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Geographic Inequities in Youth Obesity - The Role of AI and Digital Innovation

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ABSTRACT

Objective(s)

Youth obesity is a global public health crisis, with rates quadrupling from 1990 to 2022 among both boys and girls, according to the Non-Communicable Disease Risk Factor Collaboration. Obesity among youth contributes to rising healthcare costs due to obesity-related conditions like diabetes and hypertension. Moreover, youth obesity negatively impacts mental health and academic performance and increases the risk of substance abuse in adulthood. This review examines the role of digital technology and artificial intelligence (AI) in preventing and managing youth obesity, highlighting its potential to close the gaps in care, regardless of geographical location.

Methods

This review utilized a PubMed search of articles published between 2015 - 2024, focusing on the role of digital technology and artificial Intelligence (AI) in preventing and managing youth obesity. Search terms included "youth obesity," "digital health," "artificial intelligence," "machine learning," and "childhood obesity prevention." Articles were screened based on title, abstract, and full text, prioritizing studies on AI-powered tools, personalized interventions, and technologies addressing disparities in care. Key focus areas included neural networks, electronic health records, geographic information systems, and telemedicine platforms. For this review, "youth" refers to individuals aged 8–18 years.

Findings

AI and digital innovation have emerged as a transformative tool in preventing and managing youth obesity. Advanced technologies, including machine learning and neural networks, analyze vast datasets from healthcare records, nutrition surveys, and geographical information systems (GIS) to identify patterns and correlations in obesity across regions. AI systems like CHICA (Child Health Improvement through Computer Automation) integrate electronic health records to provide age-appropriate obesity screenings and data-driven decision support. Additionally, AI- powered apps and virtual coaches offer personalized, real-time nutrition and physical activity feedback. AI's capacity to map food sectors and identify "food deserts" enables targeted interventions, while AI-driven telemedicine platforms offer remote consultations, particularly benefiting underserved regions.

Conclusions

By integrating AI and digital technologies, including virtual realities and telemedicine into youth obesity strategies, stakeholders can address geographical disparities, create equitable healthcare solutions, and guide personalized, region-specific interventions. Digital technology’s role in healthcare equity offers promising pathways for more effective, targeted youth obesity management in youth worldwide.

Key words: Youth obesity, Disparities and Obesity, AI, and Obesity

INTRODUCTION

Burden of Youth Obesity

Youth obesity is a major public health problem worldwide. According to the Non- Communicable Disease Risk Factor Collaboration Data, obesity in youth increased from 1.7% (1.5-2.0) in 1990 to 6.9% (6.3-7.6) in 2022 for girls (65 million) and from 2.1% (1.9-2.3) in 1990 to 9.3% (8.5-10.2) in 2022 for boys (94 million) [1]. Youth obesity contributes to diabetes mellitus, and hypertension [2]. It leads to negative effects on the youth mental health – low self-esteem, sadness, hopelessness, anxiety, and personal dissatisfaction [3, 4]. Obese youth are at a high risk for experiencing social isolation, facing rejection, and bullying, leading to depression and suicidal thoughts [5 6]. Obesity leads to disordered eating, creating a vicious cycle of weight gain and further psychological problems [7]. Obesity in youth has been associated with poor academic and athletic performance, possibly due to absenteeism, and decreased participation in sports [8]. The mental health effects of youth obesity extend to adulthood, leading to substance abuse and chronic mental health challenges in social and occupational aspects [9].

AI and Machine Learning

For this narrative review, artificial intelligence (AI) refers to the use of advanced computational systems to mimic human decision-making and learning. AI technologies, such as machine learning and neural networks, analyze complex datasets to identify patterns, predict outcomes, and deliver personalized, data-driven interventions in youth obesity prevention and management [10]. Machine learning is a subset of artificial intelligence (AI) that enables computers to learn and improve from experience without being explicitly programmed. It relies on algorithms, including neural networks, which are computational models inspired by the structure and functioning of the human brain. Neural networks consist of interconnected nodes (neurons) that process data and identify patterns, making them particularly effective for analyzing complex datasets, predicting obesity risk factors, personalizing health interventions and optimizing strategies for youth obesity prevention and management.

Geographical Disparities and Digital Innovation

Geographical disparities significantly influence youth obesity rates, as access to healthcare, nutritious food, and physical activity opportunities vary widely across regions. Rural and underserved urban areas often lack sufficient resources, such as pediatric healthcare providers, affordable healthy food options, and safe spaces for exercise, leading to higher rates of obesity. These disparities exacerbate the public health challenge, particularly in marginalized communities, where youth face compounded barriers to achieving healthy lifestyles.

Digital technologies and artificial intelligence (AI) have the potential to bridge these gaps by providing innovative, scalable, and equitable solutions. The application of AI in medicine has evolved significantly with the advent of machine learning and neural networks, enabling AI systems to analyze and detect regional patterns with increasing accuracy [10]. The expansion has been particularly impactful in the realm of youth health, where AI is being utilized to address critical challenges such as societal attitudes and perceptions related to obesity and mental health [11]. AI-driven tools, such as predictive analytics and natural language processing, and advent of telemedicine and virtual reality-driven risk prediction are increasingly employed in personalized care to enhance education, promote engagement at a personalized level towards management strategies [12].

AI continues to advance and offers a promising future to help address health disparities among youth. There are significant knowledge gaps in addressing geographical disparities in youth obesity through AI and digital innovations. Limited research explores the deployment of AI in underserved areas, where resource constraints and infrastructure challenges persist. Existing solutions are often designed for high-resource settings, leaving underserved communities behind. Additionally, AI systems frequently rely on datasets that fail to represent diverse populations, risking biased interventions. Long-term evidence on the sustainability and the effectiveness of digital technologies in reducing obesity disparities is lacking. Lastly, while AI can identify food deserts, translating these insights into actionable, community-specific solutions remains underexplored. Our narrative highlights how digital solutions and AI can close these gaps, creating equitable and impactful strategies for youth obesity prevention and management.

METHODS

This review is based on a PubMed search of articles published between 2018 and 2024, focusing on the role of digital technology and artificial intelligence (AI) in addressing youth obesity. The search strategy utilized terms such as "youth obesity," "digital health," "artificial intelligence," "machine learning," "childhood obesity prevention," and "digital interventions." Articles (quantitative and qualitative) were screened based on their title, abstract, and full text. Inclusion criteria emphasized studies discussing AI-driven tools, personalized health interventions, and digital platforms aimed at preventing or managing youth obesity. Particular attention was given to technologies like machine learning, neural networks, geographic information systems (GIS), and telemedicine platforms. The review prioritized research on interventions addressing disparities in care, including tools for underserved populations and region-specific approaches to improving nutrition and physical activity outcomes. The main challenge in searching these articles is ensuring comprehensive coverage of diverse populations and geographical contexts, as many studies focus on high-resource settings, leaving gaps in data for underserved areas. Studies evaluating the impact of AI-powered apps, virtual coaching systems, and remote healthcare delivery on youth obesity outcomes were also included. For this review, terms like "children," "youth," "adolescents," and "young people" refer to individuals aged 8–18 years. This approach provided a comprehensive understanding of how digital innovation and AI contribute to youth obesity prevention and management strategies.

Geographical Disparities in Youth Obesity

The World Health Organization (WHO) defines childhood obesity as having a Body Mass Index (BMI) two or more standard deviations above average for a child's gender and age group [13]. Youth obesity rates vary by geographical regions within a country or across different countries, with the highest prevalence observed in high-income countries, but rapidly increasing in low- and middle-income countries [14]. These disparities can be influenced by multiple factors like socioeconomic status, cultural influences, access to healthcare, environmental, policies, and education. The United States, Mexico and Pacific Islands have one of the highest rates of obesity among youth – affecting around 19% of the youth and children (14.4 million) [15]. Obesity rates across Europe vary, with increasing rates reported in countries like the U.K., Greece, and Spain, while youth obesity rates are lowest in Belgium and Denmark (causes poorly understood) [16 17]. In low- and middle-countries (LMICs), geographical disparities in youth obesity are prevalent and especially multifaceted. A study by Yang et al. analyzing data across 58 LMICs found that the prevalence of adolescent obesity ranged from 0.1% in Vanuatu to 35.0% in Niue [18]. This same study found that compared to Southeast Asia and Africa, obesity is more common in Central and South America. A separate study by Templin et al. reported a correlation between socioeconomic status and obesity rates – as countries developed economically, overweight prevalence increased among the poorest and remained unchanged among the wealthiest [19]. More research is needed, especially among LMICs where disparities in youth obesity are the highest, to inform targeted interventions.

Geographical disparities in youth obesity are a complex issue influenced by multiple factors like socioeconomic status, cultural influences, access to healthcare, environmental, policies, and education. Understanding these geographical differences is crucial for tailoring effective interventions and public health strategies.

Factors Associated with Youth Obesity

Youth obesity is influenced by four primary factors: policy, individual, home environment, and community [20]. Policy factors include the pervasive marketing of unhealthy, nutrient-poor foods that attract young audiences, as well as disparities in under-resourced communities where access to healthy food and supportive policies is limited. Individual factors involve genetics, such as polygenic and monogenic influences, as well as prenatal and postnatal risks like parental obesity, maternal smoking, and rapid weight gain during infancy. The

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home environment plays a significant role through behaviors like snacking, insufficient sleep, limited family meals, and excessive screen time. Community factors further contribute, including the availability of resources in schools, access to fresh food, and proximity to grocery stores or safe spaces for physical activity. Together, these factors create a multifaceted challenge that requires comprehensive strategies to address youth obesity effectively.

Urbanization and Lifestyle

Urbanization contributes to high-calorie diets, sedentary lifestyles, and disparities in access to healthy foods among the poorer communities. This is more visible in high-income countries like the U.S. and Canada that are classified as high-income countries by the World Bank [21]. In 2022, the youth obesity prevalence in Canada and the U.S. was higher at 10.79% and 20.54% respectively [22]. These rates were higher than the global average rates of 8% [23].

In Latin American countries, mostly classified as low- to middle-income, youth obesity is rapidly increasing, with Mexico and Brazil facing significant public health challenges (around 35% in Mexico) [24]. This rise is attributed to urbanization, changes in traditional diet, and reduced physical activity. Differences in physical activity levels across regions also play a significant role. In middle-income Asian countries like China and India, the prevalence of youth obesity is rising due to urbanization and the adoption of westernized dietary patterns [25]. In China, the obesity rate among adolescents increased from 5.3% in 1995 to 19% in 2014, reflecting a significant public health concern [26].

Low-income countries, on the other hand, are susceptible to having lower obesity prevalence. While traditionally associated with undernutrition, sub-Saharan Africa is witnessing a dual burden of malnutrition, where undernutrition and obesity coexist [27]. Countries like South Africa have seen an increase in youth obesity rates, particularly in urban areas. In South Africa, 13% of youth were obese in 2016, with higher rates among urban populations [27]. These countries face a complex public health scenario, where the challenges of undernutrition and overnutrition are both prevalent. Apart from dietary factors, youth in rural areas of low-income countries may engage in more physical labor, while those in urban areas of high-income countries might lead more sedentary lifestyles due to increased screen time and limited access to safe outdoor spaces [28].

Policy and Public Health Interventions

Government Policies

Government policies and public health initiatives vary significantly across regions, affecting obesity rates. For instance, some European countries have implemented taxes on sugary drinks and regulations on food marketing, while other regions lack such measures [29]. While many countries have developed national guidelines that provide comprehensive recommendations for a healthier diet (emphasize the consumption of fruits, vegetables, and whole grains while advising against the intake of sugars, fats, and processed foods), these are widely adopted due to health illiteracy and financial constraints [30]. Similarly, food labeling regulations have been implemented in the European Union, Russia, China, Brazil, and Australia, but adherence to healthy dietary choices are not universal due to unequal access [31].

School-Based Interventions

In some countries, schools play a crucial role in promoting healthy behaviors through nutrition education, physical activity programs, and healthier school meal standards. The implementation and effectiveness of these programs vary widely. A comprehensive study on school interventions promoting healthy eating found that improving school meals - offering fruits and vegetables (n=27) were effective [32]. A separate systematic review of 96 studies found that increasing menu choices with cultural appropriateness/palatability of foods, providing pre-sliced fruits, establishing a healthy food reward system, allowing longer lunch times, having recess before lunch, and limiting students' access to unhealthy foods during the school day can have a significant impact on youth weight [33]. Other studies emphasize the importance of modifying food environments, integrating nutrition education into curriculum, and implementing transparent nutrition standards to promote healthy choices [34, 35, 36].

Another review of 27 articles found that school nutrition interventions reduced school-aged children's BMI and body mass index z score (BAZ), but physical activity interventions and nutrition education did not significantly affect BMI or BAZ [37]. Additionally, parental involvement and healthy food provision did not strengthen school nutrition interventions [37]. While school-based interventions are important, more data-driven and customized strategies are needed for effective and consistent outcomes.

Youth obesity is a global public health concern, prompting governments, communities, and schools to implement policies. However, these interventions have yielded mixed results due to the complex interplay of socio-economic factors, lifestyle habits, access to healthcare, dietary choices, cultural influences, and geographical disparities. This complexity makes it challenging to create uniform and generalized solutions across diverse populations.

AI has significant potential to bridge these gaps by providing innovative approaches to identify, predict, and target the root causes of youth obesity. Emerging AI solutions aim to analyze geographical and demographic data, offering tailored interventions that address regional disparities and optimize strategies to address youth obesity more effectively.

Harnessing AI and Digital Innovation to Close the Gaps

Data Collection and Personalized Interventions

AI offers actionable solutions to address the disparities by providing platforms for targeted interventions, predictive analytics, and region-specific recommendations. AI-enabled systems help analyze global and local data from reliable sources, including healthcare records, nutrition surveys, and GIS which help identify patterns and correlations related to obesity in different regions, and also assist with long-term monitoring, and resource allocation [38, 39]. For example, CHICA (Child Health Improvement through Computer Automation) system integrates electronic health records with automated decision- making support systems, which allows for data collection and age-appropriate obesity screening [40]. Based on the collected data, AI-based methods can encourage personalized dietary and exercise plans based on cultural preferences, youth's pocket money, and local food availability [41]. AI-powered apps and behavior coaches can provide real- time feedback and recommendations to youth and families to self-track and implement healthier eating habits and physical activity [42]. In Sweden, MINISTOP 1.0 (Mobile-based Intervention Intended to Stop Obesity in Pre-schoolers) was altered to version 2.0 as an interface to bring healthcare providers and families together towards customized interventions with real time feedback [43]. Another unique intervention is a video-game based feed-back loop program – Running Othello, was incorporated into South Korean school curriculum with improved youth engagement in exercise and weight loss [44]. Similarly, Xbox and Kinect games and "MyPlate Pick" exercising and dietary interventions showed improved cardiometabolic health among youth when compared to controls in another study [45, 46].

Engaging families in dietary decisions is key for sustainable results. For example, an AI-clinician decision-support system was developed to track family dietary behavior, factoring in proximity to the grocery store with healthier dietary options [47]. Results of this intervention showed that each 1-mile shorter distance to a supermarket was associated with increased fruit and vegetable intake by 0.29 servings per day and decreased BMI z-score by -0.04 units. Additionally, AI-driven educational platforms can tailor content to different regions, languages, and cultures, making nutrition education more engaging for youth worldwide. AI can personalize courses to one's needs, allowing for more effective lesson plans. These platforms are extremely beneficial for youth with low health literacy, as they can educate them about nutrition and exercise in a fun way, while providing access to resources for a healthy lifestyle [48]. One study involving racial and ethnic underrepresented girls found that AI-driven mobile apps with real-time goal setting, self-monitoring, and feedback features led to improved dietary behaviors [49]. Other studies report the effectiveness of AI in providing personalized feedback, monitoring, and recommendations based on individual user data as well as the role of AI in early identification and prevention of obesity-related health issues, especially in underserved communities [50, 51]. In 2023, Clinical Practice Statement (CPS) from the Obesity Medicine Association, describes the potential for AI to facilitate education programming related to body composition imaging, behavior coaching, nutritional intervention, and predictive modeling to assess population health on a global scale [52]. With a rapidly trending shift toward value-based care in the foreseeable future, AI has potential to revolutionize medical care, including the prevention, management, and treatment of youth patients with obesity [50].

Community and Public Health Interventions

AI algorithms have been instrumental in mapping and analyzing food sectors and identify "food deserts"[53]. Food deserts are areas, often in low-income or underserved communities, where access to affordable, fresh, and nutritious food is limited or nonexistent. These regions are characterized by a lack of grocery stores or markets offering healthy food options, forcing residents to rely on fast food or convenience stores with processed, unhealthy items. Addressing food deserts are crucial for promoting equitable nutrition and reducing obesity rates, particularly among youth. AI-based models have the capacity to tie the existing information on food supply in the context of broader environment, government taxes on unhealthy foods, healthy food subsidies, and also measuring food intakes on a global and regional scale [54]. With vast data sources, from satellite imagery of agricultural regions to social media on dietary habits, AI enables the synthesis and interpretation of this information to guide public health nutrition strategies and interventions [55].

AI can provide insights to governments and private sectors by evaluating the effectiveness of public health interventions, helping shape impactful policies and it can also assist in the equitable distribution of healthcare resources, ensuring that regions with the highest need receive adequate support with real-time data and feed-back loops [56]. AI models can help create platforms to connect communities and share best practices. AI can also monitor the impact of community-led interventions in real-time, providing feedback to adjust strategies as needed.

Telemedicine and Remote Healthcare

Technology and innovation play a major role in our communities. Since the onset of COVID-19, telehealth has been a game changer in healthcare, allowing virtual medical visits through remote platforms, enabling flexibility, and allowing patient care in their own location without needing transportation. Although underrepresented communities had less access to telehealth, there have since been efforts to close the divide with a focus on youth obesity [57]. With the alleviation of the digital divide, underserved groups have equitable access to healthcare and improved outcomes [58]. Digital innovations like telehealth and remote healthcare can also bridge geographical gaps, allowing the underrepresented to connect with resources and treatment they may not have had access to otherwise. AI-driven telemedicine platforms can help overcome language and cultural barriers ensuring equitable youth healthcare access [59].

Limitations and Challenges

Our narrative review provides an overview of youth obesity, geographical disparities, and the potential of AI to bridge these gaps; however, several challenges and limitations must be acknowledged. First, the reliance on published literature introduces potential biases, as the availability and quality of studies may vary across regions, particularly in low-resource settings. Many studies focus on high-resource environments, limiting insights into the unique challenges faced by underserved populations. Additionally, the review may not fully capture emerging, unpublished data or innovations in AI and digital health, which evolve rapidly. Another limitation is the variability in methodologies and outcomes reported in the studies reviewed, which can make it difficult to draw uniform conclusions. Finally, while this review emphasizes the potential of AI and digital technologies, practical challenges such as infrastructure gaps, data privacy concerns, and disparities in access to technology remain underexplored and warrant further investigation. These limitations underscore the need for continued research and real-world evaluations to validate and refine the proposed strategies.

CONCLUSION

Youth obesity is a critical public health issue, prevalent in low- to middle-income and high- income countries. This highlights the need for multifaceted interventions to address regional disparities, socioeconomic factors, and cultural influences. AI and digital innovation have significant potential to create personalized, data-based strategies tailored to the unique needs of individuals and communities. By integrating healthcare data, nutrition records, and geographical systems, digital advancements can accurately identify obesity patterns and inform targeted interventions. Effectively incorporating AI and latest digital technologies into healthcare and public health frameworks can enhance collaboration among clinicians, schools, community stakeholders, families and youth, towards an equitable environment where all youth have access to healthier futures.

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