Original Article

Leveraging Artificial Intelligence to Simulate Public Health Policy Impacts for Obesity Prevention in Saudi Arabia

Assim A. Alfadda[1,2,3], Satish Kumar David[2], Mohamed Rafiullah[2], Adnan Mahmood Usmani[2], Nourhan Mohamed[2]

[1]Department of Medicine, College of Medicine, King Saud University, [2]Strategic Center for Diabetes Research, College of Medicine, King Saud University, [3]Obesity Research Center, College of Medicine, King Saud University, Riyadh, Saudi Arabia

Abstract

Background: Obesity poses one of the most significant public health challenges globally, with Saudi Arabia facing particularly high prevalence rates. Traditional public health strategies often lack the precision and scalability required to address the complex and multifaceted drivers of obesity. In Saudi Arabia, where lifestyle-related diseases such as obesity and diabetes are prevalent, artificial intelligence (AI) can provide data-driven, scalable, and efficient solutions. Policymakers need effective tools to predict the impacts of interventions to reduce obesity prevalence. AI has emerged as a transformative tool for simulating and evaluating public health policies. **Research Question:** How can AI-driven simulation models be developed and utilized to evaluate the effectiveness of obesity prevention policies and guide resource allocation in Saudi Arabia? **Methods:** We will explore the novel framework for the integration of AI techniques such as machine learning and natural language processing (NLP) to develop a policy impact simulation model. The impact of policy changes will be investigated using specific case studies. Simulations will explore diverse policy interventions, including public awareness campaigns, nutritional regulations, and urban planning for physical activity promotion. **Contributions to the Field:** The policy impact simulation model will offer a glimpse of the real-time outcomes of policy implementations to prevent obesity. It will be useful to examine case studies, challenges, and potential results, offering a roadmap with actionable insight for policymakers. The proposed model is expected to inform policy decisions by providing simulated insights into the effectiveness of obesity prevention strategies, enabling data-driven prioritization of interventions, and supporting long-term planning for public health improvement in Saudi Arabia.

Keywords: Artificial intelligence, machine learning, natural language processing, obesity prevention, policy simulation, public health policy

Introduction

Obesity is a pressing global health concern, especially in the Middle East, due to rapid urbanization and lifestyle changes. Obesity affects over one billion people globally, including 650 million adults, 340 million adolescents, and 39 million children, according to the World Health Organization.[1] In Saudi Arabia, adult obesity prevalence (body mass index [BMI] ≥30 kg/m^2) is notably high at 24.7%, ranking among the highest obesity rates in the Middle East.[2] Factors contributing to this include increased consumption of processed foods and sugar-sweetened beverages, sedentary lifestyles due to rapid urbanization and motor vehicle reliance, and limited access to nutritious food and recreational facilities.[3] Saudi Arabia has witnessed a dramatic shift in dietary habits and physical activity patterns over the past four decades. A rise in sedentary behaviors and the consumption of calorie-dense foods has contributed to a rise in obesity rates over ten years in Saudi Arabia.[4] Obesity has a significant economic and social impact on healthcare systems and societies. From 2010 to 2020, obesity rates in Saudi Arabia increased by approximately 5%, resulting in an economic burden of $3.8 billion in 2019, equivalent to 4.3% of total healthcare spending.[5]

Access this article online

Quick Response Code:

Website: www.jnsmonline.org

DOI: 10.4103/jnsm.jnsm_327_25

Address for correspondence: Dr. Assim A. Alfadda, Department of Medicine, College of Medicine, King Saud University, P.O. Box 2925(98), Riyadh 11461, Saudi Arabia. E-mail: aalfadda@ksu.edu.sa

Submission: 23-11-2025 **Revision:** 11-03-2026
Acceptance: 06-04-2026 **Published:** 30-04-2026

This is an open access article distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 License (CC BY-NC-ND), where it is permissible to download and share the work provided it is properly cited. The work cannot be changed in any way or used commercially without permission from the journal.

For reprints contact: WKHLRPMedknow_reprints@wolterskluwer.com

How to cite this article: Alfadda AA, David SK, Rafiullah M, Usmani AM, Mohamed N. Leveraging artificial intelligence to simulate public health policy impacts for obesity prevention in Saudi Arabia. J Nat Sci Med 2026;9:168-75.

The rising prevalence of obesity poses a significant public health challenge, necessitating the development and implementation of comprehensive public policies aimed at its prevention and management. Obesity is a major risk factor for numerous chronic noncommunicable diseases (NCDs), including type 2 diabetes, cardiovascular disease, and certain cancers, placing a substantial burden on healthcare systems and reducing overall population productivity and quality of life.[6] A well-designed public policy can address the root causes of obesity through multisectoral approaches that promote healthy diets, encourage physical activity, regulate food marketing – especially to children – and improve urban planning to support active lifestyles. Moreover, such policies can ensure equitable access to preventive and therapeutic services, particularly for vulnerable and underserved populations.[7]

Public health policies often face limitations in addressing health issues comprehensively. These include a lack of precision, insufficient targeting of high-risk populations, and inadequate evaluation.[8] These issues can lead to generalized interventions that don't address specific community needs. In addition, policymakers may lack the tools to assess the real-time effectiveness of interventions, hindering timely adjustments and improvements. To address these limitations, a shift toward precision public health approaches, improved targeting of high-risk populations, and robust evaluation mechanisms is needed.

Artificial Intelligence (AI) can be utilized to enhance the development and implementation of public health policies for obesity prevention by modeling and simulating public health interventions, personalizing weight management programs, predicting policy outcomes, refining interventions, and tailoring strategies. AI has the potential to revolutionize public health policy through various techniques, such as machine learning (ML) models, which can forecast obesity prevalence, identify high-risk populations, and target interventions effectively. Unsupervised learning clusters communities with similar obesity determinants, while natural language processing (NLP) can evaluate public perception of obesity-related policies. Text summarization condenses complex legislative documents for quicker policy analysis. Reinforcement learning (RL) models can optimize intervention strategies[8] and propose adaptive SSB tax rates based on consumer behavior, optimizing policy impact. Agent-based modeling (ABM) simulations simulate individual behaviors, informing targeted interventions. Computer vision analyzes visual data to monitor public health trends, guiding resource allocation.[9] Systems dynamics modeling identifies how obesity policies interact with economic, behavioral, and biological factors, providing a comprehensive understanding of policy impacts.

Previous research, including Powell *et al*. and Nianogo and Arah, showed that simulation models combining school and community-based interventions effectively reduced obesity prevalence.[9-11] Giabbanelli and MacEwan (2024) further emphasized AI-driven participatory modelling for policy assessment.[12]

Policy simulation will allow policymakers to optimize strategies and predict potential outcomes before implementation, aiding in designing effective and equitable health policies.[13] Simulation modeling can be a crucial tool in public health policy, allowing policymakers to assess the effectiveness of different strategies before real-world implementation. Studies have shown that incorporating AI systems can provide nuanced insights into the potential impacts of interventions. Powell *et al*. used a systems model to simulate the impact of policy interventions on childhood obesity prevalence in Georgia, predicting that implementing daily school physical education and integrating moderate-to-vigorous physical activity into elementary classrooms could significantly reduce obesity rates among children and adolescents.[9] Nianogo and Arah used the Virtual Los Angeles Obesity Model to evaluate the long-term effectiveness of various interventions, finding that combining multiple interventions throughout an individual's lifespan could substantially mitigate obesity and type 2 diabetes.[10] Giabbanelli and MacEwan (2024) explored the integration of AI with simulation modeling, demonstrating how AI-driven participatory modeling could enhance the development and evaluation of obesity-related.[12] Therefore, the aim of this concept paper is to develop and present an AI-driven simulation framework capable of evaluating the projected impacts of public health policies for obesity prevention in Saudi Arabia. This model is intended to support evidence-informed decision-making by enabling policymakers to compare potential interventions, forecast long-term outcomes, and optimize the allocation of healthcare resources. The primary objective is to create a multimethod simulation model integrating ABM, system dynamics modeling (SDM), and RL to predict the effects of interventions on obesity prevalence, healthcare costs, and behavioral changes over a 10–20-year horizon. The model aims to facilitate evidence-based decision-making by comparing policy scenarios and optimizing resource allocation, customized to Saudi Arabia's distinct sociocultural and health context.

Methods

Study design and objectives

This study utilized a computational simulation approach to assess the impact of public health policies on obesity prevention in Saudi Arabia. The main goal was to simulate and compare policy scenarios to guide decision-making from a societal perspective, aiming to reduce obesity prevalence and related healthcare costs over a 10–20-year period. The study incorporated AI techniques, including ML, RL, and NLP, to develop a multimethod simulation model that integrates ABM and SDM for policy impact analysis. The study will proceed in four stages: data collection, model development, simulation execution, and outcome assessment.

The decision problem focused on evaluating multifaceted interventions in a high-obesity setting (adult prevalence ~35%

in Saudi Arabia). Simulation was selected over empirical trials due to ethical and logistical challenges in implementing large-scale policy experiments. A conceptual framework [Figure 1] directed the model's development to align with the research question.

Figure 1, a flowchart illustrating agent interactions, system dynamics, and policy levers, will direct the process in accordance with ISPOR-SMDM guidelines. It will feature color-coded layers (policy – yellow, agents/resources – blue/green, dynamics – light green, and outputs – orange) with clear directional arrows indicating the flow of influence. A feedback loop (dashed red) from model outputs to policy levers will reflect the ISPOR-SMDM focus on adaptive decision-making.

Data collection

Datasets and sources

The AI-driven simulation model for assessing public health policy impacts on obesity prevention in Saudi Arabia will be trained and validated using data from multiple sources, including specific attributes of these sources, to ensure comprehensive local information.

The simulation model will be trained and validated using diverse, high-quality datasets chosen for their relevance, recency (post-2015), and reliability (sourced from peer-reviewed publications or official records). A systematic search across PubMed, Google Scholar, and government portals will identify datasets, with quality evaluated using the Newcastle–Ottawa Scale (retaining datasets scoring ≥7/9). Data will be accessed through APIs (e.g., World Health Organization [WHO]), public downloads, and institutional agreements with the Ministry of Health (MOH) and King Abdullah International Medical Research Center.

Table 1 outlines the sources and their attributes.

Data types and preprocessing

Data will be organized into five categories and integrated using a PostgreSQL database:

1. Epidemiological and public health: Obesity prevalence NCD incidence (e.g., diabetes)[18,22-24]
2. Socioeconomic and demographic: Income levels, urbanization, and education levels[19]
3. Behavioral and consumer: Dietary habits (e.g., processed food intake) and physical activity (from surveys and wearables)[20,25]
4. Health policy and intervention: Programs, initiatives, and public health programs, including school-based interventions, sugar tax policies, and physical activity initiatives[21,24,26,27]
5. AI and simulation-specific: ML datasets for predicting trends.[28]

Data preprocessing

Data harmonization will be performed to ensure comparability across sources. Key variables will be standardized. Missing data and inconsistencies will be addressed through the systematic procedures. Validation procedures will be implemented to ensure the robustness of the integrated dataset.

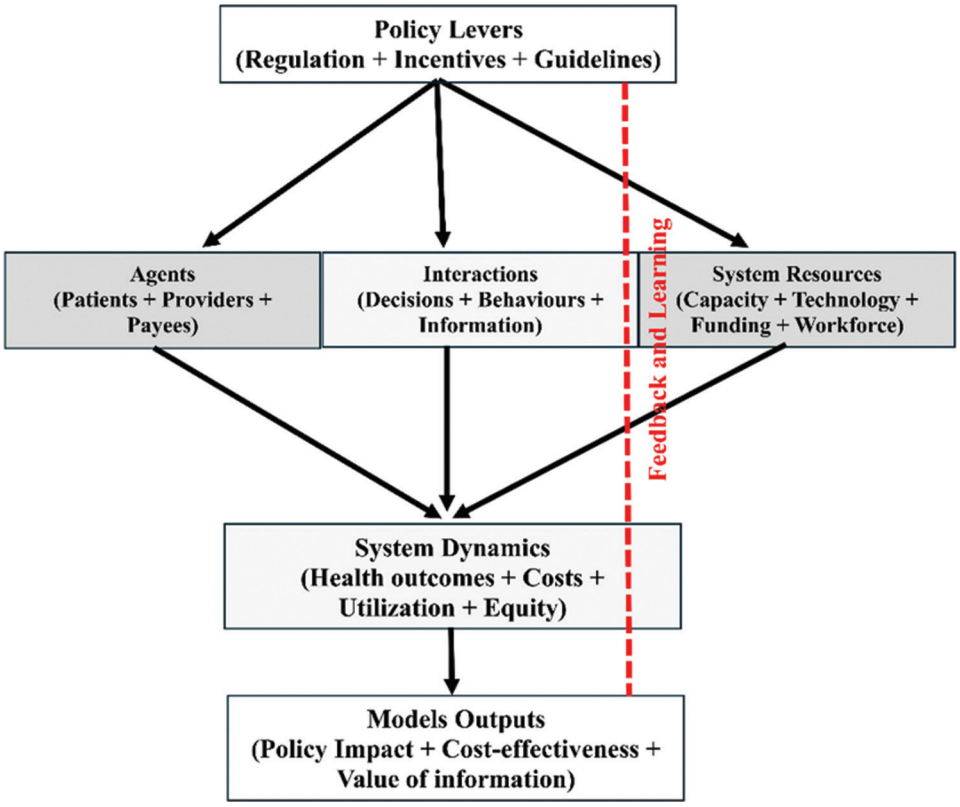


Figure 1: A conceptual model

Table 1: Outlines the sources and their attributes

Source	Attributes	Sample size
GASTAT[14]	Obesity prevalence by age/gender/region, dietary habits, and physical activity	~50,000 surveys
MOH[15]	Preventive behaviors, healthcare utilization	Aggregated, ~2300 facilities
Saudi Biobank, KAIMRC, and KFSHRC[16]	Biosamples and clinical NCD data	~10,000 participants
WHO Global Health Observatory[17]	Epidemiological trends and benchmarks	National aggregates
Saudi Health Information Survey[14]	Health behaviors and intervention outcomes	~10,000 respondents
Published research studies and governmental reports on obesity trends and intervention outcomes in Saudi Arabia[18]	Consumer behavior (e.g., supermarket data)	Variable
Census, wearables[19-21]	Demographics (urban/rural, income), physical activity	~100,000 aggregated

MOH: Ministry of Health, GASTAT: General Authority for Statistics, KAIMRC: King Abdullah International Medical Research Center, KFSHRC: King Faisal Specialist Hospital and Research Centre, WHO: World Health Organization, NCD: Noncommunicable disease

Data harmonization

1. Standardization of definitions (e.g., obesity as BMI ≥30 kg/m^2 and consistent age/gender stratifications)
2. Unit conversion and *z*-scoring for continuous variables
3. Entity resolution for overlapping concepts (e.g., reconciling regional prevalence estimates across GASTAT and MOH).

Handling missing data and inconsistencies

1. Missingness limited to <10% per dataset; addressed through multiple imputation by chained equations (MICE)
2. Cross-validation of key indicators (e.g., national obesity prevalence) against multiple sources; discrepancies resolved by prioritizing primary national sources (GASTAT/MOH) over aggregates (WHO) unless the latter provide unique benchmarks
3. Sensitivity analyses test the impact of source-specific variations (e.g., self-reported vs. measured BMI in GASTAT surveys).

Natural language processing-assisted extraction

For unstructured sources (e.g., policy documents and reports), spaCy-based NLP extracts standardized features (such as intervention parameters and sentiment), will be used to reduce manual coding bias.

Validation checks

1. Internal calibration against recent GASTAT/MOH time-series data
2. External comparison with independent benchmarks (e.g., WHO projections)
3. Probabilistic sensitivity analysis (beta/log-normal distributions) quantifies uncertainty from data sources.

Data access through APIs (e.g., WHO), public downloads, and institutional partnerships. Preprocessing steps include handling missing data (<10% per dataset, using MICEs), standardizing continuous variables (z-scoring), and resolving entities for data integration. NLP (using spaCy) will analyze ~500 policy documents and reports to extract features like policy sentiment and intervention specifics.

The AI-driven simulation model in Saudi Arabia will incorporate data from various sources to analyze adult obesity rate trends and projections, thus aiding in informed public health policy decisions to combat obesity. NLP will be used to extract insights from policy documents, research articles, and health reports, guiding the model's decision-making framework.

Model development

Developing an AI-driven simulation model to evaluate the impact of public health policies on obesity prevention in Saudi Arabia involves implementing several advanced AI models. The simulation model will integrate ABM and SDM within a multimethod framework that will be used to simulate individual actions and interactions in obesity prevention. ABMs can model individual behaviors related to diet, physical activity, and responses to public health interventions, providing insights into how these behaviors aggregate to influence obesity rates. SDMs use differential equations to represent relationships and feedback loops within complex systems, helping predict long-term trends in the prevalence of obesity. The framework enhanced by RL represents individual behaviors and system-wide dynamics to make decisions by rewarding desired outcomes, optimizing public health strategies by evaluating various policy combinations. ABM will simulate 10,000 agents (segmented by age, gender, and region) interacting in a virtual setting with policy variables (e.g., taxes and campaigns). SDM will use differential equations to model feedback loops, such as d (Obesity Rate)/dt = f (Diet, Activity, Policies). RL (via Stable Baselines3) will optimize policy combinations, prioritizing outcomes like lower BMI. Additional ML models (Random Forest and Neural Networks (NN) using TensorFlow) will forecast obesity risks, while Recurrent NN will process time-series data from EHRs/wearables, and geospatial analysis (GeoPandas) will incorporate urban planning data.[29-31]

Implementation will leverage Python 3.10, utilizing Mesa for ABM, PySD for SDM, TensorFlow for ML, and spaCy for NLP. Key settings include a learning rate of 0.001 (RL), an 80/20 train-test split (ML), and 5-fold cross-validation. Assumptions include bounded rationality for agents, a 2% annual population growth rate, and no significant external disruptions (e.g., pandemics), validated through sensitivity analysis.

The integration of AI models with localized data, such as demographics, health statistics, and behavioral patterns, will enable policymakers to simulate scenarios and design effective interventions tailored to Saudi Arabia's unique public health landscape. Figure 2 illustrates the model architecture integration of an agent-based model (ABM) and an SDM, with an RL optimizer managing policy levers and adapting based on simulation results.

Simulation execution

Simulations will be conducted to analyze the effectiveness of different policy interventions. Monte Carlo simulations are widely used in public health modeling to account for uncertainty and variability in complex systems.[32] Simulations (1000 Monte Carlo runs per scenario, with monthly time steps) will assess policy effectiveness over a 10–20-year period. Key interventions [Table 2] were parameterized using evidence-based data (e.g., tax elasticities derived from meta-analyses).

Measured outcomes included obesity prevalence (BMI ≥30), healthcare costs (SAR/year), and behavioral changes (e.g., reduced kcal intake).

Scenarios include:

1. Baseline: No interventions and current obesity trends (projected 5% increase by 2035)
2. Taxation: 20% sugar-sweetened beverage tax and subsidies for healthy foods (elasticity: −1.2 and range: −0.8 to −1.6)[33,34]
3. Regulatory: Nutritional labeling and bans on junk food in schools (compliance: 60% and range: 40%–80%)[35]
4. Lifestyle: Physical activity initiatives (e.g., cycling lanes, AI coaching apps; participation: 30%, range: 20%–50%)[36]
5. Combined: All interventions implemented together. Outcomes will measure obesity prevalence, healthcare costs (SAR/year), and behavioral shifts (e.g., reduced kcal intake, increased activity minutes). Simulations will be executed on an AWS EC2 cluster (64 cores).

The model will simulate short-term and long-term policy impacts, measuring obesity prevalence, healthcare costs, and behavioral shifts over time.

Model validation

To ensure model reliability and accuracy of the simulations, validation will include:

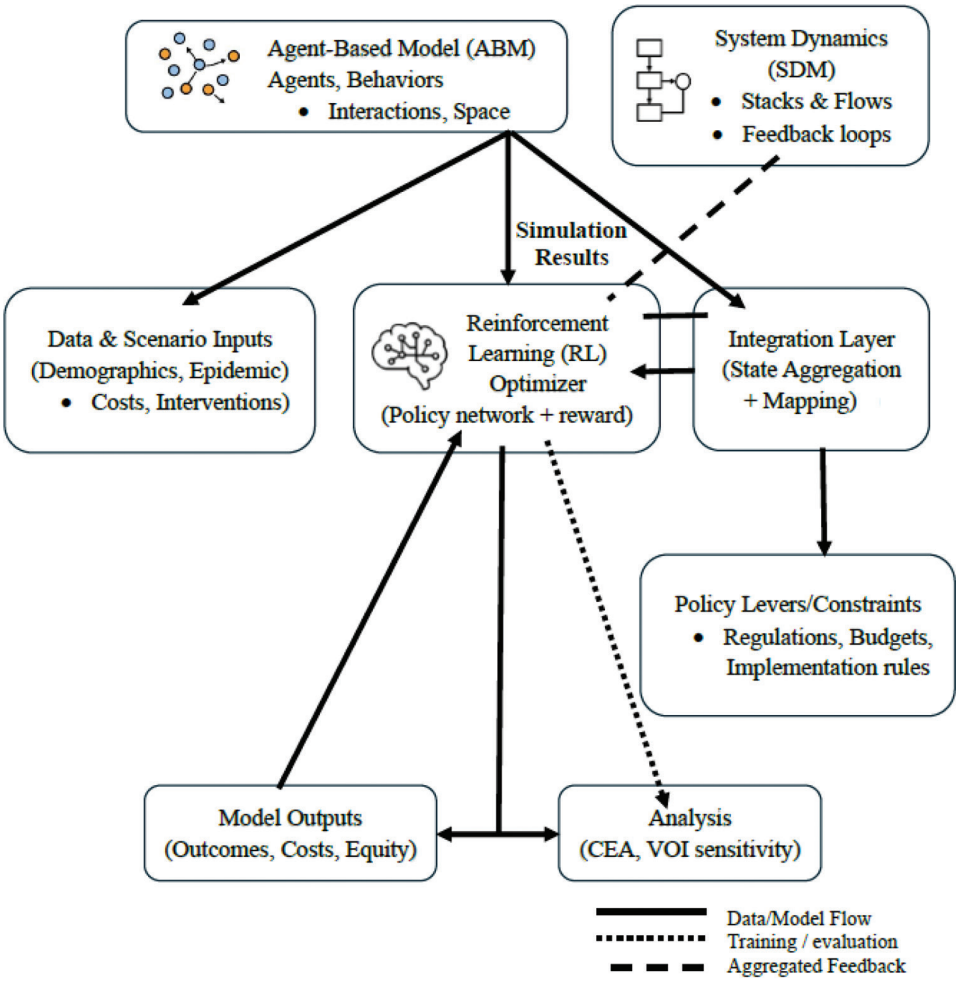


Figure 2: Model architecture diagram

Table 2: Key interventions and parameters

Category	Interventions	Parameters (base/range)
Economic/fiscal	Sugar-sweetened beverage tax (10%–20%) and healthy food subsidies	Elasticity: −1.2 (−0.8 to −1.6) (35–36)
Food environment/regulation	Nutritional labeling and junk food bans in schools	Compliance: 60% (40%–80%) (37)
Behavioral/lifestyle	Physical activity programs (e.g., cycling lanes and AI coaching apps)	Participation: 30% (20%–50%) (38)

AI: Artificial intelligence

- Internal: Unit testing to verify code logic and calibration against 2015–2023 GASTAT data (RMSE <5%) using genetic algorithms
- External: Comparison with WHO projections for 2025–2035,[17] alongside face validity assessed via the Delphi method with 15 Saudi public health experts (agreement >80%)
- Uncertainty: Probabilistic sensitivity analysis using beta distributions for probabilities and log-normal distributions for costs, plus one-way and two-way sensitivity analyses on key parameters (e.g., compliance ± 20%); structural uncertainty evaluated by comparing ABM-only versus multimethod models.

Reproducibility

Code and documentation will be openly accessible. The repository will include a data dictionary and a model flowchart. Simulations will be executed on a high-performance computing cluster (e.g., AWS EC2 with 64 cores).

The model will undergo:

- Cross-validation using historical policy data and real-world obesity trends
- Sensitivity analysis to determine how variations in input parameters (e.g., policy enforcement levels and public compliance) affect outcomes
- Expert validation through consultations with public health professionals and policymakers in Saudi Arabia.

Expected Outcomes

The simulation is expected to provide predictive insights into the effectiveness of various policy scenarios:

1. Baseline scenario: Obesity prevalence is forecasted to increase from 24.7% in 2025 to 30% by 2035, with healthcare costs rising by 5% annually, reaching approximately SAR 4.5 billion by 2035
2. Taxation scenario: A 20% tax on sugar-sweetened beverages is projected to decrease obesity prevalence by 2%–3% over a decade, yielding cost savings of SAR 500–800 million due to reduced consumption (elasticity: −1.2)
3. Regulatory scenario: School junk food bans and nutritional labeling are expected to reduce obesity by 1%–2%, with a greater impact at higher compliance rates (80%)
4. Lifestyle scenario: Physical activity initiatives are anticipated to boost daily activity by 10–20 min, lowering obesity by 1%–1.5%
5. Combined Scenario: Implementing all interventions together is projected to cut obesity by 5-7% by 2035, with cumulative cost savings of SAR 1.2–1.8 billion. Subgroup analyses will examine effects across age, gender, and regions (e.g., urban vs. rural). Sensitivity analyses will assess uncertainty (e.g., 95% CI for prevalence: ±1.5%). Results will be presented through graphs (e.g., obesity trends and cost curves) and tables summarizing scenario outcomes.

The AI-driven simulation model will generate predictive insights into the effectiveness of obesity prevention policies. By comparing intervention scenarios, policymakers will receive data-driven recommendations for optimizing resource allocation and policy implementation. This framework is expected to:

- Improve policy decision-making by forecasting long-term obesity trends and health outcomes
- Enhance public health strategies by identifying high-impact interventions
- Serve as a scalable model for global applications in obesity prevention policy
- AI-powered policy simulations can predict cost–benefit analyses of interventions, consumer behavior shifts postimplementation, and best-performing policy combinations such as tax and physical activity incentives.

The findings from this study will contribute to the growing field of AI-driven public health policy evaluation, offering a robust tool for addressing obesity in Saudi Arabia and beyond.

Key Public Health Interventions

The AI-driven simulation model will be set to assess various interventions for obesity prevention.

Economic and fiscal policies

Food taxation and pricing policies include sugar-sweetened beverage tax (ex. 15% tax on soft drinks), junk food tax (processed snacks and fast food), subsidies for healthy foods such as fruits, vegetables, and whole grains, and caloric density-based taxation, which increases the tax for ultra-processed foods. Workplace and community health incentives include employers providing wellness benefits like exercise reimbursement and tax deductions for gym memberships and fitness-related expenses. These policies aim to promote healthier eating habits and reduce the tax burden on processed foods.[33,34]

Food environment and regulation policies

School and workplace nutrition policies ban junk food

marketing, enforce healthy meal programs (compulsory fruit and vegetable servings), and enforce nutritional labeling laws (front-of-pack warning labels). Restaurant and retail policies mandate calorie labeling on menus, require healthy meal options in fast-food outlets, and impose portion size limits on oversized sugary drinks.[35]

Behavioral and lifestyle interventions

The government is promoting physical activity through government-funded sports programs, cycling lanes, pedestrian-friendly urban design, free gym access, and integrating exercise into school curricula. Technology-based solutions include AI-driven health coaching apps, smart wearables, telehealth, and AI-powered virtual dietitians.[36]

In the current protocol, the primary outcomes were selected as obesity prevalence and healthcare costs because they represent the most widely used indicators for evaluating public health policies and the economic burden associated with obesity.

Measuring the Impact in Real-World

To ensure accuracy, AI models must be validated with real-world data. We will plan the validation with real-world data after the successful demonstration of the AI simulation model. The real-world validation will include before-and-after comparisons, longitudinal tracking, time-series analysis, ML, predictive analytics, surveys, self-reported data, wearable and smart data tracking, and AI-powered sentiment analysis. Before-and-after comparisons compare key metrics such as obesity rates and food consumption before and after policy implementation using historical control groups (regions where no policy changes occurred) to differentiate actual impact. Longitudinal tracking and time-series analysis help predict trends over time, comparing simulated predictions with real-world outcomes.[37]

Discussion

This protocol presents a sophisticated AI-driven simulation framework to guide obesity prevention policies in Saudi Arabia, emphasizing precision public health. Key strengths include the multimethod approach (integrating ABM, SDM, and RL), thorough data integration, and robust validation consistent with ISPOR-SMDM and TRIPOD-ML standards. By leveraging localized data, the model ensures cultural relevance, particularly addressing Saudi Arabia's distinct sociocultural factors, such as gender norms influencing physical activity.

Limitations include the use of aggregated data, which may obscure individual differences, and assumptions of stable external conditions (e.g., absence of economic disruptions). Postsimulation validation with real-world data, such as longitudinal studies or before-and-after analyses,[37] will be essential to verify predictions. Obesity affects multiple dimensions of health and societal functioning. Quality of life, mental health, and productivity can be included in the future iterations of the simulation framework. These outcomes can be incorporated into subsequent models in the future.

Future Research

Future research should focus on:

- Developing culturally relevant AI models tailored to Saudi Arabia's demographics
- Enhancing public trust in AI-driven health tools through educational initiatives
- Encouraging partnerships among the MOH, academic institutions, and tech companies to support Saudi Vision 2030's digital transformation objectives
- Promoting public awareness and acceptance of AI in health care
- Building interdisciplinary collaborations between policymakers, healthcare professionals, and AI experts.

This framework is poised to deliver actionable, evidence-based policy recommendations, with potential applicability to other high-obesity settings worldwide.

Acknowledgment

We would like to acknowledge the Strategic Center for Diabetes Research, College of Medicine, King Saud University, Riyadh, Saudi Arabia, and the Obesity Research Center, College of Medicine, King Saud University, Riyadh, Saudi Arabia, for contributing to this work.

Financial support and sponsorship

Nil.

Conflicts of interest

There are no conflicts of interest.

References

1. Over One Billion Obese People Globally, Health Crisis Must be Reversed – WHO | UN News. UN News 2022. Available from: https://news.un.org/en/story/2022/03/1113312. [Last accessed on 2025 Oct 05].
2. Althumiri NA, Basyouni MH, AlMousa N, AlJuwaysim MF, Almubark RA, BinDhim NF, *et al*. Obesity in Saudi Arabia in 2020: Prevalence, distribution, and its current association with various health conditions. Healthcare (Basel) 2021;9:311.
3. Salem V, AlHusseini N, Abdul Razack HI, Naoum A, Sims OT, Alqahtani SA. Prevalence, risk factors, and interventions for obesity in Saudi Arabia: A systematic review. Obes Rev 2022;23:e13448.
4. Al-Hazzaa HM, Albawardi NM. Obesity, lifestyle behaviors, and dietary habits of Saudi adolescents living in Riyadh (ATLS-2 project): Revisited after a ten-year period. Life (Basel) 2021;11:1078.
5. Malkin JD, Baid D, Alsukait RF, Alghaith T, Alluhidan M, Alabdulkarim H, *et al*. The economic burden of overweight and obesity in Saudi Arabia. PLoS One 2022;17:e0264993.
6. Kee F, Taylor-Robinson D. Scientific challenges for precision public health. J Epidemiol Community Health 2020;74:311-4.
7. Li Z, Zhou H, Xu Z, Ma Q. Machine learning and public health policy evaluation: Research dynamics and prospects for challenges. Front Public Health. 2025;13:1502599.
8. Fisher S, Rosella LC. Priorities for successful use of artificial intelligence by public health organizations: A literature review. BMC Public Health 2022;22:2146.
9. Powell KE, Kibbe DL, Ferencik R, Soderquist C, Phillips MA, Vall EA, *et al*. Systems thinking and simulation modeling to inform childhood obesity policy and practice. Public Health Rep 2017;132:33S-8S.

10. Nianogo RA, Arah OA. Impact of public health interventions on obesity and type 2 diabetes prevention: A simulation study. Am J Prev Med 2018;55:795-802.
11. Gupta G, Kang L, Yu JW, Limkemann AJ, Garcia V, Bandyopadhyay D, *et al*. Long-term outcomes and transmission rates in hepatitis C virus-positive donor to hepatitis C virus-negative kidney transplant recipients: Analysis of United States national data. Clin Transplant. 2017;31:e13055. doi:10.1111/ctr.13055.
12. Giabbanelli PJ, MacEwan G. Leveraging artificial intelligence and participatory modeling to support paradigm shifts in public health: An application to obesity and evidence-based policymaking. Information 2024;15:115.
13. Freebairn L, Atkinson J, Kelly P, McDonnell G, Rychetnik L. Simulation modelling as a tool for knowledge mobilisation in health policy settings: A case study protocol. Health Res Policy Syst 2016;14:71.
14. General Authority for Statistics. Health Determinants Statistics. GASTAT. Available from: https://www.stats.gov.sa/en/statistics-tabs?tab=436312&category=123842. [Last accessed on 2025 Oct 05].
15. Ministry of Health (Saudi Arabia). Preventive Health Behaviors. Riyadh: Ministry of Health; 2021. https://www.moh.gov.sa/en/Ministry/Statistics/Indicator/Documents/2-Preventive-Health-Behaviors.pdf [Last accessed on 2025 Nov 05].
16. KAIMRC. Research Data Request Form. King Abdullah Int Med Res Cent. Available from: https://kaimrc.med.sa/En/EServices/Pages/ServiceDetails.aspx?ItemID=8. [Last accessed on 2025 Oct 12].
17. WHO. Global Health Observatory. World Health Organ. Available from: https://www.who.int/data/gho. [Last accessed on 2025 Oct 08].
18. Alfadda AA, Al-Dhwayan MM, Alharbi AA, Al Khudhair BK, Al Nozha OM, Al-Qahtani NM, *et al*. The Saudi clinical practice guideline for the management of overweight and obesity in adults. Saudi Med J 2016;37:1151-62.
19. Memish ZA, El Bcheraoui C, Tuffaha M, Robinson M, Daoud F, Jaber S, *et al*. Obesity and associated factors-Kingdom of Saudi Arabia, 2013. Prev Chronic Dis 2014;11:E174.
20. Al-Hazzaa HM, Abahussain NA, Al-Sobayel HI, Qahwaji DM, Musaiger AO. Physical activity, sedentary behaviors and dietary habits among Saudi adolescents relative to age, gender and region. Int J Behav Nutr Phys Act 2011;8:140.
21. Al-Hazzaa HM, AlMarzooqi MA. Descriptive analysis of physical activity initiatives for health promotion in Saudi Arabia. Front Public Health 2018;6:329.
22. Alqahtani B, Elnaggar RK, Alshehri MM, Khunti K, Alenazi A. National and regional prevalence rates of diabetes in Saudi Arabia: Analysis of national survey data. Int J Diabetes Dev Ctries 2023;43:392-7.
23. Ministry of Health (Saudi Arabia). Saudi Health Interview Survey: Results Report. Riyadh: Ministry of Health; 2013. Available from: https://www.healthdata.org/sites/default/files/files/Projects/KSA/Saudi-Health-Interview-Survey-Results.pdf . [Last accessed on 2026 Jan 25].
24. Almubark RA, Alqahtani SA. Epidemiology of obesity and control interventions in Saudi Arabia. East Mediterr Health J 2023;29:987-94.
25. Musaiger AO. Overweight and obesity in Eastern Mediterranean region: Prevalence and possible causes. J Obes 2011;2011:407237.
26. Alsukait R, Wilde P, Bleich S, Singh G, Folta S. Impact of Saudi Arabia's sugary drink tax on prices and purchases (P10-066-19). Curr Dev Nutr 2019;3:nzz034.P10-066-19.
27. Teng AM, Jones AC, Mizdrak A, Signal L, Genç M, Wilson N. Impact of sugar-sweetened beverage taxes on purchases and dietary intake: Systematic review and meta-analysis. Obes Rev 2019;20:1187-204.
28. Alanazi SH, Abdollahian M, Tafakori L, Almulaihan KA, ALruwili SM, ALenazi OF. Predicting age at onset of childhood obesity using regression, random forest, decision tree, and K-nearest neighbour-a case study in Saudi Arabia. PLoS One 2024;19:e0308408.
29. Ferdowsy F, Rahi KS, Jabiullah MD, Habib MD. A machine learning approach for obesity risk prediction. Curr Res Behav Sci 2021;2:100053.
30. Weltz J, Volfovsky A, Laber EB. Reinforcement learning methods in public health. Clin Ther 2022;44:139-54.
31. Nagarajan SG, Balasubramanian V, Gonugunta P, Gudla SK. Obesity level prediction using deep learning approach – A comparative analysis. Eng Appl Sci Res 2024;51:540-54.
32. Briggs AH, Weinstein MC, Fenwick EA, Karnon J, Sculpher MJ, Paltiel AD, *et al*. Model parameter estimation and uncertainty analysis: A report of the ISPOR-SMDM modeling good research practices task force working group-6. Med Decis Making 2012;32:722-32.
33. Huangfu P, Pearson F, Abu-Hijleh FM, Wahlich C, Willis K, Awad SF, *et al*. Impact of price reductions, subsidies, or financial incentives on healthy food purchases and consumption: A systematic review and meta-analysis. Lancet Planet Health 2024;8:e197-212.
34. Selimin DS, Sobri HN, Reffien MA, Rosli SA, Hassim NH, Li HY, *et al*. Soda tax impact PN soft drinks consumption: A systematic review. Glob J Public Health Med 2024;6:932-45.
35. Roberto CA, Petimar J. Restaurant calorie labeling and changes in consumer behavior. JAMA Netw Open 2023;6:e2346813.
36. Fabbrizio A, Fucarino A, Cantoia M, De Giorgio A, Garrido ND, Iuliano E, *et al*. Smart devices for health and wellness applied to tele-exercise: An overview of new trends and technologies such as IoT and AI. Healthcare (Basel) 2023;11:1805.
37. Stefanis C, Giorgi E, Kalentzis K, Tselemponis A, Nena E, Tsigalou C, *et al*. Sentiment analysis of epidemiological surveillance reports on COVID-19 in Greece using machine learning models. Front Public Health 2023;11:1191730.