

RESEARCH ARTICLE

Simulation models of sugary drink policies:
A scoping reviewNatalie Riva Smith¹, Anna H. Grummon^{2,3}, Shu Wen Ng^{4,5}, Sarah Towner Wright⁶, Leah Frerichs^{7*}

1 Department of Social and Behavioral Sciences, Harvard TH Chan School of Public Health, Boston, MA, United States of America, **2** Department of Nutrition, Harvard TH Chan School of Public Health, Boston, MA, United States of America, **3** Department of Population Medicine, Harvard Medical School / Harvard Pilgrim Health Care Institute, Boston, MA, United States of America, **4** Department of Nutrition, Gillings School of Global Public Health, Chapel Hill, NC, United States of America, **5** Carolina Population Center, UNC Chapel Hill, Chapel Hill, NC, United States of America, **6** Health Sciences Library, UNC Chapel Hill, Chapel Hill, NC, United States of America, **7** Department of Health Policy and Management, Gillings School of Global Public Health, Chapel Hill, NC, United States of America

* leahf@email.unc.edu



OPEN ACCESS

Citation: Smith NR, Grummon AH, Ng SW, Wright ST, Frerichs L (2022) Simulation models of sugary drink policies: A scoping review. PLoS ONE 17(10): e0275270. <https://doi.org/10.1371/journal.pone.0275270>

Editor: Hans-Peter Kubis, Bangor University, UNITED KINGDOM

Received: March 30, 2022

Accepted: September 13, 2022

Published: October 3, 2022

Peer Review History: PLOS recognizes the benefits of transparency in the peer review process; therefore, we enable the publication of all of the content of peer review and author responses alongside final, published articles. The editorial history of this article is available here: <https://doi.org/10.1371/journal.pone.0275270>

Copyright: © 2022 Smith et al. This is an open access article distributed under the terms of the [Creative Commons Attribution License](https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Data Availability Statement: All relevant data are within the manuscript and its [Supporting Information](#) files.

Funding: NRS was supported by T32-HD091058, P2C-HD050924, and T32-CA057711 of the

Abstract

Introduction

Simulation modeling methods are an increasingly common tool for projecting the potential health effects of policies to decrease sugar-sweetened beverage (SSB) intake. However, it remains unknown which SSB policies are understudied and how simulation modeling methods could be improved. To inform next steps, we conducted a scoping review to characterize the (1) policies considered and (2) major characteristics of SSB simulation models.

Methods

We systematically searched 7 electronic databases in 2020, updated in 2021. Two investigators independently screened articles to identify peer-reviewed research using simulation modeling to project the impact of SSB policies on health outcomes. One investigator extracted information about policies considered and key characteristics of models from the full text of included articles. Data were analyzed in 2021–22.

Results

Sixty-one articles were included. Of these, 50 simulated at least one tax policy, most often an *ad valorem* tax (e.g., 20% tax, $n = 25$) or volumetric tax (e.g., 1 cent-per-fluid-ounce tax, $n = 23$). Non-tax policies examined included bans on SSB purchases ($n = 5$), mandatory reformulation ($n = 3$), warning labels ($n = 2$), and portion size policies ($n = 2$). Policies were typically modeled in populations accounting for age and gender or sex attributes. Most studies focused on weight-related outcomes ($n = 54$), used cohort, lifetable, or microsimulation modeling methods ($n = 34$), conducted sensitivity or uncertainty analyses ($n = 56$), and included supplementary materials ($n = 54$). Few studies included stakeholders at any point in their process ($n = 9$) or provided replication code/data ($n = 8$).

National Institutes of Health (<https://www.nih.gov/>). LF was supported by K01-HL138159 (<https://www.nih.gov/>). AHG was supported by T32-HL098048 and K01-HL158608 (<https://www.nih.gov/>). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. National Institutes of Health, T32-HD091058, Natalie R Smith; National Institutes of Health, P2C-HD050924, Natalie R Smith; National Institutes of Health, T32-CA057711, Natalie R Smith; National Institutes of Health, K01-HL138159, Leah Frerichs; National Institutes of Health, T32-HL098048, Anna H Grummon; National Institutes of Health, K01-HL158608, Anna H Grummon.

Competing interests: The authors have no competing interests to declare.

Discussion

Most simulation modeling of SSB policies has focused on tax policies and has been limited in its exploration of heterogeneous impacts across population groups. Future research would benefit from refined policy and implementation scenario specifications, thorough assessments of the equity impacts of policies using established methods, and standardized reporting to improve transparency and consistency.

Introduction

Overconsumption of sugar-sweetened beverages (SSBs) is a key contributor to high and rising cases of non-communicable diseases worldwide [1, 2]. Experts agree that policy action is needed to reduce SSB consumption and prevent diet-related disease [3]. For example, the World Health Organization has called for countries to tax SSBs as one way to reduce SSB consumption [1]. Other policy options include front-of-package warning labels, limits to portion sizes, and marketing restrictions [3, 4].

Decision makers often want to consider and compare the consequences of proposed policy designs before implementation. Simulation modeling is a powerful tool for projecting likely population health outcomes under different policy scenarios. Broadly, models use existing knowledge and data to project how consumer and supply-side behaviors (e.g., SSB consumption, product reformulation) and health outcomes (e.g., obesity, diabetes) are likely to change over time in response to policy actions [5]. Modifying model parameters allows investigators to examine different ‘what if’ scenarios, such as how expected health impacts might differ if the policy was less effective, or if consumers or suppliers respond in particular ways. This functionality makes simulation modeling a compelling method for providing policymakers with information on the likely health outcomes of different policy actions to inform policy design and implementation.

A growing number of studies have used simulation models to project how SSB policy action might impact population health outcomes. To advance SSB policy research with simulation modeling, it is important to synthesize trends in the type and amount of evidence available across these studies and identify areas for improvement. Prior reviews have examined simulation models of nutrition policies generally [6–9], but have not focused specifically on SSB policies, despite their growing importance. Other work has reviewed the effects of specific SSB policies like taxes [10] or warning labels [11], without a focus on simulation modeling studies exclusively. What is missing from the current literature is a clear understanding of the variety of SSB-specific policies that have been assessed with simulation models, and the characteristics of the models.

Thus, we aimed to conduct a systematic scoping literature review to describe the current state of the SSB policy simulation modeling literature. The goal of this review was to spur thoughtful considerations of next steps for simulation modeling of SSB policies, including where policy evidence might be lacking and where methodologies can be improved. We focused on two questions: 1) what SSB policies have been evaluated using simulation modeling and 2) what are the characteristics of the simulation models used, including the models’ settings/populations, health outcomes, and modeling methods?

Methods

We used systematic scoping review methods, as our research questions were related to the broad scope of literature on SSB policy simulation models [12, 13]. Scoping reviews are broader in scope than traditional systematic reviews, but like systematic reviews, scoping reviews define eligibility criteria, systematically search the literature, and extract data from included studies [14]. A trained clinical health sciences librarian (STW) performed a systematic electronic search of publications in PubMed, Cumulative Index to Nursing and Allied Health Literature (CINAHL) via EBSCO, EMBASE via Elsevier, PsycInfo via EBSCO, Cochrane Central Register of Controlled Trials, SCOPUS, and Communication and Mass Media Complete via EBSCO, collecting results from the inception of the database through June 25, 2020. A database search update was performed on June 10, 2021. Our search terms addressed the three main concepts of the review: 1) computer simulation or computer model or economic evaluation; 2) sugar-sweetened beverages; and 3) health policy or public health or nutrition guidelines (S1 File). We included articles that used mathematical simulation modeling in a human population, presented novel findings, simulated at least one policy focused exclusively on SSBs, translated policy impacts to health outcomes beyond behavior change, and were published in English. We excluded economic modeling that simulated changes in consumption only, without translating consumption changes into health outcomes (e.g., demand system modeling [15]). We also excluded articles that included an SSB policy as one component of a multi-faceted intervention or policy (e.g., a three-component childcare intervention to increase physical activity, reduce screen time, and replace SSBs with water [16]), unless SSB-exclusive policies were examined in comparison to these multi-component policies. We also excluded articles targeting sugar consumption generally, not specifically sugar consumption from SSBs (e.g., added sugar labeling policies [17]). We used Covidence software (Veritas Health Innovation, Melbourne, Victoria, Australia) to screen abstracts and full-text articles [18].

Two investigators (NRS and LF) independently screened abstracts; AHG resolved discrepancies at this stage. The same two investigators then independently screened full text articles for inclusion and resolved discrepancies through discussion. In addition to articles identified by the database search, we included an article known to our team that was not picked up by search terms because it did not have an abstract [19]. We also screened the reference lists of full text articles from 2020 and 2021. NRS extracted data from included articles in Redcap [20] using a standardized extraction template and a random 10% of article extractions were checked by the senior author. We extracted data using only the main text of articles for all questions except for one question specifically about the inclusion of a supplement and its level of detail. We did not infer details beyond what was explicitly stated by authors.

Results

Included articles

The database search yielded 4,903 titles/abstracts after excluding duplicates (Fig 1) [21]. Of these, 4,761 were excluded during abstract screening, leaving 142 full text articles assessed for eligibility. Sixty of these were eligible for inclusion [22–81]. In the full text review stage, articles were most often excluded for not examining at least one policy focused exclusively on SSBs ($n = 32$) or because they were a conference abstract ($n = 22$). We include 61 articles in our results, adding in the article known to our team that did not include an abstract to the 60 identified via database and reference list searches [19].

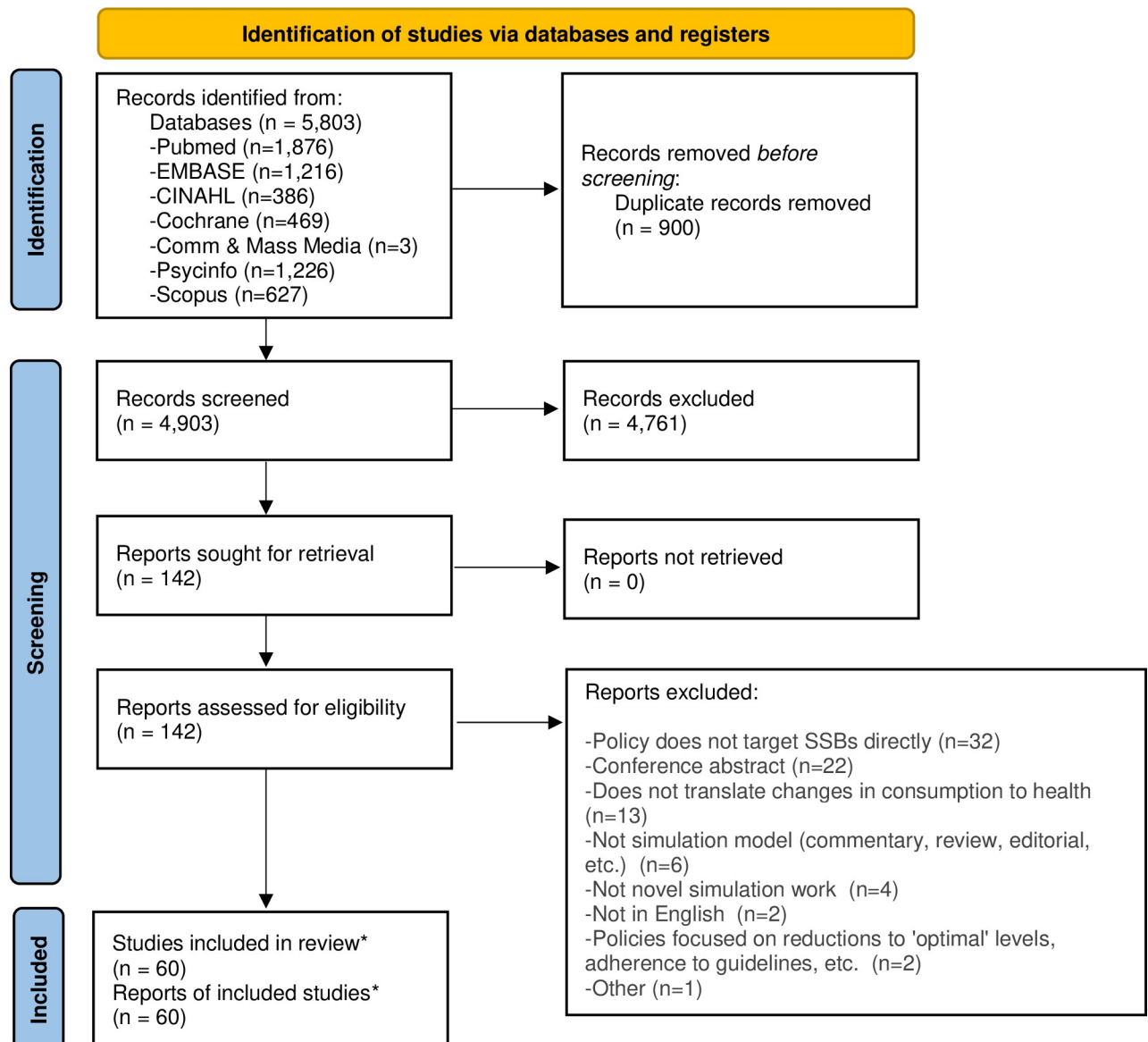


Fig 1. PRISMA 2020 flow diagram for new systematic reviews. Notes: * An additional article known to our team that was not picked up by search terms because it did not have an abstract was added after identification of articles via registers and databases, bringing the final number of studies included to 61.

<https://doi.org/10.1371/journal.pone.0275270.g001>

Included articles were published between 2011 and 2021, with over half published in 2017–2021 ($n = 37$). The main text provides aggregate statistics on the included articles; individual data for each can be found in [S1 Table](#) and in an interactive table at <https://natsmith.shinyapps.io/Article-Information/>.

RQ1: What policies have been evaluated using simulation modeling?

Most articles ($n = 54$) simulated one SSB policy. Six articles simulated two SSB-focused policies, and one simulated three. Some articles simulated SSB policies in comparison to other health promotion policies ($n = 10$). For example, Basu *et al.* 2013 simulated a ban on SSB purchasing with nutrition assistance dollars and a one-cent-per-fluid-ounce SSB volumetric excise

tax (two SSB-focused policies) alongside two fruit and vegetable incentive policies (other health promotion policies) [27].

Fifty out of 61 included articles examined at least one tax policy (Fig 2). To fully characterize taxes, we extracted information on both the tax rate (e.g., *ad valorem*/percentage-based, such as 20%, or unit-based, such as 1 cent-per-fluid-ounce) and how that tax rate would be implemented (i.e., excise, sales, other, unclear), based on the exact language used in the article [3, 5]. *Ad valorem* tax rates were the most commonly examined tax (n = 25), with most studies of tax policies examining a 20% tax on SSBs (n = 20/25). Volumetric taxes were the second most common (n = 23, also referred to as volume-based taxes); 13 of these evaluated 1-cent-per-fluid-ounce taxes. Among articles that described tax implementation, most evaluated taxes were implemented as excise taxes; however, many articles did not specify implementation mechanisms (Fig 2). Two articles noted that they were specifically not discussing tax implementation mechanisms to minimize the modeling assumptions required. Studies generally simulated impacts on consumption by first estimating changes in SSB prices under tax policies, using assumptions about baseline prices of SSBs and the percent of tax passed through (i.e., the amount of tax that the taxed entity ‘passes through’ to consumers via price increases). Changes in prices were then translated to changes in consumption using price elasticities (which quantify the percent change in consumption for a percentage change in price).

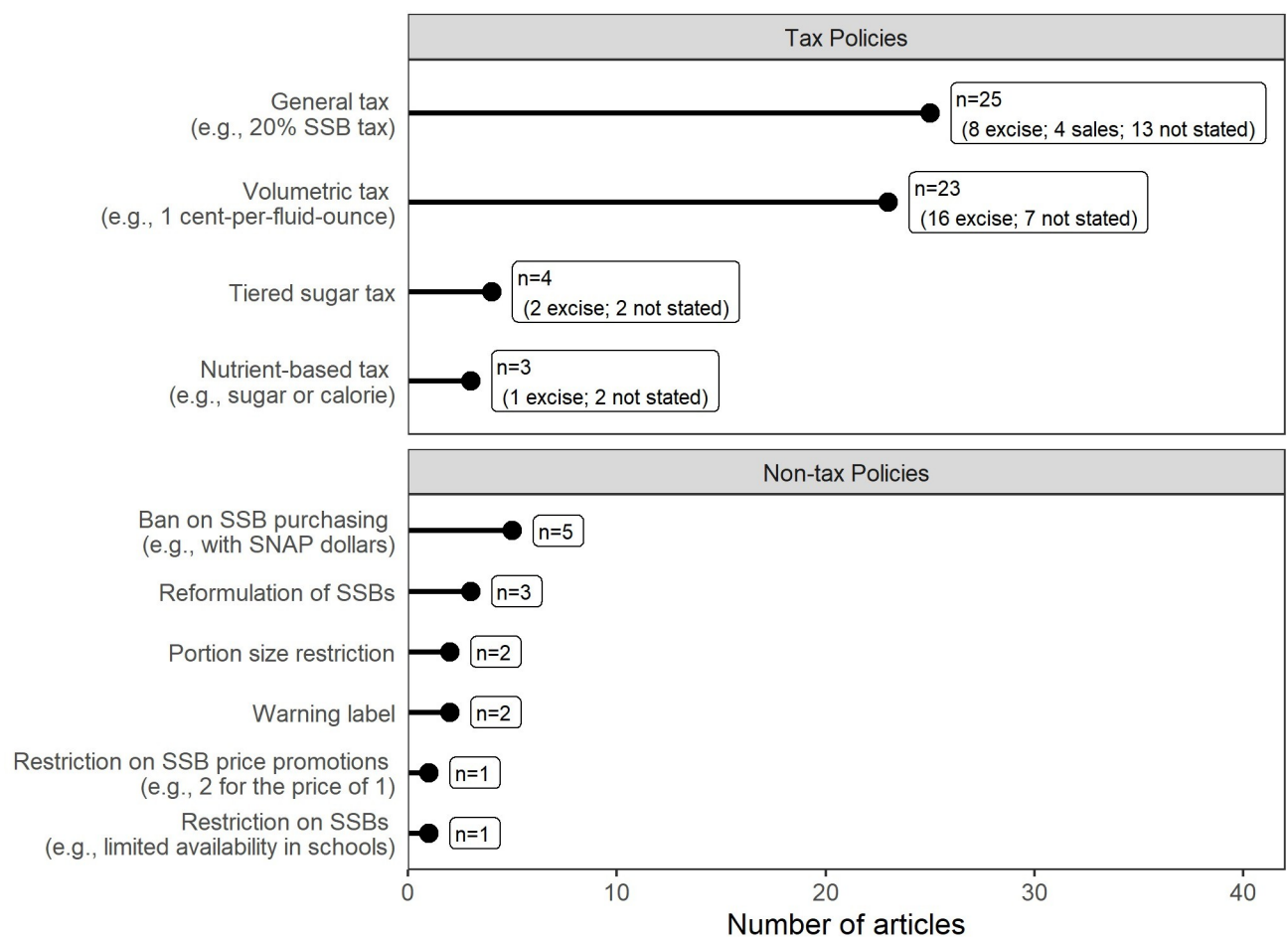


Fig 2. Sugar-sweetened beverage policies examined by simulation modeling studies (n = 61). Notes: SNAP = Supplemental Nutrition Assistance Program.

<https://doi.org/10.1371/journal.pone.0275270.g002>

Thirteen of the 61 articles simulated a non-tax policy (two simulated both a tax and non-tax policy, Fig 2). Five studies modeled bans on SSB purchases. Policies to ban SSBs most commonly focused on prohibiting SSB purchases using US Supplemental Nutrition Assistance Program benefits. Articles also examined policies designed to restrict the use of price promotions for SSBs ($n = 1$, stores could not sell SSBs under ‘two-for-one’ deals) or restrict the availability of SSBs in schools ($n = 1$). Two studies, both in the US, examined policies requiring warning labels on SSBs. Two studies examined portion size policies that would prohibit the sale of SSBs larger than 375 milliliters (about 12.7 fluid ounces) or 250 milliliters (about 8.5 fluid ounces). Finally, three studies considered policies requiring reformulation targets for SSBs (e.g., policies requiring manufacturers to reduce added sugars in SSBs by a given percentage). Simulations of these policies used estimated impacts from published behavioral science research or assumptions about behavioral responses to these changes. For example, a warning label simulation model used observed effects on purchases of SSBs from a randomized trial in a mock convenience store [43, 82]. Another model simulated the consumption effects of a portion size policy by assuming any modeled individual who drank a beverage larger than the portion size cap in the policy would reduce their consumption after policy implementation to drink exactly the portion size specified in the policy [35].

RQ2: What are the characteristics of SSB policy simulation models?

A wide range of countries were represented in the included texts, with the US being the most commonly modeled country ($n = 24$, Table 1). To simulate potential health effects of policies in these countries, models use hypothetical populations with characteristics that are similar to the population of interest (e.g., adults in the US, children aged 5–18 in Australia). Nearly all studies modeled hypothetical populations with age ($n = 59$) and gender or sex attributes ($n = 58$, Table 1). Studies generally presented results by population subgroups ($n = 48$), which can shed light on a policy’s potential to affect disparities in health outcomes (specific subgroups examined by included studies are shown in Table 1).

Table 1 also displays major health outcomes simulated. All but 7 studies translated changes in SSB consumption into impacts on weight ($n = 54$), typically using energy balance approaches [83–89]. These approaches translate changes in energy intake (e.g., decreases in calories from SSBs under a policy change) into changes in body weight [83]. Forty studies used some form of an energy balance equation (or heuristic based on an energy balance equation) in their modeling approach, with equations from Hall *et al.* being the most commonly used ($n = 24/40$). Notably, five studies assumed that eating 3,500 fewer calories equates to 1 pound of weight lost, an energy balance heuristic that has been widely criticized [83, 90–92]. Nine studies used estimates of direct effects of SSB intake on weight change from published literature.

Language used to describe modeling methods varied widely (Table 2). When stated, the most commonly used simulation methods were cohort models (Markov or life table modeling, $n = 6$ and 15, respectively) or microsimulation models ($n = 13$). Six studies stated that they used comparative risk assessment methods, two used system dynamics modeling, and two used agent-based modeling.

Studies typically simulated outcomes over a 10-year ($n = 18$), 20-year ($n = 5$), or lifetime ($n = 14$) time horizon. In some cases ($n = 14$) the time horizon was not clearly stated. Nearly half of the studies stated that their work was based on an existing model or modeling framework ($n = 26$, e.g., ACES-Obesity [93], CHOICES [94], CVD-PREDICT [95]). Thirty of the included studies included a visual of their logic model or modeling flow. Forty-six articles included a descriptive table of input parameters, though the specific format of tables varied

Table 1. Populations and outcomes modeled in included studies (n = 61).

Variable	N	%
Countries modeled		
US	24	39%
Australia	8	13%
Mexico	5	8%
South Africa	4	7%
UK	3	5%
All other countries ^a	17	28%
Attributes given to simulated populations ^b		
Age	59	97%
Sex or gender	58	95%
Income	21	34%
Race, ethnicity, nativity, or related	14	23%
Education	4	7%
SNAP	4	7%
Socioeconomic status	4	7%
Attributes for results stratification (n = 48 out of 61 that stratified results) ^b		
Age	33	69%
Sex or gender	26	54%
Income	18	38%
Race, ethnicity, nativity, or related	12	25%
Socioeconomic status	2	4%
Outcome ^b		
Weight or BMI	54	89%
Diabetes	30	49%
Cardiovascular disease	24	39%
Cancer	12	20%
Dental caries	7	11%
Osteoarthritis	8	13%
Kidney disease	2	3%
Quality of life outcome ^c	20	33%
Economic outcome ^d	36	59%

Notes: US = United States, UK = United Kingdom, SNAP = Supplemental Nutrition Assistance Program, BMI = Body Mass Index.

^aOther countries simulated in fewer than 3 studies include Germany (n = 2), Thailand (n = 2), Canada (n = 1), Colombia (n = 1), Ecuador (n = 1), England (n = 1), Global (n = 1), India (n = 1), Indonesia (n = 1), Ireland (n = 1), Netherlands (n = 1), New Zealand (n = 1), Philippines (n = 1), Portugal (n = 1), Zambia (n = 1).

^bArticles could simulate more than one attribute or outcome, so percentages will not sum to 100.

^cFor example, quality-adjusted life years.

^dFor example, disease-attributable healthcare costs, cost-effectiveness ratios.

<https://doi.org/10.1371/journal.pone.0275270.t001>

widely. Some articles presented high-level overviews and included information like data citations or distributional assumptions (e.g., Lal *et al.*, 2017 [49]). Other articles presented more granular information on specific parameters such as average SSB consumption among different age groups (e.g., Ma *et al.*, 2016 [56]). All studies mentioned assumptions of their work, and most studies performed some form of sensitivity or uncertainty analysis (n = 56).

Table 2. Modeling methods of included studies (n = 61).

Variable	N	%
Modeling Methods		
Life table modeling	15	25%
Microsimulation	13	21%
Markov cohort modeling	6	10%
Comparative risk assessment	6	10%
System dynamics modeling	2	3%
Agent-based modeling	2	3%
Other or not stated	17	28%
Time Horizon^a		
10 years	18	29%
20 years	5	8%
Lifetime	14	23%
Unclear	14	23%
Other (e.g., 1 year, 50 years)	13	21%
Methods Details		
Existing model or modeling framework	26	43%
Visual of modeling flow or logic	30	49%
Table of input parameters	46	75%
Assumptions mentioned	61	100%
Included sensitivity or uncertainty analyses	56	92%
Supplementary materials	54	89%
Replication code, pseudocode, or data provided	8	13%
Included stakeholders	9	15%

Notes: ^aArticles could simulate over multiple primary time horizons (e.g., 10 years and over the cohort lifetime), so percentages will not sum to 100.

<https://doi.org/10.1371/journal.pone.0275270.t002>

Most studies included supplemental files (n = 54) with varying levels of detail. Twenty supplemental files only presented additional tables/figures, without any further exposition on the modeling methods. Particularly useful appendices included detailed descriptions of how the authors came to modeling decisions (e.g., Wilde *et al.*, 2019 [80]) or how a method was implemented (e.g., Basu *et al.*, 2013 [27]). Although supplements were quite common, including data or code to replicate models was much less common (n = 8). Examples of methods for providing replication code included posting datasets in publicly accessible repositories and discussing equations and pseudocode (i.e., narrative/plain language description of computer code) in supplemental files [22], or providing code directly on GitHub [25].

Stakeholder involvement—of any stakeholder, at any time in modeling work—was described by 9 studies. For example, Urwannachotima *et al.* engaged stakeholders in exercises to help build the structure of their model [77]. Models from the CHOICES group in the US incorporate stakeholder input into their intervention selection and implementation considerations [42, 54, 55].

Discussion

We identified 61 studies that used simulation modeling methods to project the potential health impacts of policies targeting SSB consumption. Use of simulation models to evaluate SSB policies has grown over time; all studies were published after 2011, and over half were published

within the past four years (2017–2021). Consistent with prior literature, we find that the most commonly evaluated SSB policy is a tax, with the tax literature dominated by *ad valorem* and volumetric tax policies [8, 9]. We also document an emerging literature that includes other policy options such as purchasing bans, warning labels, and portion size restrictions. Most models we reviewed used either cohort or microsimulation modeling methods, simulated a population defined by age and gender or sex, and projected changes in weight, diabetes, or cardiovascular disease. These results are in line with findings from other reviews of food policies [8, 9]. Our results point to norms in the literature and highlight areas for future work to build on this strong foundation.

A closer examination of the articles revealed that future policy design and dissemination work would benefit from models including more explicit details about policy design and implementation. For example, some articles examining taxes modeled only on the final price change in SSBs induced by the tax. This could be problematic because some tax designs can have markedly different impacts on SSB consumption and health outcomes [19, 51, 96], even when they raise prices by the same amount [19]. For example, one study found that taxing sugar content instead of beverage volume would increase the public health benefits of an SSB tax by 30% because sugar-based taxes could create price incentives for consumers to substitute from higher- to lower-sugar SSBs, while volumetric taxes would not [19]. Additionally, many articles we reviewed did not specify how a given tax rate would be implemented. This could lead to inaccurate or imprecise results from simulation models because, for example, research shows that consumers tend to respond less strongly to taxes that are added at the register (e.g., sales taxes) compared to those reflected in the shelf price (e.g., excise taxes) [97]. In the case of excise taxes, strategic responses by manufacturers or distributors may also result in differential price-pass through of the tax and/or reformulations to minimize the tax (under sugar-based taxes) across their product portfolios and their market shares or dominance in product categories which could vary geographically [96, 98, 99]. New evidence also suggests that the way shelf prices show (or do not show) the inclusion of an SSB tax also impacts efficacy [100].

Researchers could also provide more policy details and implementation scenarios around non-tax policies, which would provide valuable implementation advice for policymakers. For example, when evaluating a warning label policy, the topic (health or nutrient warning) and design (text or graphic) of the warning label used to develop estimates of efficacy should be specified. These details are important because nutrient warnings have been shown to generate substantial product reformulation as companies seek to reduce nutrient densities to below the regulatory thresholds that trigger warnings [101, 102]; these supply-side changes are likely to amplify demand-side effects of warnings and should be incorporated into simulation models of warning policies. For policies such as portion size restrictions, clearly defining what SSBs would be targeted and where restrictions would be in place is critical; observational and experimental research also indicates that focusing on unsealed drinks sold in food service establishments, targeting large drinks sold at convenience stores, or limiting free refills can greatly impact potential reductions in consumption and health outcomes [103–105].

Broadly, future modeling research should seek to be attentive to real-world policymaking and implementation questions. Modeling results will be more useful for policy implementation when researchers clearly define tax and non-tax policies and include implementation details in their models, including the scope of regulated SSBs and associated implementation scenarios. Models can be used to probe how different contexts impact policy implementation, or how industry responses to policy implementation could impact policies' realized health effects [33]. With an eye towards informing policymaking and implementation, engaging stakeholders will be critical to ensure that models have the best chance to inform advocacy efforts and contribute to policymaking and implementation.

We found that all articles discussed the assumptions their model made, and nearly all reported some form of sensitivity or uncertainty analyses, though the descriptions of such analyses and language used varied widely. Future work should build from this base to include more concrete discussions of how assumptions, and their potential violations, might impact results, and should be specific about the strength of parameter estimate(s) used. Including these details is important both to establish confidence in modeled results (e.g., if there are concerns about the causal strength or appropriateness of parameter estimates used) [106] and to help policymakers understand what to expect under different implementation scenarios [107]. For example, included studies evaluating excise tax policies often assumed a 100% pass-through rate in their primary models and examined results assuming alternative rates in sensitivity analyses. This approach is useful and could be strengthened by linking results to a discussion of when and why we might expect pass through rates to vary (for example, based on different implementation considerations or industry responses given known market concentration). The SSB modeling literature would also benefit from using methods such as probabilistic Value of Information (VOI) analyses [108, 109] which offer a structured way to prioritize research dollars towards future behavioral science or policy research that would reduce decision uncertainty.

Most models we reviewed focused on one policy. An important next step will be for researchers to simulate multiple policy options within one modeling framework to compare policy effectiveness, and possibly expand into comparing policy options with other types of public health action such as community-based programs or interventions. Comparative assessments can help policymakers considering multiple policy options identify tradeoffs given potential limited resources for implementation and limited political capital, potentially making research more useful to policymakers and increasing its use in policy decision making. Modeling also offers a way to anticipate the potential impacts of multi-policy, multi-sectoral obesity and chronic disease prevention plans [110]. Modeling multiple policies could also help researchers uncover potential interactions between policies, though additional behavioral science research will be needed to support this by providing evidence on how consumers respond to different combinations of policies (e.g., warning labels combined with taxes) [111].

Most studies we reviewed modeled SSB policy impacts on weight, diabetes, cardiovascular diseases (including stroke and hypertension), and cancers. Emerging work has considered additional health outcomes, including dental caries, kidney disease, and osteoarthritis. Models typically presented population average outcomes alongside outcomes by subgroups, with most focused on age or sex or gender groups and fewer studies evaluating results by income, race, ethnicity, education, or other sociodemographic characteristics. Future research should continue to include individual heterogeneity to paint a more complete picture of policies' potential to affect health equity. Researchers should also consider methods specifically designed to consider equitable impacts of policies, particularly those drawn from the field of economic evaluation [112–115] such as equity-based weighting, extended cost-effectiveness analysis, distributional cost-effectiveness analysis, and multi-criteria decision analysis [112]. For example, equity-based weighting involves increasing (or decreasing) the contribution of outcomes for different groups (e.g., increasing the weight of quality-adjusted life years gained among low-income cohorts or individuals) [112, 114]. As authors seek to further consider equity implications, techniques like microsimulation models that allow for using distributions from the relevant population(s) in question will become increasingly important [9].

Future research should consider a number of other improvements to modeling methods. For example, methods like agent-based and system dynamics modeling allow analysts to incorporate important complexity when studying SSB policies, such as interactions between individuals and their social and physical environments and feedback loops between health

behaviors [116]. Applying these methods to SSB policies is a fruitful new area of research, as the models we reviewed generally did not consider how policy impacts may differ due to social network effects. Failing to account for how social relationships may relate to food consumption [117], other health behaviors [118, 119], and downstream health effects like weight [120–122] could lead to estimates of policy impact, both overall and within subgroups, that are over- or under-estimated.

Another area for improvement is replicability. Very few articles we reviewed provided code or data to replicate their work, and supplementary material often focused more on supplementary results rather than providing additional methodological details that would support replication. We advocate for increased transparency and code sharing of simulation models, as other reviews have called for [8, 9]. For example, researchers should consider the framework set out by Alarid-Escudero and colleagues [123] and utilize platforms such as GitHub or the Open Science Framework.

Standardized reporting guidelines for simulation modeling could also help push the field towards more consistent and transparent modeling [8, 9]. In our study, data extraction was at times challenging due to the many disciplines (e.g., health economics, epidemiology, behavioral science) represented in this research. Although multi-disciplinarity offers many benefits, the diversity of disciplines engaging in SSB policy modeling also led to articles using different simulation vocabulary, informal reporting norms (e.g., what details are reported in the main text versus supplementary material), and formal reporting requirements (e.g., journal word and figure limits). Past research has provided guidance for improving modeling research practices [124], but to our knowledge there are no standardized systems for reporting on simulation models. Existing guidelines are either focused on specific types of modeling [125, 126] or economic evaluation more broadly [127, 128]. The CHEERS checklist, for example, is targeted towards economic evaluations but lacks specific guidance for simulation models [127, 128]. Reporting guidelines for simulation modeling could set out common language for discussing sensitivity and uncertainty analyses, specify what methods details should be in the main text of an article versus in supplementary material (e.g., time horizon, time step used for discrete models), and set standards for reporting and discussing model assumptions. Given the large number of analytic decisions involved in developing a simulation model, clear guidance about what to report is critical for building confidence in published models, creating comparability across models, and helping researchers make better *a priori* decisions. While the specific details relevant to different kinds of models may differ (e.g., there is no specific time component in comparative risk assessment models [129]) reporting guidelines will help make these differences clear.

Limitations

As with any review, we may have missed relevant articles in our search. However, we built a comprehensive and systematic search along with a trained information specialist, and used terms similar to previously published reviews of simulation modeling [130] and SSB warning labels [11]. Our inclusion/exclusion criteria enabled us to include a range of studies, yielding a comprehensive commentary on the state of the science and allowing us to identify important considerations for future SSB policy simulation modeling. Although errors may have been made in the data extraction process, we used a standardized extraction template to ensure consistency between articles and a random 10% of article extractions were checked by the senior author.

Conclusions

Simulation modeling is a powerful tool for projecting how SSB policies could impact public health. Many SSB policies have shown potential for improving population-level health, but

decision making requires more specific and nuanced understanding of policy effects. Our review indicates key areas for improvements in simulation modeling methods, including that future work should incorporate more details regarding how policies would be implemented, thoroughly assess the equity impacts of policies using established methods, and standardize reporting to improve transparency and consistency. These improvements will lead to higher-quality simulation models that better inform public health decision making.

Supporting information

S1 File. Database specific search terms.

(PDF)

S2 File. PRISMA-ScR checklist.

(PDF)

S3 File. Full text exclusions.

(XLSX)

S1 Table. Individual article information.

(DOCX)

Author Contributions

Conceptualization: Natalie Riva Smith, Anna H. Grummon, Shu Wen Ng, Leah Frerichs.

Data curation: Natalie Riva Smith, Sarah Towner Wright, Leah Frerichs.

Formal analysis: Natalie Riva Smith.

Investigation: Natalie Riva Smith.

Methodology: Natalie Riva Smith, Anna H. Grummon, Sarah Towner Wright, Leah Frerichs.

Project administration: Natalie Riva Smith.

Supervision: Shu Wen Ng, Leah Frerichs.

Visualization: Natalie Riva Smith.

Writing – original draft: Natalie Riva Smith.

Writing – review & editing: Natalie Riva Smith, Anna H. Grummon, Shu Wen Ng, Sarah Towner Wright, Leah Frerichs.

References

1. World Health Organization. Taxes on sugary drinks: Why do it? 2017.
2. Malik VS, Popkin BM, Bray GA, Després J-P, Hu FB. Sugar-sweetened beverages, obesity, type 2 diabetes mellitus, and cardiovascular disease risk. *Circulation*. 2010; 121: 1356–1364. <https://doi.org/10.1161/CIRCULATIONAHA.109.876185> PMID: 20308626
3. Krieger J, Bleich SN, Scarmo S, Ng SW. Sugar-Sweetened Beverage Reduction Policies: Progress and Promise. *Annual Review of Public Health*. 2021; 42: null. <https://doi.org/10.1146/annurev-publhealth-090419-103005> PMID: 33256536
4. Pomeranz JL. Advanced policy options to regulate sugar-sweetened beverages to support public health. *Journal of Public Health Policy*. 2012; 33: 75–88. <https://doi.org/10.1057/jphp.2011.46> PMID: 21866177
5. Ng SW, Colchero MA, White M. How should we evaluate sweetened beverage tax policies? A review of worldwide experience. *BMC Public Health*. 2021; 21: 1941. <https://doi.org/10.1186/s12889-021-11984-2> PMID: 34702248

6. Eyles H, Ni Mhurchu C, Nghiem N, Blakely T. Food pricing strategies, population diets, and non-communicable disease: a systematic review of simulation studies. *PLoS Med*. 2012/12/11 ed. 2012; 9: e1001353–e1001353. <https://doi.org/10.1371/journal.pmed.1001353> PMID: 23239943
7. Grieger JA, Johnson BJ, Wycherley TP, Golley RK. Evaluation of Simulation Models that Estimate the Effect of Dietary Strategies on Nutritional Intake: A Systematic Review. *The Journal of nutrition*. 2017/04/14 ed. 2017; 147: 908–931. <https://doi.org/10.3945/jn.116.245027> PMID: 28404833
8. Emmert-Fees KMF, Karl FM, von Philipsborn P, Rehfuess EA, Laxy M. Simulation Modeling for the Economic Evaluation of Population-Based Dietary Policies: A Systematic Scoping Review. *Adv Nutr*. 2021. <https://doi.org/10.1093/advances/nmab028> PMID: 33873201
9. Mertens E, Genbrugge E, Ocira J, Peñalvo JL. Microsimulation Modelling in Food Policy: A Scoping Review of Methodological Aspects. *Advances in Nutrition*. 2021. <https://doi.org/10.1093/advances/nmab129> PMID: 34694330
10. Powell LM, Chriqui JF, Khan T, Wada R, Chaloupka FJ. Assessing the potential effectiveness of food and beverage taxes and subsidies for improving public health: a systematic review of prices, demand and body weight outcomes. *Obesity reviews*. 2013; 14: 110–128. <https://doi.org/10.1111/obr.12002> PMID: 23174017
11. Grummon AH, Hall MG. Sugary drink warnings: A meta-analysis of experimental studies. *PLOS Medicine*. 2020; 17: e1003120. <https://doi.org/10.1371/journal.pmed.1003120> PMID: 32433660
12. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. *International Journal of Social Research Methodology*. 2005; 8: 19–32. <https://doi.org/10.1080/1364557032000119616>
13. Levac D, Colquhoun H, O'Brien KK. Scoping studies: advancing the methodology. *Implementation science: IS*. 2010/09/22 ed. 2010; 5: 69. <https://doi.org/10.1186/1748-5908-5-69> PMID: 20854677
14. Munn Z, Peters MDJ, Stern C, Tufanaru C, McArthur A, Aromataris E. Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC Medical Research Methodology*. 2018; 18: 143. <https://doi.org/10.1186/s12874-018-0611-x> PMID: 30453902
15. Caro JC, Valizadeh P, Correa A, Silva A, Ng SW. Combined fiscal policies to promote healthier diets: Effects on purchases and consumer welfare. *Plos one*. 2020; 15: e0226731. <https://doi.org/10.1371/journal.pone.0226731> PMID: 31940371
16. Wright DR, Kenney EL, Giles CM, Long MW, Ward ZJ, Resch SC, et al. Modeling the Cost Effectiveness of Child Care Policy Changes in the U.S. *Am J Prev Med*. 2015; 49: 135–147. <https://doi.org/10.1016/j.amepre.2015.03.016> PMID: 26094234
17. Huang Y, Kyridemos C, Liu J, Lee Y, Pearson-Stuttard J, Collins B, et al. Cost-Effectiveness of the US Food and Drug Administration Added Sugar Labeling Policy for Improving Diet and Health. *Circulation*. 2019; 139: 2613–2624. <https://doi.org/10.1161/CIRCULATIONAHA.118.036751> PMID: 30982338
18. Veritas Health Innovation. Covidence systematic review software. Melbourne, Australia; Available: <https://www.covidence.org>
19. Grummon AH, Lockwood BB, Taubinsky D, Allcott H. Designing better sugary drink taxes. *Science*. 2019; 365: 989–990. <https://doi.org/10.1126/science.aav5199> PMID: 31488678
20. Harris PA, Taylor R, Minor BL, Elliott V, Fernandez M, O'Neal L, et al. The REDCap consortium: Building an international community of software platform partners. *Journal of Biomedical Informatics*. 2019; 95: 103208. <https://doi.org/10.1016/j.jbi.2019.103208> PMID: 31078660
21. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*. 2021; 372: n71. <https://doi.org/10.1136/bmj.n71> PMID: 33782057
22. Barrientos-Gutierrez T, Zepeda-Tello R, Rodrigues ER, Colchero-Aragones A, Rojas-Martínez R, Lazcano-Ponce E, et al. Expected population weight and diabetes impact of the 1-peso-per-litre tax to sugar sweetened beverages in Mexico. *PLoS One*. 2017;12. <https://doi.org/10.1371/journal.pone.0176336> PMID: 28520716
23. Basto-Abreu A, Barrientos-Gutiérrez T, Vidaña-Pérez D, Colchero MA, Hernández-F M, Hernández-Ávila M, et al. Cost-Effectiveness Of The Sugar-Sweetened Beverage Excise Tax In Mexico. *Health Affairs*. 2019; 38: 1824–1831. <https://doi.org/10.1377/hlthaff.2018.05469> PMID: 31682510
24. Basto-Abreu A, Braverman-Bronstein A, Camacho-García-Formentí D, Zepeda-Tello R, Popkin BM, Rivera-Dommarco J, et al. Expected changes in obesity after reformulation to reduce added sugars in beverages: A modeling study. *PLoS Med*. 2018; 15: e1002664. <https://doi.org/10.1371/journal.pmed.1002664> PMID: 30289898
25. Basu S, Jacobs LM, Epel E, Schillinger D, Schmidt L. Cost-Effectiveness Of A Workplace Ban On Sugar-Sweetened Beverage Sales: A Microsimulation Model. *Health Aff (Millwood)*. 2020; 39: 1140–1148. <https://doi.org/10.1377/hlthaff.2019.01483> PMID: 32634357

26. Basu S, Lewis K. Reducing added sugars in the food supply through a cap-and-trade approach. *Am J Public Health*. 2014; 104: 2432–8. <https://doi.org/10.2105/AJPH.2014.302170> PMID: 25365146
27. Basu S, Seligman H, Bhattacharya J. Nutritional policy changes in the supplemental nutrition assistance program: a microsimulation and cost-effectiveness analysis. *Medical decision making: an international journal of the Society for Medical Decision Making*. 2013/07/03 ed. 2013; 33: 937–48. <https://doi.org/10.1177/0272989X13493971> PMID: 23811757
28. Basu S, Vellakkal S, Agrawal S, Stuckler D, Popkin B, Ebrahim S. Averting obesity and type 2 diabetes in India through sugar-sweetened beverage taxation: an economic-epidemiologic modeling study. *PLoS Med*. 2014; 11: e1001582. <https://doi.org/10.1371/journal.pmed.1001582> PMID: 24409102
29. Basu S, Seligman HK, Gardner C, Bhattacharya J. Ending SNAP subsidies for sugar-sweetened beverages could reduce obesity and type 2 diabetes. *Health Affairs*. 2014; 33: 1032–1039. <https://doi.org/10.1377/hlthaff.2013.1246> PMID: 24889953
30. Bourke EJ, Veerman JL. The potential impact of taxing sugar drinks on health inequality in Indonesia. *BMJ Global Health*. 2018; 3: e000923. <https://doi.org/10.1136/bmjgh-2018-000923> PMID: 30555724
31. Briggs ADM, Mytton OT, Kehlbacher A, Tiffin R, Rayner M, Scarborough P. Overall and income specific effect on prevalence of overweight and obesity of 20% sugar sweetened drink tax in UK: Economic and comparative risk assessment modelling study. *BMJ (Online)*. 2013;347. <https://doi.org/10.1136/bmj.f6189> PMID: 24179043
32. Briggs AD, Mytton OT, Madden D, O'Shea D, Rayner M, Scarborough P. The potential impact on obesity of a 10% tax on sugar-sweetened beverages in Ireland, an effect assessment modelling study. *BMC Public Health*. 2013; 13: 860. <https://doi.org/10.1186/1471-2458-13-860> PMID: 24044370
33. Briggs ADM, Mytton OT, Kehlbacher A, Tiffin R, Elhussein A, Rayner M, et al. Health impact assessment of the UK soft drinks industry levy: a comparative risk assessment modelling study. *The Lancet Public Health*. 2017; 2: e15–e22. [https://doi.org/10.1016/S2468-2667\(16\)30037-8](https://doi.org/10.1016/S2468-2667(16)30037-8) PMID: 28804786
34. Choi SE, Wright DR, Bleich SN. Impact of Restricting Sugar-Sweetened Beverages From the Supplemental Nutrition Assistance Program on Children's Health. *American Journal of Preventive Medicine*. 2021; 60: 276–284. <https://doi.org/10.1016/j.amepre.2020.08.023> PMID: 33349472
35. Cleghorn C, Blakely T, Mhurchu CN, Wilson N, Neal B, Eyles H. Estimating the health benefits and cost-savings of a cap on the size of single serve sugar-sweetened beverages. *Preventive Medicine*. 2019. <https://doi.org/10.1016/j.ypmed.2019.01.009> PMID: 30660706
36. Cobiac LJ, Tam K, Veerman L, Blakely T. Taxes and Subsidies for Improving Diet and Population Health in Australia: A Cost-Effectiveness Modelling Study. *PLoS Med*. 2017; 14: e1002232. <https://doi.org/10.1371/journal.pmed.1002232> PMID: 28196089
37. Collins B, Capewell S, O'Flaherty M, Timpson H, Razzaq A, Cheater S, et al. Modelling the Health Impact of an English Sugary Drinks Duty at National and Local Levels. *PLoS One*. 2015; 10: e0130770. <https://doi.org/10.1371/journal.pone.0130770> PMID: 26121677
38. Crino M, Sacks G, Wu JH. A review of population-level actions targeting reductions in food portion sizes to address obesity and related non-communicable diseases. *Current nutrition reports*. 2016; 5: 323–332.
39. Dharmasena S, Capps O Jr. Intended and unintended consequences of a proposed national tax on sugar-sweetened beverages to combat the U.S. obesity problem. *Health Econ*. 2012; 21: 669–94. <https://doi.org/10.1002/hec.1738> PMID: 21538676
40. Du M, Griecchi CF, Kim DD, Cudhea F, Ruan M, Eom H, et al. Cost-Effectiveness of a National Sugar-Sweetened Beverage Tax to Reduce Cancer Burden and Disparities in the United States. *JNCI Cancer Spectrum*. 2020. <https://doi.org/10.1093/jncics/pkaa073> PMID: 33409452
41. Goiana-da-Silva F, Severo M, Silva DC e, Gregório MJ, Allen LN, Muc M, et al. Projected impact of the Portuguese sugar-sweetened beverage tax on obesity incidence across different age groups: A modelling study. *PLOS Medicine*. 2020; 17: e1003036. <https://doi.org/10.1371/journal.pmed.1003036> PMID: 32163412
42. Gortmaker SL, Wang YC, Long MW, Giles CM, Ward ZJ, Barrett JL, et al. Three Interventions That Reduce Childhood Obesity Are Projected To Save More Than They Cost To Implement. *Health affairs (Project Hope)*. 2015/11/04 ed. 2015; 34: 1932–9. <https://doi.org/10.1377/hlthaff.2015.0631> PMID: 26526252
43. Grummon AH, Smith NR, Golden SD, Frerichs L, Taillie LS, Brewer NT. Health Warnings on Sugar-Sweetened Beverages: Simulation of Impacts on Diet and Obesity Among U.S. Adults. *Am J Prev Med*. 2019; 57: 765–774. <https://doi.org/10.1016/j.amepre.2019.06.022> PMID: 31630966
44. Hangoma P, Bulawayo M, Chewe M, Stacey N, Downey L, Chalkidou K, et al. The potential health and revenue effects of a tax on sugar sweetened beverages in Zambia. *BMJ Glob Health*. 2020;5. <https://doi.org/10.1136/bmjgh-2019-001968> PMID: 32354785

45. Huse O, Ananthapavan J, Sacks G, Cameron AJ, Zorbas C, Peeters A, et al. The potential cost-effectiveness of mandatory restrictions on price promotions for sugar-sweetened beverages in Australia. *International Journal of Obesity*. 2019. <https://doi.org/10.1038/s41366-019-0495-9> PMID: 31792336
46. Jevdjevic M, Trescher AL, Rovers M, Listl S. The caries-related cost and effects of a tax on sugar-sweetened beverages. *Public Health*. 2019; 169: 125–132. <https://doi.org/10.1016/j.puhe.2019.02.010> PMID: 30884363
47. Kao KE, Jones AC, Ohinmaa A, Paulden M. The health and financial impacts of a sugary drink tax across different income groups in Canada. *Econ Hum Biol*. 2020;38. <https://doi.org/10.1016/j.ehb.2020.100869> PMID: 32442926
48. Kristensen AH, Flottesmesch TJ, Maciosek MV, Jenson J, Barclay G, Ashe M, et al. Reducing childhood obesity through US federal policy: a microsimulation analysis. *American journal of preventive medicine*. 2014; 47: 604–612.
49. Lal A, Mantilla-Herrera AM, Veerman L, Backholer K, Sacks G, Moodie M, et al. Modelled health benefits of a sugar-sweetened beverage tax across different socioeconomic groups in Australia: A cost-effectiveness and equity analysis. *PLoS medicine*. 2017/06/28 ed. 2017; 14: e1002326. <https://doi.org/10.1371/journal.pmed.1002326> PMID: 28654688
50. Lee BY, Ferguson MC, Hertenstein DL, Adam A, Zenkov E, Wang PI, et al. Simulating the Impact of Sugar-Sweetened Beverage Warning Labels in Three Cities. *American journal of preventive medicine*. 2017/12/19 ed. 2018; 54: 197–204. <https://doi.org/10.1016/j.amepre.2017.11.003> PMID: 29249555
51. Lee Y, Mozaffarian D, Sy S, Liu J, Wilde PE, Marklund M, et al. Health impact and cost-effectiveness of volume, tiered, and absolute sugar content sugar-sweetened beverage tax policies in the United States: a microsimulation study. *Circulation*. 2020; 142: 523–534. <https://doi.org/10.1161/CIRCULATIONAHA.119.042956> PMID: 32564614
52. Lin B-H, Smith TA, Lee J-Y, Hall KD. Measuring weight outcomes for obesity intervention strategies: the case of a sugar-sweetened beverage tax. *Econ Hum Biol*. 2011; 9: 329–341. <https://doi.org/10.1016/j.ehb.2011.08.007> PMID: 21940223
53. Liu S, Osgood N, Gao Q, Xue H, Wang Y. Systems simulation model for assessing the sustainability and synergistic impacts of sugar-sweetened beverages tax and revenue recycling on childhood obesity prevention. *Journal of the Operational Research Society*. 2016; 67: 708–721. <https://doi.org/10.1057/jors.2015.99>
54. Long MW, Gortmaker SL, Ward ZJ, Resch SC, Moodie ML, Sacks G, et al. Cost effectiveness of a sugar-sweetened beverage excise tax in the US. *American journal of preventive medicine*. 2015; 49: 112–123.
55. Long MW, Polacsek M, Bruno P, Giles CM, Ward ZJ, Craddock AL, et al. Cost-Effectiveness Analysis and Stakeholder Evaluation of 2 Obesity Prevention Policies in Maine, US. *J Nutr Educ Behav*. 2019; 51: 1177–1187. <https://doi.org/10.1016/j.jneb.2019.07.005> PMID: 31402290
56. Ma Y, He FJ, Yin Y, Hashem KM, MacGregor GA. Gradual reduction of sugar in soft drinks without substitution as a strategy to reduce overweight, obesity, and type 2 diabetes: a modelling study. *Lancet Diabetes Endocrinol*. 2016; 4: 105–114. [https://doi.org/10.1016/S2213-8587\(15\)00477-5](https://doi.org/10.1016/S2213-8587(15)00477-5) PMID: 26777597
57. Manyema M, Veerman JL, Chola L, Tugendhaft A, Labadarios D, Hofman K. Decreasing the Burden of Type 2 Diabetes in South Africa: The Impact of Taxing Sugar-Sweetened Beverages. *PLoS One*. 2015; 10: e0143050. <https://doi.org/10.1371/journal.pone.0143050> PMID: 26575644
58. Manyema M, Veerman LJ, Tugendhaft A, Labadarios D, Hofman KJ. Modelling the potential impact of a sugar-sweetened beverage tax on stroke mortality, costs and health-adjusted life years in South Africa. *BMC Public Health*. 2016; 16: 405. <https://doi.org/10.1186/s12889-016-3085-y> PMID: 27240422
59. Manyema M, Veerman LJ, Chola L, Tugendhaft A, Sartorius B, Labadarios D, et al. The potential impact of a 20% tax on sugar-sweetened beverages on obesity in South African adults: A mathematical model. *PLoS One*. 2014;9. <https://doi.org/10.1371/journal.pone.0105287> PMID: 25136987
60. Mekonnen TA, Odden MC, Coxson PG, Guzman D, Lightwood J, Wang YC, et al. Health Benefits of Reducing Sugar-Sweetened Beverage Intake in High Risk Populations of California: Results from the Cardiovascular Disease (CVD) Policy Model. *PLoS One*. 2013; 8: e81723. <https://doi.org/10.1371/journal.pone.0081723> PMID: 24349119
61. Nomaguchi T, Cunich M, Zapata-Diomedes B, Veerman JL. The impact on productivity of a hypothetical tax on sugar-sweetened beverages. *Health Policy*. 2017; 121: 715–725. <https://doi.org/10.1016/j.healthpol.2017.04.001> PMID: 28420538
62. Pearson-Stuttard J, Bandosz P, Rehm CD, Penalvo J, Whitsel L, Gaziano T, et al. Reducing US cardiovascular disease burden and disparities through national and targeted dietary policies: A modelling study. *PLoS Med*. 2017; 14: e1002311. <https://doi.org/10.1371/journal.pmed.1002311> PMID: 28586351

63. Peñalvo JL, Cudhea F, Micha R, Rehm CD, Afshin A, Whitsel L, et al. The potential impact of food taxes and subsidies on cardiovascular disease and diabetes burden and disparities in the United States. *BMC Med.* 2017; 15: 208. <https://doi.org/10.1186/s12916-017-0971-9> PMID: 29178869
64. Phonsuk P, Vongmongkol V, Ponguttha S, Suphanchaimat R, Rojroongwasinkul N, Swinburn BA. Impacts of a sugar sweetened beverage tax on body mass index and obesity in Thailand: A modelling study. *PLoS One.* 2021;16. <https://doi.org/10.1371/journal.pone.0250841> PMID: 33914822
65. Rosettie KL, Micha R, Cudhea F, Peñalvo JL, O'Flaherty M, Pearson-Stuttard J, et al. Comparative risk assessment of school food environment policies and childhood obesity, and future cardiometabolic mortality in the United States. *PLoS One.* 2018;13. <https://doi.org/10.1371/journal.pone.0200378> PMID: 29979761
66. Ruff RR, Zhen C. Estimating the effects of a calorie-based sugar-sweetened beverage tax on weight and obesity in New York City adults using dynamic loss models. *Ann Epidemiol.* 2015; 25: 350–357. <https://doi.org/10.1016/j.annepidem.2014.12.008> PMID: 25659449
67. Sánchez-Romero LM, Penko J, Coxson PG, Fernández A, Mason A, Moran AE, et al. Projected Impact of Mexico's Sugar-Sweetened Beverage Tax Policy on Diabetes and Cardiovascular Disease: A Modelling Study. *PLoS Med.* 2016;13. <https://doi.org/10.1371/journal.pmed.1002158> PMID: 27802278
68. Saxena A, Koon AD, Lagrada-Rombaua L, Angeles-Agdeppa I, Johns B, Capanzana M. Modelling the impact of a tax on sweetened beverages in the Philippines: an extended cost—effectiveness analysis. *Bull World Health Organ.* 2019; 97: 97–107. <https://doi.org/10.2471/BLT.18.219980> PMID: 30728616
69. Schwendicke F, Stolpe M. Taxing sugar-sweetened beverages: impact on overweight and obesity in Germany. *BMC Public Health.* 2017; 17: 88. <https://doi.org/10.1186/s12889-016-3938-4> PMID: 28095809
70. Schwendicke F, Thomson WM, Broadbent JM, Stolpe M. Effects of Taxing Sugar-Sweetened Beverages on Caries and Treatment Costs. *J Dent Res.* 2016; 95: 1327–1332. <https://doi.org/10.1177/0022034516660278> PMID: 27671690
71. Segovia J, Orellana M, Sarmiento JP, Carchi D. The effects of taxing sugar-sweetened beverages in Ecuador: An analysis across different income and consumption groups. *PLoS One.* 2020; 15: e0240546. <https://doi.org/10.1371/journal.pone.0240546> PMID: 33048990
72. Sharma A, Hauck K, Hollingsworth B, Siciliani L. The effects of taxing sugar-sweetened beverages across different income groups. *Health Econ.* 2014; 23: 1159–1184. <https://doi.org/10.1002/hec.3070> PMID: 24895084
73. Sowa PM, Keller E, Stormon N, Laloo R, Ford PJ. The impact of a sugar-sweetened beverages tax on oral health and costs of dental care in Australia. *Eur J Public Health.* 2019; 29: 173–177. <https://doi.org/10.1093/eurpub/cky087> PMID: 29796599
74. Stacey N, Summan A, Tugendhaft A, Laxminarayan R, Hofman K. Simulating the impact of excise taxation for disease prevention in low-income and middle-income countries: an application to South Africa. *BMJ Glob Health.* 2018; 3: e000568. <https://doi.org/10.1136/bmjgh-2017-000568> PMID: 29515917
75. Summan A, Stacey N, Birckmayer J, Blecher E, Chaloupa FJ, Laxminarayan R. The potential global gains in health and revenue from increased taxation of tobacco, alcohol and sugar-sweetened beverages: A modelling analysis. *BMJ Glob Health.* 2020;5. <https://doi.org/10.1136/bmjgh-2019-002143> PMID: 32337082
76. Torres-Álvarez R, Barrán-Zubaran R, Canto-Osorio F, Sánchez-Romero LM, Camacho-García-Formentí D, Popkin BM, et al. Body weight impact of the sugar-sweetened beverages tax in Mexican children: A modeling study. *Pediatr Obes.* 2020. <https://doi.org/10.1111/ijpo.12636> PMID: 32282131
77. Urwannachotima N, Hanvoravongchai P, Ansah JP, Prasertsom P, Koh VRY. Impact of sugar-sweetened beverage tax on dental caries: a simulation analysis. *BMC Oral Health.* 2020; 20: 76. <https://doi.org/10.1186/s12903-020-1061-5> PMID: 32183817
78. Vecino-Ortiz AI, Arroyo-Ariza D. A tax on sugar sweetened beverages in Colombia: Estimating the impact on overweight and obesity prevalence across socio economic levels. *Social Science and Medicine.* 2018; 209: 111–116. <https://doi.org/10.1016/j.socscimed.2018.05.043> PMID: 29857325
79. Veerman JL, Sacks G, Antonopoulos N, Martin J. The impact of a tax on sugar-sweetened beverages on health and health care costs: a modelling study. *PloS one.* 2016;11. <https://doi.org/10.1371/journal.pone.0151460> PMID: 27073855
80. Wilde P, Huang Y, Sy S, Abrahams-Gessel S, Jardim TV, Paarlberg R, et al. Cost-Effectiveness of a US National Sugar-Sweetened Beverage Tax With a Multistakeholder Approach: Who Pays and Who Benefits. *American Journal of Public Health.* 2019; 109: 276–284. <https://doi.org/10.2105/AJPH.2018.304803> PMID: 30571305
81. Wang YC, Coxson P, Shen Y-M, Goldman L, Bibbins-Domingo K. A Penny-Per-Ounce Tax On Sugar-Sweetened Beverages Would Cut Health And Cost Burdens Of Diabetes. *Health Affairs.* 2012; 31: 199–207. <https://doi.org/10.1377/hlthaff.2011.0410> PMID: 22232111

82. Grummon AH, Taillie LS, Golden SD, Hall MG, Ranney LM, Brewer NT. Sugar-Sweetened Beverage Health Warnings and Purchases: A Randomized Controlled Trial. *American Journal of Preventive Medicine*. 2019; 57: 601–610. <https://doi.org/10.1016/j.amepre.2019.06.019> PMID: 31586510
83. Hall KD, Sacks G, Chandramohan D, Chow CC, Wang YC, Gortmaker SL, et al. Quantification of the effect of energy imbalance on bodyweight. *Lancet*. 2011; 378: 10.1016/S0140-6736(11)60812-X. [https://doi.org/10.1016/S0140-6736\(11\)60812-X](https://doi.org/10.1016/S0140-6736(11)60812-X) PMID: 21872751
84. Hall KD, Schoeller DA, Brown AW. Reducing Calories to Lose Weight. *JAMA*. 2018; 319: 2336–2337. <https://doi.org/10.1001/jama.2018.4257> PMID: 29896621
85. Guo J, Brager DC, Hall KD. Simulating long-term human weight-loss dynamics in response to calorie restriction. *Am J Clin Nutr*. 2018; 107: 558–565. <https://doi.org/10.1093/ajcn/nqx080> PMID: 29635495
86. Swinburn BA, Sacks G, Lo SK, Westerterp KR, Rush EC, Rosenbaum M, et al. Estimating the changes in energy flux that characterize the rise in obesity prevalence. *Am J Clin Nutr*. 2009; 89: 1723–1728. <https://doi.org/10.3945/ajcn.2008.27061> PMID: 19369382
87. Schofield WN. Predicting basal metabolic rate, new standards and review of previous work. *Hum Nutr Clin Nutr*. 1985; 39 Suppl 1: 5–41. PMID: 4044297
88. Wang YC, Gortmaker SL, Sobol AM, Kuntz KM. Estimating the energy gap among US children: a counterfactual approach. *Pediatrics*. 2006; 118: e1721–1733. <https://doi.org/10.1542/peds.2006-0682> PMID: 17142497
89. Christiansen E, Garby L, Sørensen TIA. Quantitative analysis of the energy requirements for development of obesity. *J Theor Biol*. 2005; 234: 99–106. <https://doi.org/10.1016/j.jtbi.2004.11.012> PMID: 15721039
90. Hall KD. What is the required energy deficit per unit weight loss? *Int J Obes (Lond)*. 2008; 32: 573–576. <https://doi.org/10.1038/sj.ijo.0803720> PMID: 17848938
91. Hall K, Chow C. Why is the 3500 kcal per pound weight loss rule wrong? *Int J Obes (Lond)*. 2013; 37: 10.1038/ijo.2013.112. <https://doi.org/10.1038/ijo.2013.112> PMID: 23774459
92. Hall KD. Modeling Metabolic Adaptations and Energy Regulation in Humans. *Annu Rev Nutr*. 2012; 32: 35–54. <https://doi.org/10.1146/annurev-nutr-071811-150705> PMID: 22540251
93. Carter R, Moodie M, Markwick A, Magnus A, Vos T, Swinburn B, et al. Assessing Cost-Effectiveness in Obesity (ACE-Obesity): an overview of the ACE approach, economic methods and cost results. *BMC Public Health*. 2009; 9: 419. <https://doi.org/10.1186/1471-2458-9-419> PMID: 19922625
94. Gortmaker SL, Long MW, Resch SC, Ward ZJ, Craddock AL, Barrett JL, et al. Cost Effectiveness of Childhood Obesity Interventions: Evidence and Methods for CHOICES. *American Journal of Preventive Medicine*. 2015; 49: 102–111. <https://doi.org/10.1016/j.amepre.2015.03.032> PMID: 26094231
95. Pandya A, Sy S, Cho S, Alam S, Weinstein MC, Gaziano TA. Validation of a Cardiovascular Disease Policy Microsimulation Model Using Both Survival and Receiver Operating Characteristic Curves. *Medical Decision Making*. 2017; 37: 802–814. <https://doi.org/10.1177/0272989X17706081> PMID: 28490271
96. Hernández JCS, Ng SW. Simulating international tax designs on sugar-sweetened beverages in Mexico. *PLOS ONE*. 2021; 16: e0253748. <https://doi.org/10.1371/journal.pone.0253748> PMID: 34411108
97. Chetty R, Looney A, Kroft K. Saliency and Taxation: Theory and Evidence. *American Economic Review*. 2009; 99: 1145–1177. <https://doi.org/10.1257/aer.99.4.1145>
98. Colchero MA, Salgado JC, Unar-Munguía M, Molina M, Ng S, Rivera-Dommarco JA. Changes in Prices After an Excise Tax to Sweetened Sugar Beverages Was Implemented in Mexico: Evidence from Urban Areas. *PLOS ONE*. 2015; 10: e0144408. <https://doi.org/10.1371/journal.pone.0144408> PMID: 26675166
99. Salgado JC, Ng SW. Understanding heterogeneity in price changes and firm responses to a national unhealthy food tax in Mexico. *Food Policy*. 2019; 89: 101783. <https://doi.org/10.1016/j.foodpol.2019.101783> PMID: 32489228
100. Donnelly GE, Guge PM, Howell RT, John LK. A Salient Sugar Tax Decreases Sugary-Drink Buying. *Psychol Sci*. 2021; 09567976211017022. <https://doi.org/10.1177/09567976211017022> PMID: 34714702
101. Reyes M, Smith Taillie L, Popkin B, Kanter R, Vandevijvere S, Corvalán C. Changes in the amount of nutrient of packaged foods and beverages after the initial implementation of the Chilean Law of Food Labelling and Advertising: A nonexperimental prospective study. *PLoS Med*. 2020; 17: e1003220. <https://doi.org/10.1371/journal.pmed.1003220> PMID: 32722710
102. Barahona N, Otero C, Otero S, Kim J. Equilibrium Effects of Food Labeling Policies. *Social Science Research Network*. 2020 [cited 17 Mar 2022]. <https://doi.org/10.2139/ssrn.3698473>
103. Smith NR, Grummon AH, Frerichs LM. Demographic Groups Likely Affected by Regulating Sugar-Sweetened Beverage Portion Sizes. *Am J Prev Med*. 2020; 59: e135–e139. <https://doi.org/10.1016/j.amepre.2020.02.021> PMID: 32576417

104. Roberto CA, Pomeranz JL. Public Health and Legal Arguments in Favor of a Policy to Cap the Portion Sizes of Sugar-Sweetened Beverages. *American journal of public health*. 2015/11/. 2015; 105: 2183–2190. <https://doi.org/10.2105/AJPH.2015.302862> PMID: 26378833
105. John LK, Donnelly GE, Roberto CA. Psychologically Informed Implementations of Sugary-Drink Portion Limits. *Psychological Science*. 2017; 28: 620–629. <https://doi.org/10.1177/0956797617692041> PMID: 28362567
106. Eddy DM, Hollingworth W, Caro JJ, Tsevat J, McDonald KM, Wong JB. Model transparency and validation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force-7. *Value in health*. 2012; 15: 843–850. <https://doi.org/10.1016/j.jval.2012.04.012> PMID: 22999134
107. Smith NR, Knocke KE, Hassmiller Lich K. Using decision analysis to support implementation planning in research and practice. *Implementation Science Communications*. 2022; 3: 83. <https://doi.org/10.1186/s43058-022-00330-1> PMID: 35907894
108. Kunst N, Wilson ECF, Glynn D, Alarid-Escudero F, Baio G, Brennan A, et al. Computing the Expected Value of Sample Information Efficiently: Practical Guidance and Recommendations for Four Model-Based Methods. *Value in Health*. 2020; 23: 734–742. <https://doi.org/10.1016/j.jval.2020.02.010> PMID: 32540231
109. Heath A, Kunst N, Jackson C, Strong M, Alarid-Escudero F, Goldhaber-Fiebert JD, et al. Calculating the Expected Value of Sample Information in Practice: Considerations from 3 Case Studies. *Medical Decision Making*. 2020; 40: 314–326. <https://doi.org/10.1177/0272989X20912402> PMID: 32297840
110. Childhood obesity: a plan for action. In: GOV.UK [Internet]. [cited 1 Mar 2022]. Available: <https://www.gov.uk/government/publications/childhood-obesity-a-plan-for-action/childhood-obesity-a-plan-for-action>
111. Bollard T, Maubach N, Walker N, Mhurchu CN. Effects of plain packaging, warning labels, and taxes on young people's predicted sugar-sweetened beverage preferences: an experimental study. *International Journal of Behavioral Nutrition and Physical Activity*. 2016; 13: 95. <https://doi.org/10.1186/s12966-016-0421-7> PMID: 27580589
112. Ward T, Mujica-Mota RE, Spencer AE, Medina-Lara A. Incorporating Equity Concerns in Cost-Effectiveness Analyses: A Systematic Literature Review. *Pharmacoeconomics*. 2021. <https://doi.org/10.1007/s40273-021-01094-7> PMID: 34713423
113. Verguet S, Kim JJ, Jamison DT. Extended Cost-Effectiveness Analysis for Health Policy Assessment: A Tutorial. *Pharmacoeconomics*. 2016; 34: 913–923. <https://doi.org/10.1007/s40273-016-0414-z> PMID: 27374172
114. Dukhanin V, Searle A, Zwerling A, Dowdy DW, Taylor HA, Merritt MW. Integrating Social Justice Concerns into Economic Evaluation for Healthcare and Public Health: A Systematic Review. *Soc Sci Med*. 2018; 198: 27–35. <https://doi.org/10.1016/j.socscimed.2017.12.012> PMID: 29274616
115. Lal A, Mohebi M, Sweeney R, Moodie M, Peeters A, Carter R. Equity Weights for Socioeconomic Position: Two Methods-Survey of Stated Preferences and Epidemiological Data. *Value Health*. 2019; 22: 247–253. <https://doi.org/10.1016/j.jval.2018.07.006> PMID: 30711071
116. Luke DA, Stamatakis KA. Systems science methods in public health: dynamics, networks, and agents. *Annual Review of Public Health*. 2012; 33: 357–376. <https://doi.org/10.1146/annurev-publhealth-031210-101222> PMID: 22224885
117. Fortin B, Yazbeck M. Peer effects, fast food consumption and adolescent weight gain. *Journal of health economics*. 2015; 42: 125–38. <https://doi.org/10.1016/j.jhealeco.2015.03.005> PMID: 25935739
118. De La Haye K, Robins G, Mohr P, Wilson C. How physical activity shapes, and is shaped by, adolescent friendships. *Social science & medicine*. 2011; 73: 719–728.
119. Long E, Barrett TS, Lockhart G. Network-behavior dynamics of adolescent friendships, alcohol use, and physical activity. *Health Psychology*. 2017; 36: 577–586. <https://doi.org/10.1037/hea0000483> PMID: 28277703
120. Smith NR, Zivich PN, Frerichs L. Social Influences on Obesity: Current Knowledge, Emerging Methods, and Directions for Future Research and Practice. *Current Nutrition Reports*. 2020; 9: 31–41. <https://doi.org/10.1007/s13668-020-00302-8> PMID: 31960341
121. Valente TW. *Social networks and health: Models, methods, and applications*. Oxford University Press; 2010.
122. Valente TW, Fujimoto K, Chou C-P, Spruijt-Metz D. Adolescent Affiliations and Adiposity: A Social Network Analysis of Friendships and Obesity. *Journal of Adolescent Health*. 2009; 45: 202–204. <https://doi.org/10.1016/j.jadohealth.2009.01.007> PMID: 19628148
123. Alarid-Escudero F, Krijkamp EM, Pechlivanoglou P, Jalal H, Kao SZ, Yang A, et al. A Need for Change! A Coding Framework for Improving Transparency in Decision Modeling. *Pharmacoeconomics*. 2019/09/25 ed. 2019; 37: 1329–1339. <https://doi.org/10.1007/s40273-019-00837-x> PMID: 31549359

124. Caro JJ, Briggs AH, Siebert U, Kuntz KM. Modeling good research practices—overview: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force-1. *Value in health*. 2012; 15: 796–803. <https://doi.org/10.1016/j.jval.2012.06.012> PMID: 22999128
125. Grimm V, Berger U, DeAngelis DL, Polhill JG, Giske J, Railsback SF. The ODD protocol: a review and first update. *Ecological modelling*. 2010; 221: 2760–2768.
126. Müller B, Bohn F, Dreßler G, Groeneveld J, Klassert C, Martin R, et al. Describing human decisions in agent-based models—ODD+ D, an extension of the ODD protocol. *Environmental Modelling & Software*. 2013; 48: 37–48.
127. Husereau D, Drummond M, Petrou S, Carswell C, Moher D, Greenberg D, et al. Consolidated Health Economic Evaluation Reporting Standards (CHEERS) statement. *Journal of Medical Economics*. 2013; 16: 713–719. <https://doi.org/10.3111/13696998.2013.784591> PMID: 23521434
128. Husereau D, Drummond M, Augustovski F, de Bekker-Grob E, Briggs AH, Carswell C, et al. Consolidated Health Economic Evaluation Reporting Standards 2022 (CHEERS 2022) Statement: Updated Reporting Guidance for Health Economic Evaluations. *Appl Health Econ Health Policy*. 2022; 20: 213–221. <https://doi.org/10.1007/s40258-021-00704-x> PMID: 35015207
129. Briggs ADM, Wolstenholme J, Blakely T, Scarborough P. Choosing an epidemiological model structure for the economic evaluation of non-communicable disease public health interventions. *Population Health Metrics*. 2016; 14: 17. <https://doi.org/10.1186/s12963-016-0085-1> PMID: 27152092
130. Frerichs L, Smith NR, Lich KH, BenDor TK, Evenson KR. A scoping review of simulation modeling in built environment and physical activity research: Current status, gaps, and future directions for improving translation. *Health Place*. 2019; 57: 122–130. <https://doi.org/10.1016/j.healthplace.2019.04.001> PMID: 31028948