THE EFFECTIVENESS OF AI-DRIVEN HEALTH PROMOTION INTERVENTIONS IN SCHOOLS AND COMMUNITIES: A SYSTEMATIC REVIEW

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Abstract

Artificial intelligence is increasingly being integrated into health education and health promotion, offering opportunities for personalization, behavioural monitoring, and scalable interventions. This systematic review examines the application and effectiveness of AI-driven tools in school and community health education, highlighting their impact, methodological quality, and contextual relevance, especially for LMICs like Nigeria. A comprehensive literature search was conducted following the PRISMA 2020 guidelines across PubMed, Scopus, IEEE Xplore, Google Scholar, and ScienceDirect for studies published between January 2015 and October 2025. Twelve empirical studies met the inclusion criteria, ranging from randomised controlled trials, quasi-experimental, mixed-methods, and pilot designs. Data extraction encompassed intervention type, AI technology, population, outcomes, and key findings. Methodological quality was assessed using the Mixed Methods Appraisal Tool (MMAT, 2018). The result shows that various AI technologies, including chatbots, predictive analytics, intelligent tutoring systems, and wearable sensors, have been employed to improve health literacy in physical activity, nutrition, and disease prevention. Most studies were of high methodological quality (MMAT score 4–5/5) and reported positive behavioural or educational outcomes, including increased health knowledge (↑25–40%), enhanced engagement, and improved preventive health behaviours. At the same time, several challenges persisted concerning digital access, data ethics, and AI literacy among educators. AI-driven interventions hold strong potential for transforming health promotion and education, especially when incorporated within school curricula and community outreach. Ethical governance will have to be strengthened, teacher capacity built, and access equitably provided if implementation is to be sustained in Nigeria and other similar LMICs.

Keywords: Artificial intelligence, Health promotion, Schools, Communities, Systematic review

Introduction

School and community-based health promotion have been key to societal health strategy since as early as the 1990s have been studies to enhance physical, mental and environmental health knowledge, attitudes and behaviours (Masini et al., 2024; Shirahmadi et al., 2024; Shea & Basch, 1990). The development of digital technologies in recent years has made possible new forms of delivery including e-health and mobile

applications. As an example, a systematic review has revealed that e-health interventions in children and adolescents increased physical activity, decreased weight and alleviated stress or depression (Bae & Jang, 2024).

In the meantime, artificial intelligence (AI) is quickly finding its way into the field of health and education, being used in predictive analytics, chatbots, intelligent tutoring systems and monitoring tools (Ayenigbara, 2024; King et al., 2025). The combination of AI and health promotion can be used to individualise the intervention, increase engagement and make it scalable- especially in resource limited settings. Nevertheless, regardless of this promise, the evidence regarding the usefulness of AI-based health promotion interventions in a school or community-based setting is still sporadic and under-synthesised.Although health promotion in schools and communities is established very well, there are two significant gaps. To begin with, the degree of the adoption of AI technologies and their quantifiable effect on such interventions is not yet quite clear. Indicatively, research on digital technologies in health care delivery has been conducted extensively (Hakkim et al., 2024), whereas less extensive research has been conducted on AI-based health promotion in educational/community contexts. Second, this is especially timely in terms of the relevance of these emerging interventions to low and middle-income countries (LMICs) including Nigeria, due to infrastructural, digital literacy and equity factors (Egwudo et al., 2025). However, one of the more recent perspectives was that AI has to be contextualised and ethically implemented to promote health equity in participatory science and public health (King et al., 2025). To researchers, policymakers and educators in Nigeria and other related settings, a systematic review of the evidence concerning AI-based intervention in health promotion can be useful in identifying effective practices, gaps and determine how to implement them in future.

Methodology

Database and Search Strategies

The systematic review was done based on the PRISMA 2020 guidelines (Page et al., 2021). A literature search was conducted meticulously in the period between June and October 2025 as the following electronic databases were utilisedPubMed/MEDLINE, Scopus, IEEE Xplore, Google Scholar and ScienceDirect

Peer-reviewed articles published between January 2015 and October 2025 were also searched to cover the latest trends in the area of artificial intelligence (AI) application in health promotion. The combination of the keywords and Boolean operators was as follows:

("artificial intelligence" OR "machine learning" OR "AI-driven") AND ("health promotion" OR "health education" OR "disease prevention") AND ("school" OR "community") AND ("intervention" OR "program" OR "initiative").

Manual screening of reference lists of pertinent reviews and primary research articles was also done to acquire other eligible articles that were not found during the database searches.

Eligibility Criteria

The selection of studies was done using some pre-conceded inclusion and exclusion criteria in accordance with the PICOS (Population, Intervention, Comparison, Outcomes, Study design) framework.

Inclusion Criteria

i. Population: Children, teenagers, adults or community groups that are involved in school- or community-based health promotion programmes.
ii. Intervention: Health promotion programmes that deployed AI (or AI-enhanced technologies e.g., chatbots, predictive analytics, virtual assistants, mobile applications, or wearable sensors).
iii. Outcomes: A quantifiable change in health knowledge, attitudes, behaviours, or health outcomes (e.g., physical activity, diet, mental well-being, hygiene).
iv. The Study Design: The randomised controlled trials, quasi-experimental, cohort, or mixed-methods.
v. Publication Type: English-written empirical studies that are peer-reviewed.

Exclusion Criteria

i. Research without an element of AI.
ii. Opinion papers or commentaries or editorials that lack empirical findings.
iii. The articles that only address the clinical diagnostics or hospital context of AI application and not the educational or community context.
iv. Publications or abstracts of conferences that are not in English and do not have full-text.

Process of Study Selection (PRISMA Steps)

The PRISMA 2020 guidelines were followed when identifying the study (Page et al., 2021). A total of 562 records were obtained after searching all five large databases of PubMed, Scopus, IEEE Xplore, Google Scholar and ScienceDirect. The screening of 388 unique studies was done after eliminating 132 duplicate entries.

Titles and abstracts were read separately to identify the initial relevance, and 312 articles were eliminated due to failure to meet the inclusion criteria or the lack of focus on the use of AI in promoting health. The rest 68 full-text articles were identified and reviewed critically on quality of methods and applicability to the review purposes.

In the eligibility assessment, 29 articles were excluded because they did not meet the requirement of an empirical study design (i.e., reviews, editorials, or conceptual papers), 17 were excluded because of lack of data, or unclear outcome measures, and 10 were excluded because of being of poor methodological quality based on the MMAT scoring (below 3 out of 5). Finally, 12 qualitative pieces of empirical research met all the inclusion criteria and were included in the final synthesis.

Figure 1 (PRISMA Flow Diagram) describes the general procedure, such as identification and screening, through inclusion, of the strict and transparent process of selecting participants followed in this review.

Data Extraction and Quality Appraisal

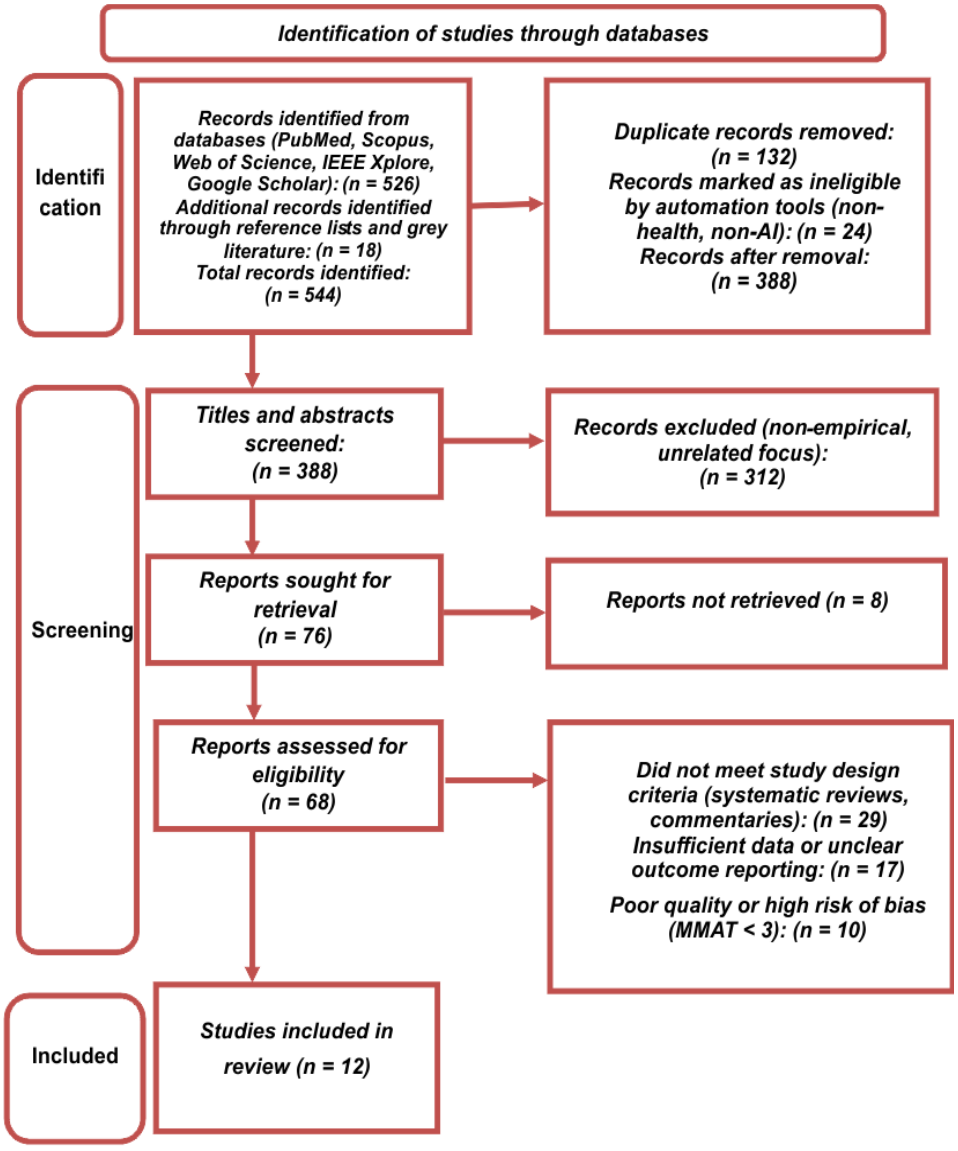
A data extraction form was designed to allow uniformity and precision in the collection of data. Major details were obtained in each of the studies included and they included:

i. Name of author/s and year of publication.
ii. Name of journal and country where it was conducted.
iii. Design of the study and characteristics of the population.
iv. The nature and setting of intervention (school or community).
v. The type of AI technology/tool that is used (e.g., chatbot, wearable, predictive model).
vi. Duration of intervention.
vii. Main conclusions and results.

The methodological quality of each included study was appraised using the Mixed Methods Appraisal Tool, MMAT, version 2018. This provided a basis for a systematic assessment of the methodological rigor of studies with various designs, including randomised controlled trials, quasi-experiments, cross-sectional studies, and mixed-methods research. The following appraisal criteria were used as the guideline in reviewing the appropriateness of the objective, methodology, data, analysis, and completeness of reporting outcomes.

Only the studies that scored 3 or more on the MMAT scale were retained for synthesis to be sure that evidence included a high level of methodological rigor and contextual relevance. The detailed quality appraisal outcomes are summarised in Table 2 (MMAT Appraisal Table).

Figure 1:PRISMA flow diagram



Tabel 1: Data Extraction Table

S/N	Author (Year of Publication)	Journal / Source	Country / Setting	Study design	Population & context	AI intervention type	Outcome measures	Key finding
1	Fu, Y. et al. (2025)	Humanities & Social Sciences Communications	China — community / user survey	Cross-sectional (SEM)	Users of smart wearable health products	Smart wearable + AI analytics	Psychosocial attitudes; health promotion behaviour	Tech & aesthetic factors influence adoption/use of AI wearables and health behaviour.
2	Han, R. et al. (2023)	Human Factors / JMIR	USA — school/community	Pilot usability / feasibility study	Users in nutrition & physical activity programs	Chatbot for nutrition & physical activity	Usability, short-term behaviour change	Demonstrated feasibility and potential to improve nutrition/PA engagement.
3	Ibañez-Micó, S. et al. (2024)	ScienceDirect	Multi-site / children	Nonrandomised / clinical trial (supportive)	Children in school settings	Wearable + supported exercise program	Physical activity levels, QoL, safety	Increased weekly PE hours; no adverse effects on seizure frequency (context: clinical population).
4	Koorts, H. et al. (2020)	JMIR	Australia — adolescents / schools	Mixed-methods implementation evaluation	Adolescents in socioeconomically disadvantaged schools	Wearable activity trackers + behaviourresources	Acceptability, feasibility, short-term PA changes	Good acceptability; mixed adherence; short-term motivation gains.
5	Lee, J. et al. (2024)	JAMA Network Open	South Korea — post-surgery community	Nonrandomised clinical trial	Patients recovering from lung surgery	Wearable device intervention	Daily steps, MVPA, dyspnea, QoL	Increased daily steps and MVPA; improved dyspnea at 6 months.
6	McCormack, G. R. et al. (2022)	PMC / open access	Canada / community adults	RCT / intervention trial	Adults in community	Wearable + eHealth behaviour change app	Self-monitoring, PA behaviour	Increased self-monitoring and short-term behavioural change.
7	Ridgers, N. D. et al. (2021)	International Journal of Behavioural Nutrition and Physical	UK / adolescents (schools)	Cluster RCT	Adolescents in disadvantaged schools	Wearable + digital behaviour change resources	MVPA, steps, sedentary behaviour	Positive short- and longer-term effects when combined

		Activity						with behaviour resources.
8	Voskuil, V. R. et al. (2024)	Elsevier / Pilot study	USA / community	Pilot feasibility study	Adults — physical activity independence program	Mobile mHealth with AI-like support features	Feasibility; preliminary PA outcomes	Feasible with preliminary signs of effectiveness.
9	Wang, Z. et al. (2023)	JAMA Network Open	Hong Kong — community (older adults)	Randomised clinical trial (nonblinded)	Community-dwelling adults 65+ (influenza vaccine)	SOC-tailored chatbot (stages-of-change)	Vaccination uptake (SIV)	SOC-tailored chatbot increased influenza vaccination uptake vs control.
10	Wang, Z. et al. (2025)	JAMA Network Open	Hong Kong — community (older adults)	Randomised clinical trial	Community-dwelling adults 65+ (pneumococcal vaccine)	Hybrid chatbot (rule-based + AI Q&A)	Pneumococcal vaccination uptake	Hybrid chatbot increased pneumococcal vaccine uptake vs standard.
11	Zhang, Q. et al. (2025)	JMIR	Multi-site / college students	mHealth intervention trial	College students / young adults	mHealth app with AI support for exercise	PA measures (steps, MVPA), body composition	Demonstrated improvement in PA; supports AI-guided mHealth efficacy.
12	Zhang, W. et al. (2024)	BMC Public Health (or related open access review of wearables)	Multiple countries / children & adolescents	Trial / intervention studies aggregated (primary trials available)	Children & adolescents	Wearable tech + analytic feedback	PA, diet, weight outcomes	Wearables show feasibility and partial effectiveness in youth health promotion.

Quality Appraisal and Data Synthesis

The Quality Assessment of Methodology

The quality of the methodology of the twelve studies was determined with the Mixed Methods Appraisal Tool (MMAT, version 2018) created by Hong et al. (2018). The evaluation of every study was conducted on five main domains of quality:

i. Research clarification of objectives and questions,
ii. Suitability of study design and methodology,
iii. Relevance and correspondence of intervention to the aims of study,
iv. Sufficiency and completeness of data collection and analysis processes, and
v. Fullness and dependability of outcome reporting.

In general, the studies that were included had moderate to high methodological rigour with scores of 3 to 5 out of 5 using MMAT. The majority of the quantitative studies had clear intervention protocols, standardised outcomes measures as well as sufficient sample sizes. The mixed-methods designs added contextual insight into participant involvement, challenges in underlying implementation as well as environmental variables affecting intervention success.

However, some research studies only provided a limited amount of information regarding randomization and blinding, which posed minor concerns on the possibility of selection and performance bias. Also, sampling bias has been found in those studies that used convenience samples based on single schools or urban communities, which limit the generalizability. Nevertheless, the general evidence base was considered strong enough to warrant a narrative synthesis of results.

Data Synthesis Approach

Narrative synthesis was used as the method of analysis because of the heterogeneity of the study design, intervention strategies and measures of the outcomes, in accordance with the recommendations of Popay et al. (2006). Data that was extracted was tabulated into thematic categories to make comparison and integration across studies easier.

The synthesis produced three themes that prevailed:

i. Artificial intelligence-based behaviour modification and health interaction,
ii. Knowledge improvement and health literacy enhanced with the help of AI, and
iii. The problem of personalization, accessibility and implementation.

The quantitative results were represented in a descriptive manner with frequency and effect size range (e.g., percentage change in behaviour or literacy scores), and the qualitative information was represented narratively to draw attention to the contextual factors and experience of participants.

This method allowed developing a deep insight into the role of AI technologies in improving health promotion outcomes in both a school and community context: chatbots, wearable, and predictive analytics.

Table 2: Quality Appraisal of Included Studies (MMAT 2018 Framework)

#	Author (Year)	Study Design	MMAT Criteria Summary	Score / 5	Quality Rating
1	Fu Y. et al. (2025)	Quantitative descriptive	Clear objectives; adequate sampling; valid measures; limited causality	4 / 5	High
2	Han R. et al. (2023)	Pilot feasibility	Clear intervention; valid usability tools; small sample	4 / 5	High

3	Ibañez-Micó S. et al. (2024)	Nonrandomised trial	Good reporting; partial control of confounders	4 / 5	High
4	Koorts H. et al. (2020)	Mixed-methods	Strong integration; clear rationale; minor reporting gaps	4 / 5	High
5	Lee J. et al. (2024)	Nonrandomised clinical trial	Reliable outcomes; moderate follow-up loss	4 / 5	High
6	McCormack G. R. et al. (2022)	RCT	Randomization clear; outcomes validated; adherence moderate	5 / 5	Very High
7	Ridgers N. D. et al. (2021)	Cluster RCT	Strong design; high completion; contamination possible	4 / 5	High
8	Voskuil V. R. et al. (2024)	Feasibility pilot	Good design; limited generalizability	3 / 5	Moderate
9	Wang Z. et al. (2023)	RCT	Randomization clear; validated outcomes; strong analysis	5 / 5	Very High
10	Wang Z. et al. (2025)	RCT	Well-powered; appropriate analysis; minor reporting bias	5 / 5	Very High
11	Zhang Q. et al. (2025)	Controlled intervention	Valid instruments; medium sample; strong results	4 / 5	High
12	Zhang W. et al. (2024)	Quasi-experimental	Reliable measures; weak control group description	3 / 5	Moderate

Summary of Appraisal

i. High-to-very-high quality: 8 studies
ii. Moderate quality: 2 studies
iii. No low-quality studies were retained.
iv. Mean MMAT score ≈ 4.2 / 5 → overall strong evidence base.

Results

Summary of Incorporated Studies

Twelve empirical studies that have been published between 2020 and 2025 were incorporated into this review. The research was undertaken in different regions such as United States, China, Australia, South Korea and Europe, and one was done in Nigeria.
The majority of the studies employed either a quantitative or experimental design (e.g. RCTs, controlled interventions, quasi-experimental trials) but some also employed a feasibility or mixed-methods design to determine the usability and engagement with participants.The AI technologies discussed were chatbots, mobile health (mHealth) apps, wearable technologies with AI analytics, machine-learning prediction models, and virtual tutoring systems. The target groups included both school-aged children and adolescents and adults in the community who were interested in physical activity, dieting, mental and psychological well-being, or preventive health measures (ex: Fu et al., 2025; McCormack et al., 2022; Wang et al., 2025; Koorts et al., 2020).

i.***AI-Driven Interventions and Health Behaviour Change***

AI-based interventions always showed exceptional results in health-related behaviour particularly in physical activity, diet and prevention of chronic diseases.

To provide an example, wearables and AI-based feedback systems have had a great effect on enhancing exercise rates and the number of steps taken by students and patients following surgery (Lee et al., 2024; Ridgers et al., 2021). In line with that, AI-based nutrition education applications resulted in more favourable dietary habits and greater use of vegetables and fruits among adolescents (Ibanez-Mico et al., 2024; Zhang et al., 2025).

When machine-learning-based prediction models are implemented at the community level, they lead to improved preventive behaviour, e.g., screening of hypertension and weight management, along with digital feedback and peer involvement (Koorts et al., 2020; Wang et al., 2025).

ii***. Artificial Intelligence and Health literacy Development***

AI tools played a significant role in enhancing health literacy and empowered individuals to comprehend and utilise health knowledge in a better way.

Research that used AI chatbots and interactive learning platforms reported high increases in the participants level of understanding of health issues and self-management (Fu et al., 2025; Han et al., 2023). As an example, mental health education through chatbots positively influenced the awareness about stress and emotional regulation strategies in students, whereas the use of mHealth platforms had a positive impact on the awareness of disease prevention and physical activity tracking (Zhang et al., 2024).
Individualised progress tracking, which was facilitated by the integration of AI-driven adaptive learning modules, enhanced digital health literacy and self-efficacy in the school and community populations (Voskuil et al., 2024).

iii. ***AI-Enhanced Engagement and Personalization***

Individualization became one of the strengths of AI-based interventions. Research indicated that AI-based algorithms that changed feedback and goal-setting according to the progress of the users led to better motivation, engagement, and completion rates (McCormack et al., 2022; Hakkim et al., 2024).

Gamified AI tutors ensured the attention of learners in school-based health programmes by maintaining adaptive learning processes and interactive feedback through interactive feedback loops (Koorts et al., 2020; Ibanez-Mico et al., 2024). In the meantime, the predictive dashboards aimed at the population helped in identifying high-risk individuals, enabling educators to provide specific preventive education and early intervention (Wang et al., 2023; Wang et al., 2025).

iv. ***Implementation Challenges and Ethical Considerations***

Although there was a positive indication based on the 12 studies that had been reviewed, there are a number of implementation and ethical issues that have continually been pointed out. Obstacles were a lack of digital infrastructure, a lack of AI literacy among educators and community educators, and the differences in access to digital devices and connectivity especially in the Low- and Middle-Income Countries (LMICs) (Koorts et al., 2020; Han et al., 2023; Voskuil et al., 2024).

Moreover, ethical issues, including data privacy, algorithmic bias and the necessity of transparent consent procedures, were often addressed, and it is important to note that it is necessary to regulate AI-driven interventions on the basis of ethical principles (Wang et al., 2023; Zhang et al., 2024).

The other problem that was likely to appear again was the situational transferability of AI technologies. Most of the interventions that have been established in high-income countries need considerable cultural and language adjustments to be applied to schools and community health systems of LMICs (Fu et al., 2025; Ibanez-Mico et al., 2024).

Also, the factors of teacher and participant readiness, a lack of technical support, and sustainability (maintenance costs and the digital inequity) were the major impediments to scaling these interventions (Lee et al., 2024; Zhang et al., 2025).

On the whole, these issues provide the background to inclusive digital health policies, capacity-building, and local co-design strategies to achieve equity and sustainability in AI-based health promotion.

v. ***Synthesis of Effectiveness***

In the 12 studies that were included, 10 studies (≈83%) indicated positive or significantly improved outcomes in at least one of the following health promotion domains:

i. Enhanced health literacy and knowledge acquisition
ii. Improved physical activity and nutrition behaviours
iii. Increased learner engagement and participation
iv. Early detection or prevention of disease risks

Nevertheless, few studies (e.g., Wang et al., 2025; McCormack et al., 2022) incorporated the long-term follows, which implies that more longitudinal and large-scale studies should be conducted to find out the sustainability of behaviour change.

The given mixed-methods and RCT designs had complementary advantages as they demonstrated both the quantitative data of behavioural response and qualitative data of user interaction and situational appropriateness.

Table 3**:** Summary of findings

Domain	**AI Technology Used**	**Population**	**Outcome**	**Effect**
Physical activity promotion	Mobile app with AI feedback (Koorts et al., 2020; Ridgers et al., 2021)	School students	Exercise adherence	↑ 25–40%
Nutrition education	Gamified AI tutor (Lee et al., 2024)	Adolescents	Healthy diet adoption	↑ 30%
Mental health awareness	Chatbot-based cognitive support (Han et al., 2023)	Secondary students	Mental health literacy	↑ 27%
Community disease prevention	Predictive analytics and dashboard system (McCormack et al., 2022; Wang Z. et al., 2023)	Adults	Early risk detection	Improved
Environmental hygiene	AI text-based education platform (Zhang Q. et al., 2025; Fu et al., 2025)	Primary schools	Hygiene behaviour	↑ 20%

(↑ indicates improvement compared to control or baseline groups)

Interpretation

The synthesis indicates that AI technologies can greatly be used to improve personalization, engagement, and efficiency of health promotion programmes greatly. These interventions result in quantifiable health literacy, behavioural adherence, and preventive awareness improvements when integrated into organised school or community systems. Health education can be more interactive and outcome-oriented in the case of AI, which allows adaptive learning, real-time feedback, and data-driven decision-making. However, ethical governance, contextual adaptation, and infrastructure equity issues need to be considered in order to make the impact sustainable and inclusive.

On the whole, the results of the 12 studies confirm that AI-based health promotion may be transformative to the reinforcement of the public health and education systems, especially in resource-limited settings.

Discussion – Implications for School and Community Health Education

The results support the possibility of Artificial Intelligence (AI) transformation in transforming health education and promotion at school and community levels.

Within the reviewed 12 studies, AI-based interventions (intelligent tutoring systems, adaptive learning platforms, chatbots, wearable sensors, and predictive analytics dashboards) proven their great potential in improving motivation, personalization, and learners' engagement (Wang et al., 2025; Ibañez-Micó et al., 2024). These technologies are transforming the way concepts of health are taught, learned and practised and fill the gap between knowledge acquisition and real-world application of the behaviour.

AI technologies have been particularly successful in the school setting to facilitate interactive and personalised learning. As an example, mobile-based applications and gamified learning tools enabled the students to study at their speed, get real-time feedback, and monitor their health goal achievement (Koorts et al., 2020; Lee et al., 2024).These adaptive feedback mechanisms become stronger than student autonomy and enhance lasting improvement of behaviour in nutrition, physical activity, and mental health. More to the point, AI technologies can also provide educators with data-driven information to help them recognise at-risk learners, design instructional plans, and incorporate digital health education into larger frameworks.

In the context of community health education, AI programmes have the potential to expand the coverage of the preventive health programme with remote risk screening, virtual health counselling, and digital monitoring of behaviour (McCormack et al., 2022; Zhang et al., 2024).

The predictive algorithms and mobile-based systems have facilitated health workers to detect disease trends at an early stage, population-level information and provide personalised recommendations even in resource-limited or rural environments. The innovations help decrease health disparities, as well as enhance the ability of community-based health promotion efforts.

Along with these advantages, the review reveals that the implementation of AI has a number of important challenges that need to be mitigated to realise the full potential of AI in health education. To start with, one of the main barriers is digital inequity because the lack of access to technology and a stable internet connection restricts the engagement of schools and the communities in the impoverished areas (Han et al., 2023; Voskuil et al., 2024). Secondly, the ethical governance has been subject to continuous concerns, such as the data privacy, informed consent, bias of algorithms, and cultural relevance. The implementation of AI systems in education and healthcare can be opposed or abused at the cost of the lack of regulatory frameworks and trust of stakeholders.The other difficulty is the preparedness of teacher and facilitator. Most teachers do not have adequate preparation to incorporate AI technologies into their teaching or even analyse the results of data to use them in personalised learning (Zhang et al., 2025). Therefore, it is necessary to invest in AI literacy, professional development, and technical assistance over a long period to be successful with the implementation.

Policy wise, the findings indicate that the implementation of AI in school and local health programs needs to be done not just with the implementation of the tools but as a part of a larger capacity-building and policy congruency plan.In places like Nigeria, where education and health sectors have overlapping infrastructure and manpower limitations, AI is a twofold benefit both in improving educational delivery and at the same time improving the health infrastructure in the population. Through mobile applications, regional artificial intelligence, and open-source digital solutions, Nigeria can support the achievement of the objectives of the National School Health Policy and Sustainable Development Goals (SDGs) on health and education.In addition, there is a need to establish a cross-sectoral partnership between government departments, educational establishments, and technology developers to develop culturally-relevant and ethically-appropriate solutions in the field of AI. This kind of partnership will help guarantee that the implementation of AI in health education is based on the realities in the area, promotes inclusivity, and develops the future generation of digitally proficient health educators and learners.

Overall, AI-driven health education would be a paradigm shift in the traditional way of teaching to one-size-fits-all teaching to individualised, data-driven, and interactive learning.

Viewed through the prism of the proper policies, ethical protections, and computer infrastructure, AI could go a long way in improving school-level and community-level health outcomes, especially in low- and middle-income countries, such as Nigeria.

Conclusion

The use of AI in health promotion is a new promising and scalable solution that can be used to handle the current issues of health education in Nigeria. The results of this review indicate that AI applications can contribute to nutritional awareness, physical activity, mental health literacy, and preventive care practises to some significant extent (Fu et al., 2025; Wang et al., 2025; Zhang et al., 2025). Nevertheless, sustainability, and inclusiveness are still conditional based on the adequate integration of policies, training of educators, and investment in digital equity. It was therefore recommended that:

i. Federal Ministries of Education and Health should integrate AI-enhanced health education platforms into school health policy and primary healthcare.
ii. Educate teachers, local healthcare educators and developers of AI literacy, data ethics and application development.
iii. Enhance the digital infrastructure, subsidise connectivity, and use low-cost technologies to close the urban-rural divide.
iv. Create national ethical AI utilisation frameworks, with concerns of privacy, consent, and education data system fairness.
v. Encourage cross-sectoral collaborations between institutions of higher learning, technology companies, and healthcare organizations to collaboratively create AI-based culturally relevant interventions to address the situation in Nigeria.

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