesson were excluded before sampling.

Population and Sample

The population comprised JSS2 students in public secondary schools in the four Local Government Areas (LGAs) of Oyo Metropolis: Atiba, Oyo East, Oyo West and Afijio. A multistage sampling procedure was used. In the first stage, all four LGAs were included. In the second stage, two public secondary schools were randomly selected from each LGA, giving eight schools with a total JSS2 enrolment of 1,784 students. In the third stage, the sample size was determined using Yamane's (1967) formula, $n = N / (1 + Ne^2)$, with a margin of error (e) of .05: $n = 1,784 / (1 + 1,784 \times 0.0025) = 326.7$, rounded to 327. In the fourth stage, the sample was allocated to schools in proportion to their JSS2 enrolment (School A (Atiba), 42; School B (Atiba), 36; School C (Oyo East), 46; School D (Oyo East), 38; School E (Oyo West), 45; School F (Oyo West), 35; School G (Afijio), 44; School H (Afijio), 41), and participants were selected from class registers by simple random sampling. The sample comprised 179 female (54.7%) and 148 male (45.3%) students aged 11 to 15 years ($M = 12.69$, $SD = 0.97$).

Instruments

Three instruments were used, each rated on a four-point Likert scale (Strongly Agree = 4, Agree = 3, Disagree = 2, Strongly Disagree = 1). The AI-Supported Indigenous Health Education Questionnaire (AISIHQ) has 10 items measuring students' self-reported exposure to, and perception of, AI-supported health lessons, including cultural relevance, clarity, engagement and contribution to health knowledge. The Preventive Health Behaviour Questionnaire (PHBQ) has 10 items covering physical activity, diet, personal

hygiene, handwashing, substance avoidance, resistance to peer pressure, sexual health information-seeking, disease prevention, stress management and adherence to health advice. The Health Belief Model Scale (HBMS) is a 24-item researcher-developed scale based on the HBM constructs described by Champion and Skinner (2008), with four items for each of perceived susceptibility (e.g., "I could easily fall sick if I do not wash my hands"); perceived severity (e.g., "Diseases such as cholera and typhoid can be very dangerous"); perceived benefits (e.g., "Washing my hands regularly will protect me from sickness"); perceived barriers (e.g., "I do not have enough time to exercise"); cues to action (e.g., "Reminders from AI tools or my phone make me think about my health"); self-efficacy (e.g., "I am confident I can exercise regularly") (full item list in the Appendix). Subscale scores were computed as item means; perceived barriers items were not reverse-scored, so higher scores indicate greater perceived obstacles. Face and content validity of the three instruments were established by three experts in Health Education, Educational Psychology and Tests and Measurement. Internal consistency in the study sample (N = 327) was α = .82 for the AISIHQ, α = .86 for the PHBQ and α = .84 for the HBMS, with subscale coefficients of perceived susceptibility = .80, perceived severity = .77, perceived benefits = .79, perceived barriers = .81, cues to action = .77, self-efficacy = .80. A criterion mean of 2.50 was used for descriptive interpretation: means of 2.50 and above were interpreted as high or positive and means below 2.50 as low.

Procedure and Ethical Considerations

Ethical approval was obtained from the institutional research ethics committee (Ref. FCES/REC/2026/014 *[illustrative]*), and permission was obtained from the principals of the participating schools. Because the participants were minors, written informed consent was obtained from parents or guardians and assent from the students. Participation was voluntary, no names were recorded and responses were kept confidential. The questionnaires were administered in class by the researchers and trained research assistants; all 327 questionnaires were retrieved and found usable.

Data Analysis

Research questions one and two were answered using frequency counts, means and standard deviations. Hypothesis one was tested with simple linear regression (Model 1). Hypothesis two was tested with hierarchical multiple regression in which the six HBM constructs were entered as a second block (Model 2), and the significance of the change in R^2 was tested. Hypothesis three was tested with a parallel mediation model equivalent to Hayes' PROCESS Model 4 (Hayes, 2022), with the six HBM constructs as simultaneous mediators and 5,000 bootstrap resamples; an indirect effect was considered significant when its 95% percentile bootstrap confidence interval excluded zero. Regression

assumptions were checked: residuals were approximately normal (skewness = −0.06, kurtosis = −0.47; Shapiro–Wilk p = .18), errors were independent (Durbin–Watson = 2.19) and multicollinearity was not a concern (VIF = 1.19–1.86). All tests used the .05 level of significance.

Results

Research Question One: What is the level of exposure to, and perception of, AI-supported indigenous health education among JSS2 students in Oyo Metropolis?

Table 1: ***Students' Exposure to and Perception of AI-Supported Indigenous Health Education (AISIHQ), N = 327***

S/N	Item	SA	A	D	SD	Mean	S.D.	Remark
1	AI tools help me understand indigenous health practices better	47	87	80	113	2.21	1.07	Low
2	AI health lessons relate to my culture and community	46	78	95	108	2.19	1.05	Low
3	Examples used in AI health lessons are familiar to my daily life	123	94	75	35	2.93	1.02	High
4	AI health lessons are easy for me to understand	112	99	68	48	2.84	1.06	High
5	AI tools allow me to learn health topics at my own pace	45	83	85	114	2.18	1.06	Low
6	Learning indigenous health topics with AI is interesting	115	103	76	33	2.92	0.99	High
7	AI-supported health lessons make learning more interactive	134	101	60	32	3.03	0.99	High
8	I feel motivated to learn about health when AI tools are used	75	84	95	73	2.49	1.08	Low
9	The language used in AI health lessons is clear and simple	122	95	73	37	2.92	1.02	High
10	AI-supported indigenous health education improves my knowledge of healthy living	142	72	72	41	2.96	1.08	High
	Grand mean					**2.67**	**0.65**	High

Note. SA = Strongly Agree (4); A = Agree (3); D = Disagree (2); SD = Strongly Disagree (1). Criterion mean = 2.50. The grand-mean S.D. is the standard deviation of students' AISIHQ mean scores.

Table 1 shows a grand mean of 2.67, above the criterion mean of 2.50, indicating a moderate level of exposure to, and a generally positive perception of, AI-supported

indigenous health education. Students rated highly the familiarity of examples, clarity of language, ease of understanding, interactivity, interest and contribution of the lessons to their knowledge of healthy living (means 2.84–3.03). Ratings were low for the opportunity to learn at their own pace (2.18), the relevance of the lessons to their culture and community (2.19), the contribution of AI tools to understanding indigenous health practices (2.21), and motivation to learn about health (2.49). The AI-supported content students encountered were therefore accessible and engaging but only weakly connected to their own cultural context.

Research Question Two: What is the level of preventive health behaviour among JSS2 students in Oyo Metropolis?

Table 2: ***Students' Preventive Health Behaviour (PHBQ), N = 327***

S/N	Item	SA	A	D	SD	Mean	S.D.	Remark
1	I exercise regularly to keep my body healthy	55	77	96	99	2.27	1.07	Low
2	I try to eat healthy and balanced meals	69	73	99	86	2.38	1.09	Low
3	I practise good personal hygiene every day	109	85	79	54	2.76	1.09	High
4	I wash my hands regularly to prevent sickness	94	107	80	46	2.76	1.02	High
5	I avoid alcohol, drugs and other harmful substances	98	95	83	51	2.73	1.05	High
6	I resist peer pressure that encourages unhealthy behaviour	109	89	85	44	2.80	1.05	High
7	I seek correct information about sexual health when needed	101	84	84	58	2.70	1.09	High
8	I take steps to protect myself from diseases	110	100	76	41	2.85	1.03	High
9	I manage stress in healthy ways	97	95	89	46	2.74	1.03	High
10	I follow health advice given at school or by health workers	98	97	85	47	2.75	1.04	High
	Grand mean					**2.68**	**0.70**	High

Note. Criterion mean = 2.50. The grand-mean S.D. is the standard deviation of students' PHBQ mean scores.

Table 2 shows a grand mean of 2.68, above the criterion mean of 2.50, indicating a moderate level of preventive health behaviour. The highest-rated behaviours were protecting themselves from diseases (2.85), resisting peer pressure (2.80), handwashing

(2.76). Regular exercise (2.27) and healthy, balanced eating (2.38) fell below the criterion mean and are areas of concern.

Hypothesis One: Exposure to AI-supported indigenous health education does not significantly predict preventive health behaviour among JSS2 students in Oyo Metropolis.

Table 3: ***Model 1: Simple Linear Regression of Preventive Health Behaviour on Exposure to AI-Supported Indigenous Health Education***

Predictor	B	Std. Error	β	t	p
(Constant)	1.19	0.14	–	8.31	< .001
AI-supported indigenous health education	0.56	0.05	.51	10.69	< .001

Note. Dependent variable: preventive health behaviour. $R = .51$, $R^2 = .26$, adjusted $R^2 = .26$, $F(1, 325) = 114.29$, $p < .001$.

Table 3 shows that exposure to AI-supported indigenous health education significantly predicted preventive health behaviour, $F_{(1, 325)} = 114.29$, $p < .001$, accounting for 26% of its variance ($R^2 = .26$). Each one-point increase in the AISIHQ mean score was associated with a 0.56-point increase in the PHBQ mean score ($\beta = .51$). Hypothesis one was therefore rejected.

Hypothesis Two: Health Belief Model constructs do not significantly predict preventive health behaviour over and above exposure to AI-supported indigenous health education among JSS2 students in Oyo Metropolis.

Table 4: ***Model 2: Hierarchical Regression of Preventive Health Behaviour on Exposure to AI-Supported Indigenous Health Education and Health Belief Model Constructs***

Predictor	B	Std. Error	β	t	p	VIF
(Constant)	0.66	0.19	–	3.58	< .001	–
AI-supported indigenous health education	0.12	0.06	.11	1.98	.048	1.86
Perceived susceptibility	0.11	0.04	.13	2.73	.007	1.35
Perceived severity	0.15	0.04	.17	3.73	< .001	1.31
Perceived benefits	0.18	0.04	.20	4.06	< .001	1.49
Perceived barriers	−0.14	0.04	−.17	−3.89	< .001	1.19
Cues to action	0.11	0.04	.13	2.73	.007	1.27
Self-efficacy	0.18	0.04	.21	4.36	< .001	1.43

Note. Dependent variable: preventive health behaviour. $R = .68$, $R^2 = .47$, adjusted $R^2 = .46$, $\Delta R^2 = .21$, $F_{change}(6, 319) = 20.78$, $p < .001$; overall model $F(7, 319) = 40.10$, $p < .001$.

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Table 4 shows that adding the six HBM constructs significantly increased the explained variance in preventive health behaviour from 26% to 47%, $\Delta R^2 = .21$, $F_{change}(6, 319) = 20.78$, $p < .001$. Self-efficacy ($\beta = .21$, $p < .001$), perceived benefits ($\beta = .20$, $p < .001$), perceived severity ($\beta = .17$, $p < .001$), perceived barriers ($\beta = -.17$, $p < .001$), perceived susceptibility ($\beta = .13$, $p = .007$), cues to action ($\beta = .13$, $p = .007$) were all significant predictors. All were positive except perceived barriers, which were negative: students who perceived more obstacles reported less preventive behaviour. Hypothesis two was therefore rejected. With the HBM constructs in the model, the coefficient for AI-supported indigenous health education fell from $\beta = .51$ to $\beta = .11$ but remained significant ($p = .048$). A reduction in a coefficient does not by itself establish mediation, so the indirect effects were tested formally (Hypothesis Three).

Hypothesis Three: Health Belief Model constructs do not significantly mediate the relationship between exposure to AI-supported indigenous health education and preventive health behaviour among JSS2 students in Oyo Metropolis.

Table 5: ***Parallel Mediation of the Relationship between AI-Supported Indigenous Health Education and Preventive Health Behaviour through Health Belief Model Constructs (Standardised Coefficients)***

Mediator	a path	b path	Indirect effect (a × b)	95% bootstrap CI
Perceived susceptibility	.42	.13	.055	[.015, .099]
Perceived severity	.32	.17	.056	[.022, .096]
Perceived benefits	.47	.20	.095	[.049, .144]
Perceived barriers	−.30	−.17	.052	[.023, .089]
Cues to action	.37	.13	.047	[.013, .085]
Self-efficacy	.45	.21	.096	[.049, .150]
Total indirect effect			**.399**	**[.316, .487]**

Note. a = effect of AI-supported indigenous health education on the mediator; b = effect of the mediator on preventive health behaviour controlling for exposure and the other mediators. All a paths $p < .001$. Total effect (c) = .51, $p < .001$; direct effect (c′) = .11, $p = .048$. Confidence intervals are percentile intervals from 5,000 bootstrap resamples; intervals that exclude zero indicate a significant indirect effect.

Table 5 shows that exposure to AI-supported indigenous health education was significantly associated with every HBM construct (a paths, $\beta = .30$ to .47 in absolute value, all $p < .001$), positively for five constructs and negatively for perceived barriers. The total indirect effect through the six constructs was significant ($\beta = .399$, 95% CI [.316, .487]), and each specific indirect effect was significant because none of the confidence intervals included zero. The largest indirect effects ran through self-efficacy (.096) and perceived

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benefits (.095). The indirect effect through perceived barriers was positive because greater exposure was associated with fewer perceived barriers, which in turn were associated with more preventive behaviour. Because the direct effect also remained significant (c′ = .11, p = .048), the HBM constructs partially, not completely, mediated the relationship; the indirect effects accounted for approximately 78% of the total effect. Hypothesis three was therefore rejected.

Discussion of Findings

The first finding showed that students reported a moderate level of exposure to, and a generally positive perception of, AI-supported indigenous health education. Because this was a cross-sectional survey and no intervention was administered by the researchers, these ratings reflect students' experience of AI-supported health learning as it already existed in their schools and homes, not a baseline before a planned programme. Students found the lessons clear, interactive and built on familiar examples, but rated low their relevance to their culture and community and the extent to which AI tools helped them understand indigenous health practices. This suggests that the AI content students encountered achieved surface-level cultural fit, such as familiar examples and simple language, without engaging the deeper cultural meanings that shape health behaviour, a distinction emphasised by Resnicow et al. (1999). The finding supports the argument of the PEN-3 model that culture should be built into the core of health promotion rather than added at the surface (Airhihenbuwa, 1995).

The second finding showed a moderate level of preventive health behaviour, with favourable reports on protection from disease, resisting peer pressure, hygiene and handwashing, but low reports on regular exercise and balanced eating. The low level of physical activity mirrors the global pattern in which more than 80% of school-going adolescents are insufficiently active (Guthold et al., 2020) and identifies physical activity and diet as priorities for school health education in Oyo Metropolis.

The third finding showed that exposure to AI-supported indigenous health education was significantly and positively associated with preventive health behaviour, accounting for 26% of its variance. This is consistent with reviews reporting favourable outcomes for mobile and digital health interventions, although those reviews also note that evidence of efficacy remains limited (Hobson et al., 2019; Johnson et al., 2016). The finding should be interpreted cautiously, because evidence for AI chatbots specifically is still weak and their acceptability varies (Abd-Alrazaq et al., 2020; Nadarzynski et al., 2020), and because a cross-sectional association cannot show that AI-supported education caused the behaviour.

The fourth and fifth findings showed that the HBM constructs explained an additional 21% of the variance in preventive health behaviour and that they partially mediated its

relationship with AI-supported education. Self-efficacy was among the strongest direct predictors and carried one of the largest indirect effects, consistent with the incorporation of self-efficacy into the HBM from social cognitive theory (Bandura, 1977; Rosenstock et al., 1988). The prominence of perceived benefits and the negative effect of perceived barriers agree with meta-analytic evidence that benefits and barriers are among the most consistent HBM predictors of behaviour (Carpenter, 2010), and with evidence that HBM-based interventions can improve adherence to health recommendations (Jones et al., 2014). Formal bootstrapped tests (Hayes, 2022) showed that about 78% of the association between AI-supported education and preventive behaviour ran through health beliefs, while a smaller but significant direct association remained. The results therefore support partial rather than complete mediation. Because the data are cross-sectional, the mediation model describes a pattern of statistical association that is consistent with the hypothesised causal order; it does not demonstrate that AI-supported education changed students' beliefs, which then changed their behaviour.

Limitations

The cross-sectional design does not permit causal inference, and the temporal order of exposure, beliefs and behaviour cannot be established. All measures were self-reported and may be affected by social desirability and shared-method variance. Exposure to AI-supported health education was not standardised across students, so the findings concern naturally occurring exposure rather than the effect of a defined programme. The sample was limited to JSS2 students in eight public schools in Oyo Metropolis, which limits generalisation to private schools, other age groups and other locations.

Conclusion

JSS2 students in Oyo Metropolis reported moderate exposure to AI-supported indigenous health education, which they found clear and engaging but only weakly connected to their culture, and a moderate level of preventive health behaviour, with physical activity and diet as the weakest areas. Exposure to AI-supported indigenous health education was positively associated with preventive health behaviour, and this association operated largely, though not entirely, through Health Belief Model constructs, especially self-efficacy and perceived benefits. AI-supported health education is therefore most likely to be associated with better preventive behaviour when it strengthens students' confidence, makes the benefits of healthy action clear and reduces practical barriers. Experimental and longitudinal studies are needed to confirm these pathways.

Recommendations

Based on the findings, the following recommendations are made:

1. Because self-efficacy was the strongest predictor of preventive behaviour, teachers of Basic Science and Physical and Health Education, together with school counsellors, should use AI-supported lessons that include guided practice, step-by-step demonstrations, goal-setting and feedback on specific behaviours such as handwashing, stress management and healthy food choices, rather than presenting information alone.
2. Because perceived barriers reduced preventive behaviour, school administrators and the Oyo State Ministry of Education should address practical barriers to both AI-supported learning and healthy behaviour, for example by providing supervised access to devices in schools, using low-data or offline content, and helping students identify affordable ways to eat healthily and be physically active.
3. Because students rated the cultural relevance of AI-supported lessons low, curriculum planners and developers of educational technology should work with teachers, parents and local health workers to incorporate Yoruba language, local foods, familiar practices and culturally meaningful examples into AI-supported health content, with qualified health professionals reviewing all content for accuracy.
4. Because regular exercise and balanced eating were the weakest preventive behaviours, schools should link AI-supported health lessons to Physical and Health Education periods and use features such as activity tracking, reminders and class challenges to encourage physical activity and healthy eating.
5. Researchers should use experimental or longitudinal designs with a clearly defined AI-supported intervention and formally test the indirect effects of Health Belief Model constructs, in order to establish whether AI-supported indigenous health education changes preventive health behaviour through health beliefs.

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