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Health Research Policy and Systems

REVIEW

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Web-based models to inform health policy: A scoping review

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Abstract

Health policies must be continually updated as new evidence is generated to ensure the optimal delivery of health interventions and prevention measures. Models are often used to study health problems, but their complexity limits their use by policy-makers. One way to facilitate their use among non-modellers is to develop user-friendly interfaces and make them available online. We conducted a scoping review of journal articles to identify and describe the currently available, interactive, freely available web-based health models that aim to inform health policy relevant to any disease or health issue affecting human populations. This scoping review included 16 web-based models covering 13 diseases or health issues, of which the most common were coronavirus disease 2019 (COVID-19) and malaria. The most common model outputs were epidemiological indicators (14/16), such as case numbers, incidences, or results from diagnostic screening, followed by the cost of implementing the intervention or health measure of interest (10/16). Model validation was performed in 6 of the 16 studies by comparing the model results with the previously published evidence or comparing simulated outcomes with observed data. Sensitivity and scenario analyses were conducted for 62.5% of models (10/16); however, in most cases, the user can perform these analyses by changing the model parameters in the user interface. This review explores the potential of web-based models to support health policy decisions and resource allocation. Despite their limited number, the 16 interactive web-based health models provide valuable insights into various health issues, primarily infectious diseases. The usability of the currently available web-based health models is impacted by the accuracy of the model description, the ability of the user to alter parameter values and the model assumptions that limit their generalizability. Such models must be validated and incorporate appropriate sensitivity analyses to be reliable and helpful to policy-makers.

Keywords Health policy, Web-based model, Web-based tool

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Introduction

Health policies provide governments and organizations with guidelines on how to effectively promote and safeguard the population's health and should be continually updated in accordance with new evidence on what interventions are effective and cost–effective, and how intervention impact can be improved. Over the past two decades, mechanistic and statistical models used to investigate the impact of interventions and control measures on health outcomes have been increasingly used to inform health policy decisions.

While mechanistic models cannot replace randomized controlled trials, population surveys, or other empirical studies, they are less costly and provide a simplified view of reality that can be used to predict future events, investigate counterfactual scenarios [1], synthesize evidence across empiric studies [2], or investigate the impact of individual factors on the outcome of interest [3–5]. These include infectious disease transmission models used to inform the national response to influenza outbreaks [6], and in recent years, those used to inform reopening plans during the COVID-19 pandemic [6, 7].

Models have historically been inaccessible to the public or communities outside of academic research; however, the number of interactive and web-based models has increased in recent years. These models allow policymakers (and the public) to change model parameters to investigate the potential impact of healthcare interventions in various contexts. The capacity of these models to influence health policy in a meaningful way, however, is determined, in part, by (1) the ability to change the model parameters so that the outputs are generalizable to different contexts, (2) the interpretability of model outputs, (3) the reliability of the model outputs and (4) how easy it is to navigate within the web-based model. This scoping review explores the web-based health models currently available and published in the literature, their utility and limitations and the extent to which their outputs have informed health policy.

Methods

Search strategy and selection criteria

To identify papers describing web-based health policy models, one reviewer searched Ovid Medline and Web of Science databases using the search strategy provided in Additional file 1. To be eligible for inclusion, articles needed to describe a freely available, interactive, digital health technology, hosted online to support health or disease related policy decisions. The model needed to be accessible at the time of data extraction using a link provided by the authors. The web-based model must be related to healthcare or health policy and address a decision problem. Articles were limited to those published from 1 January 2010 to 16 May 2022 and excluded if the text or abstract were unavailable or the article was not reported in English.

Search results were uploaded onto the Covidence platform, where duplicate articles were identified and removed. Covidence is a web-based platform that streamlines the screening and data extraction process for systematic and other literature reviews. One reviewer screened all titles and abstracts, and a second independently screened a random third of the articles. Conflicts were resolved through discussion between the two reviewers. One reviewer screened the full texts of articles deemed eligible on the basis of the title and abstract. Although not always applicable, the reporting of the scoping review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-analyses extension for Scoping Reviews (PRISMA-ScR) [8] checklist, provided in Additional file 2. The protocol for this scoping review has not been previously published.

Data extraction

Using a data extraction template developed by two reviewers in Excel, one reviewer extracted information from the articles included in the scoping review. Following completion, a second independent reviewer checked the data extraction. Conflicts were resolved through discussion between the two reviewers.

Extracted information included the disease or health issue modelled, the aim of the model, the origin (country or region) of the data used in the model and model validation and checks. The country or region of data origin was classified as low-, middle- or high-income. This was provided in the paper or determined by a reviewer using economic indicators from the World Bank [9]. The type of intervention investigated was classified as medical or public health. Medical interventions were those in which treatment was delivered to individual patients, and public health interventions were interventions or efforts that aimed to improve physical or mental health at the population level. The description of the model type was assessed by three reviewers on the basis of their field of expertise.

Synthesis of results

The web-based models described in the included studies were summarized according to their structure, application, internal and external validation, and findings. Usability was also assessed, focusing on factors such as the transparency of the model setup, the ability to upload external data, and the option to download results. Model validation was examined in terms of whether internal and/or external validation was performed. Because this scoping review was not restricted to a particular disease, health issue or modelling approach, commonalities and differences were described across all included studies.

Results

The search strategy identified 9054 studies published between 1 January 2010 and 16 May 2022. After screening the titles and abstracts, the full texts of 85 potentially relevant studies were reviewed for inclusion. This resulted in the exclusion of 58 studies, the inclusion of 15 studies and 13 studies that met the inclusion criteria but did not provide a working link to the model (Fig. 1). An email was sent to the authors of these studies requesting a working link. While six authors responded, six did not respond after two email attempts, and the authors of one study could not be contacted. For the latter, the first author's email did not work, no alternative email could be found for the first author and secondary authors could provide no further information on the model. Of the six studies with authors who responded, a working link was provided for one model, and the remaining five models were either not hosted online, terminated or still under development [10]. In addition to the 15 studies identified from systematic searches, 1 further study that met the inclusion criteria was added to the included studies [11]. The main reasons were that the model described in the study was not hosted online (20/70), was used for data visualization only (17/70) or was not accessible without a login (8/70) or that the health outcomes were assessed at the individual level, such as prognostic models designed to predict the risk of mortality in individual patients, rather than at the population level (8/70).

The models identified in this scoping review investigated the impact of possible changes in health policy relevant to a wide range of health issues and diseases. Links to these models are provided in Table S1, Additional file 3. Most models were developed in the previous 5 years, with the oldest model developed in 2016. The majority of models were used to study infectious diseases (75%, 12/16), with the most common being COVID-19 (31%, 5/16) and malaria (19%, 3/16). One COVID-19

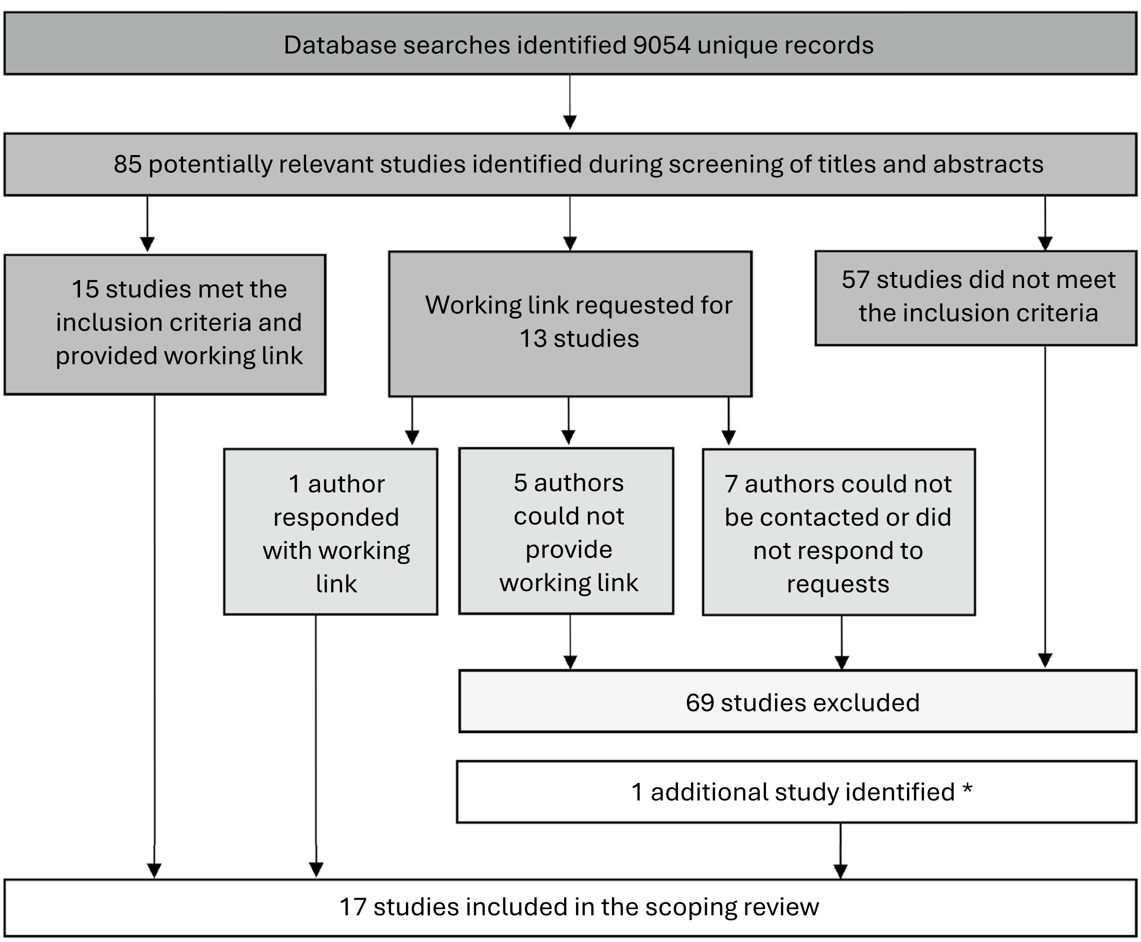

Fig. 1 PRISMA flow diagram of articles included in the scoping review. *One additional study was known to the authors but not identified during screening

model focused not on the risk of infection but on the impact of delayed elective surgeries during the pandemic [12].

The models were constructed using data from a wide geographical scope and income levels (Table 1). In some instances, the application of these models was limited to the country or region of origin of the data used to construct the model (5/16). In contrast, the outputs from 11 models (69%) could be adapted to any country of interest through selection from a drop-down menu [13, 14] or by altering the parameter values to reflect different contexts [12, 15–22].

The programming language used to construct these models was provided in 13 of the 16 studies (81%), with R being the most common (77%; 10/13). The code used for model construction was provided for five models [11, 19, 20, 22, 23] (Table 1). In 13 models, the values of the parameters could be changed using sliding bars [10, 20], manually inputting numbers or ticking boxes [14, 16, 18, 24, 25] or a combination of both methods [11, 13, 15, 17, 19, 20, 23]. Alternatively, three models allowed users to upload data containing some or all parameter values [18, 21, 26].

Model outputs were displayed using a variety of formats: graphs and tables for six models [12, 14, 18, 20, 22, 24], tables only for five models [11, 15, 16, 19, 21], graphs only for two models [13, 17], maps for two models [23, 26] and text only for one model [25]. The most common model outputs were epidemiological indicators (14/16), including case numbers, incidences, or results from screening, followed by the cost of implementing the intervention or health measure of interest, such as quality-adjusted life-years (QALYs) (10/16) (Table 1).

The most common limitation described by the authors of the included studies was the exclusion of parameters or simplifications to the model due to unreliable or missing data [11, 13, 15, 19, 21]. For example, Alfaro-Murillo et al. acknowledged that the interventions delivered to control the Zika outbreak would likely improve health outcomes for other diseases transmitted by the same mosquito vector (for example, dengue, chikungunya and yellow fever), which would increase the impact of these interventions. Still, those effects were not considered in their model [13]. In another example from Chaillon et al., the model did not consider changes in the life expectancy of human immunodeficiency virus (HIV)-infected individuals receiving or not receiving antiretroviral therapy (ART), despite evidence to suggest that adhering to ART can result in a normal life expectancy, which would have an impact on the total costs of implementing ART [15].

The outputs from six models (38%) were validated externally or internally (Table 2). In several studies, difficulty validating the model outputs was listed as a limitation [16, 18, 24], or the evaluation of the model was described as subjective [24]. One model by Wozniak et al. was described as validated, but details on the methods used were not provided [25]. Internal validation was conducted for three models by comparing model simulations to observed data [18, 20, 21]. For two of these models, the simulation results appear to conform to the empirical data in the overlaid graphs, but the authors do not explicitly discuss the internal validity of the results [18, 21]. For the third model (Incerti et al.), both internal and external validation were performed [20]. The model was internally validated by confirming that the results from model simulations were consistent with the observed empirical data related to rheumatoid arthritis [20]. External validation was performed by comparing model results with results from three other models for cost–effectiveness in the USA that describe treatment strategies for rheumatoid arthritis [27–29]. This external validation revealed similar results for health sector costs but differences in expected life years, which the authors attributed to differences in the included parameters [20].

External validation was conducted for the final three models by comparing the model outputs to results published in other studies from a different country or region [24] or with data from the same country or region but collected using different methods [12, 16]. External validation of the model for the USA, described by Lanza et al., was done by comparing the model outputs with results from a study conducted in China [24]. Both studies aimed to investigate the effect of lifestyle change on the risk of type 2 diabetes, but the results differed (smaller amounts of weight loss were needed for similar reductions in type 2 diabetes risk in the Chinese population) [24]. These differences could likely be attributed to contextual factors influencing diabetes risk that vary between the Chinese and American populations. In the model described by Custer et al., external validation revealed differences in the cost–effectiveness results for blood screening of HIV, hepatitis C, and hepatitis B between their models for the USA and the Netherlands when compared with results published in studies conducted in those respective countries [16]. The authors emphasized that, despite these variations, the results were within "the same order of magnitude", deeming the model results valid [16]. Similarly, results from the model described by Rovers et al., which investigates the economic and health impacts of delayed elective surgeries in the Netherlands during the COVID-19 pandemic, were externally validated by comparing them with the results obtained from a nationwide survey conducted in the Netherlands [12].

Sensitivity analyses were conducted in seven studies (44%) to explore the impact of altering individual model parameters on model results [11, 15–17, 19, 20,

Table 1 Description of studies included in the scoping review

First author, year	Disease or health issue	Model's aim	Country or region of origin of data used in the model	Country or region income bracket[a]	Country or region that the model can be applied to	Was the type of model clearly described?	Type of model[b]
Alfaro-Murillo, 2016 [13]	Zika Public health and Medical	Evaluate the cost–effectiveness of Zika control interventions	Brazil and Colombia	Middle	Any (from a drop-down menu)	No	Outputs based on a combination of reported cases and a forecast of case incidence using linear regression
Chaillon, 2016 [15]	HIV Public health/ Medical	Estimate the cost and impact on HIV incidence of PrEP and TasP	USA	High	Not specified	No	Crude rate of growth model that is based on a probabilistic model for estimating the number of new HIV infections each year from the prevalence and treatment coverage in the preceding year, and assuming a constant probability of exposure per partnership
Chande, 2020 [23]	COVID-19 Public health	Quantify the expected risk of COVID-19 infections at gatherings of different sizes	Many	High	USA Reduced number of outputs for Europe	Yes	Probability model that computes the probability that one or more randomly selected individuals in a population of given size and infection prevalence (based on case data adjusted for underreporting) is infected
Custer, 2017 [16]	HIV, hepatitis C and hepatitis B Public health	Assess the risk and cost-utility of screening blood donations for HIV, hepatitis C and hepatitis B	Brazil, Ghana, the Netherlands, South Africa, Thailand and the USA	Low to high	Not specified	No	Epidemiological model with three options for transmission risk assessment, including a yield model[c], prevalence model and incidence model
Devine, 2021 [11]	Malaria (*Plasmodium vivax*) Public health/medical	Estimate the cost–benefit of radical cure after G6PD testing	Middle East, Asia Pacific and South America	Low to middle	Middle East, Asia Pacific and South America	Yes	Total cost burden
Devine, 2017 [17]	Malaria (*P. vivax*) Public health/medical	Evaluate the cost–effectiveness of using G6PD rapid diagnostic tests before prescribing primaquine treatment	Thailand and Myanmar	Middle	Not specified	Yes	Decision tree

Table 1 (continued)

First author, year	Disease or health issue	Model's aim	Country or region of origin of data used in the model	Country or region income bracket[a]	Country or region that the model can be applied to	Was the type of model clearly described?	Type of model[b]
Getz, 2021 [18]	COVID-19 Public health	Evaluate the impact of changes to COVID-19 control measures on incidence and mortality rates	Many	Middle to high	Not specified	Yes	Compartmental model of disease transmission based on susceptible–exposed–infectious–recovered paradigm
Giorgi, 2021 [26]	Malaria (*P. falciparum*) Public health	Predict the annual malaria prevalence over space	Sub-Saharan Africa	Low to middle	Sub-Saharan Africa	Yes	Statistical geospatial
Harper, 2021 [19]	COVID-19 Public health	Estimate the number of COVID-19 infections resulting from potentially infectious university students returning home	Wales	High	Not specified	Yes	Number of secondary infections calculated as the sum of secondary household infections caused by returning students, computed using a probabilistic model from prevalence and household size distribution data
Incerti, 2019 [20]	Rheumatoid arthritis Medical	Estimate the value of alternative treatment sequences and the impact of various factors on the estimates of value	Many	Middle to high	Not specified	Yes	Discrete-time individual patient simulation
Lanza, 2019 [24]	Type 2 diabetes Public health	Forecast the economic costs and benefits of implementing or covering the National Diabetes Prevention Program Lifestyle Change Program	USA	High	States of the USA (selected from a drop-down menu)	Yes	Dynamic risk forecasting
Miller, 2020 [14]	Tuberculosis Public health	Model the potential outcomes of tuberculosis screening programs	Any	Low to high	Any (from a drop-down menu)	No	Unclear
Moriña, 2020 [21]	HPV and cervical cancer Public health	Evaluate the cost–effectiveness of cervical cancer prevention strategies	Any	Low–high	Not specified	Yes	Discrete-time, stochastic Markov chain

Table 1 (continued)

First author, year	Disease or health issue	Model's aim	Country or region of origin of data used in the model	Country or region income bracket[a]	Country or region that the model can be applied to	Was the type of model clearly described?	Type of model[b]
Rovers, 2022 [12]	Elective surgery in the context of COVID-19 Medical	Compare the impact of delays in elective surgery due to the COVID-19 pandemic on patient health and healthcare costs	Many	High	Not specified	No	Static data analysis
Wozniak, 2018 [25]	Drug-resistant infections in hospitals Medical	Estimate the additional burden of antimicrobial resistance to the Australian healthcare system	Australia	High	Australia	Yes	Cost
Zafari, 2021 [22]	COVID-19 Public health	Estimate the cost–effectiveness of interventions to prevent the spread of COVID-19 during the re-opening of universities	USA	High	Not specified	Yes	Number of infections computed using a probabilistic model with a fixed prevalence of infectious individuals through time

G6PD, glucose-6-phosphate dehydrogenase; HIV, human immunodeficiency virus; HPV, human papillomavirus; PrEP, pre-exposure prophylaxis; TasP, treatment as prevention

[a] Provided by the study authors or determined by a reviewer using economic indicators from the World Bank [9]

[b] Type of model based on the model description provided in the studies

[c] A yield model describes the observed yield from testing (positive counts)

Table 2 Usability and validity of the web-based models included in the scoping review

First author, year	All data sources reported (Y/N)	Model code provided (Y/N)	Possible to upload outside data (Y/N)	Model validation (N/internally/externally)	Sensitivity analysis (Y/N)	Scenario analysis (Y/N)	Other types of uncertainty analysis	Parameter assumptions clearly stated (Y/N)	Appropriate safeguards (limits on inputs) in place (Y/N)	Results downloadable (Y/N)
Alfaro-Murillo, 2016 [13]	Y	N	N	N	N	Y	N	Y	Y	N
Chaillon, 2016 [15]	Y	N	N	N	Y[a]	Y	N	Y	Y	N
Chande, 2020 [23]	Y	Y	N	N	N	N	N	Y	Y	N
Custer, 2017 [16]	Y	N	N	Externally[b]	Y	N	N	Y	N	Y
Devine, 2021 [11]	Y	Y	N	N	Y	Y	N	Y	Y	N
Devine, 2017 [17]	Y	N	N	N	Y	N	N	Y	Y	N
Getz, 2021 [18]	Y	N	Y	Internally	N	N	N	Y	Not stated[c]	N
Giorgi, 2021 [26]	Y	N	Y	N	N	N	N	Y	Y	Y
Harper, 2021 [19]	Y	Y	N	N	Y[a]	N	Monte Carlo simulation	Y	Y	N
Incerti, 2019 [20]	Y	Y	N	Internally and externally	Y	Y	Monte Carlo simulation	Y	Y	N
Lanza, 2019 [24]	Y	N	N	Externally	N	N	N	Y	Y	Y
Miller, 2020 [14]	Y	N	N	N	N	Y	N	N	N	Y
Moriña, 2020 [21]	Y	N	Y	Internally	N	Y	Output calibrated matrices	Y	Y	Y
Rovers, 2022 [12]	Y	N	N	Externally	N	N	N	Y	Y	N
Wozniak, 2018 [25]	Y	N	N	Not specified[d]	N	N	Monte Carlo simulation	N	N	N
Zafari, 2021 [22]	Y	Y	N	N	Y[a]	Y	Monte Carlo simulation	Y	Y	N

[a] Not all variables were analysed in the sensitivity analysis

[b] Model outputs were compared with previously published results. The results do not present details of model validation

[c] Authors do not provide details on safeguards in the publication, and the user needs to upload data to the platform to see the full suite of options

[d] Authors state this model was based on the validated model but do not provide details

22] (Table 2) and were described for only a subset of all model parameters in three studies [15, 19, 22]. Additionally, scenario analyses were conducted in seven studies to investigate the impact of altering multiple parameters on the model results (to reflect changes in the delivery of the intervention or the study context) [11, 13–15, 20–22]. For example, Zafari et al. investigated the cost–effectiveness of different university re-opening strategies during the COVID-19 pandemic under three prevalence scenarios (low, moderate and high prevalence) [22]. Other uncertainty analyses included Monte Carlo simulation to investigate the range of possible outcome values [19, 20, 22, 25] and calibration matrices, which were used by Moriña et al. to dictate how individuals transitioned between disease states for human papillomavirus (HPV) and cervical cancer and to check whether the model fitted well to the data by comparing the input values of the matrix to the target values [21].

Only one model was reported to inform health policy changes before publication [19]. This study assessed the impact of students returning home from university on COVID-19 case numbers in Wales, finding that students returning home, particularly those returning to multigenerational households, would expose individuals in that household to a higher risk of infection [19]. These findings influenced the policy of the Welsh government, which, based on these findings, advised students not to socialize in the days leading up to departure from the University, implemented staggered departure times for the students and set up mass testing facilities for students to get tested prior to travelling home [19].

Discussion

Web-based models are becoming increasingly relevant in informing changes to health policy, as they can be used to inform decisions in real-time and are publicly available. Interactive, user-friendly web-based models allow users to modify model parameters to better understand the potential impact of policy changes on health outcomes in various contexts. While the results obtained from statistical and mathematical models can be used to inform evidence-based policy changes, their utility relies on the policy-makers' ability to interpret them accurately. This scoping review summarizes 16 web-based health-related models to describe their application, and strengths and limitations. These models presented results relevant to 13 diseases or health issues, with the majority of tools focused on understanding the epidemiological impact and cost of intervention delivery.

While some of these models were well-described, others lacked sufficient detail. For example, Custer et al. [16] listed "yield", "prevalence", and "incidence" modelling options without providing any further methodological details and directing readers to another article. For a number of studies, it was not clear whether the chosen model was appropriate given the natural history of the disease or epidemiological context. For example, Alfaro-Murillo et al. did not directly model infection dynamics; instead, they assumed that cases would change linearly through time according to a linear regression model fit to weekly case data [13]. As another example, the model described by Chaillon et al. did not consider the relationship between population susceptibility and infections through time, which would have likely impacted the model outcomes (for example, infection incidence). In addition, the model presented by Miller et al. was described as a "tool" without a clear description of the model type [15].

The usability of interactive web-based models is determined, in part, by how easily parameter values can be changed and how easy it is to interpret the model outputs. In nine models, at least one of the parameter values was selected using a sliding bar where the user selects a value from a visualized range [11–13, 15, 17, 19, 20, 22, 23]. This could be beneficial in the interpretation of whether that value is considered high or low in the model and in avoiding input errors; however, it may take longer to select the values of interest when compared with values that are typed and may reduce the precision of input values (for example, it may be difficult or not possible to select a value with decimal places). In 12 of the 16 models, safeguards were in place to ensure the values selected were appropriate by limiting the range of values a user can choose from (for example, a percentage could not be greater than 100%) [11–13, 15, 17, 19–24, 26]. However, these safeguards limit the flexibility of the model in exploring extreme parameter values, which may be relevant in other settings, thus limiting generalizability. For example, in the model described by Chaillon et al., the impact of treatment and prophylactic pharmaceuticals on new HIV infections was limited to a follow-up period of up to 15 years (this was not described as a limitation in the study) [15]. Another example, from Harper et al., limits the number of students considered when investigating the risk of secondary cases of COVID-19 following the return home of university students to a maximum of 25,000, which is smaller than the population of some universities [19]. Model usability is also influenced by model accessibility. During screening for this review, many models could not be located on the basis of the information provided in the manuscript, and some models that were once accessible were no longer maintained.

Three models allow the user to upload data [18, 21, 26]. Models that are parameterized using user data can improve the efficiency of the model (uploading data saves time when compared with manually inputting parameter values); improve the accuracy of parameter values, as it minimizes the risk of manually entering an incorrect value; promote model flexibility, as users can make use of their own data to obtain results specific to their context; and can allow for more complex model parameterization when longitudinal data are uploaded [18, 21, 26]. However, data must conform to the data format accepted by the model, so data may need to be reformatted [26], which may be a hurdle for some users. For example, prevalence data are uploaded into the model described by Giorgi et al. to generate prevalence maps for Kenya or Tanzania [26]. When users do not have appropriate data, example data provided in the model platform can be used.

Models that present results in graphs or maps alongside text descriptions, such as in Devine et al. (2017; 2021), can promote a clearer understanding of model findings when compared with text or graphs alone [11, 17]. This is particularly true when small-scale differences in the outcome may be lost in summary graphs, such as in the outputs from the model described by Alfaro-Murillo et al., where the impact of small changes in the cost of the intervention cannot be determined at the resolution used [13].

Timely changes to health policy are crucial in improving health outcomes and minimizing the costs associated with interventions and prevention strategies. As the field of web-based health models continues to evolve, there is a greater ability for evidence-based policy decisions to be made promptly, contributing to more effective and efficient healthcare systems. Results generated in 5 of the 16 models aimed to inform changes to the delivery of control and prevention strategies during significant public health events, including the Zika outbreak [13] and the COVID-19 pandemic [18, 19, 22, 23]. Changes in health policy can be facilitated during these periods of urgency by presenting these results to policy-makers in an interactive, easy-to-understand format.

A limitation described in the studies included in this review was that it was necessary to make assumptions around parameters that may limit the generalizability of results to contexts where these assumptions are valid. Assumptions can also influence the accuracy of model estimates. For instance, a model that assumes the same transmissibility of a pathogen across a geographic area may fail to capture the spatial heterogeneity in transmission patterns. Accordingly, it is important to clearly describe the assumptions made when choosing parameters, allowing the user to assess the validity of those assumptions within their specific context of interest.

Stochastic (that is, first-order) and parameter (that is, second-order) uncertainty analyses are essential in understanding the limitations and potential variability in model estimates and predictions [30]. Sensitivity analyses were conducted in seven studies to investigate how changes to specific parameter values affect the model results [11, 15–17, 19, 20, 22], and scenario analyses were conducted in seven studies to explore how the model results change under a range of hypothetical scenarios by altering multiple parameter values simultaneously [11, 13–15, 20–22]. The results from the sensitivity and scenario analyses can improve the understanding of the complex relationships between the parameters and the outcome. While uncertainty analyses were not conducted in all studies, the interactive nature of web-based models allows users to perform some sensitivity and scenario analyses themselves, allowing policy-makers to make informed decisions while considering the uncertainties and variability of model results.

This scoping review has several limitations. First, this review only includes web-based models published in the literature. Second, the construction and use of web-based models are relatively novel, so the terms used to describe them in the literature are inconsistent. This may have resulted in the unintentional omission of some web-based models from our review. Furthermore, we found that the model type was often not clearly stated. However, we appreciate that there were contexts within which unconventional modelling paradigms needed to be developed to address the health questions under investigation, and therefore, in some cases, the authors were not able to classify their models based on well-established types. The taxonomy of model types for health economic models is widely available in the literature [30, 31], and while there are standard approaches to describing epidemiological models, it may be helpful if a taxonomy of model types could be developed. Many of the limitations in the web-based models identified in our review align with issues identified in the modelling literature [32]. With this in mind, we have developed a list of recommendations for studies that describe the development and use of web-based models to improve their usability, quality and uptake (Table S2, Additional file 4). These recommendations should be complemented by addressing additional criteria from relevant checklists on good modelling practices and reporting standards [33, 34].

Conclusion

This review highlights the potential of web-based models to support the effective delivery of health resources and improvements to health policy. The 16 models discussed in this review provide valuable insight into various health issues across a wide range of settings. The results from this scoping review suggest that (1) the usability of web-based models could be improved by ensuring the user can easily change parameter values in the user interface,

(2) the ability to conduct sensitivity and scenario analyses should be considered when developing models and interpreting model results and (3) model descriptions need to be more carefully considered. With improvements in the ease of web-based model development and the increasing amount of freely available data, the number of web-based models used to inform health policy will continue to increase, leading to more timely, well-informed policy changes.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12961-025-01367-z.

Additional file 1. Search strategy

Additional file 2. Preferred Reporting Items for Systematic Reviews and Meta-analyses extension for Scoping Reviews (PRISMA-ScR) checklist

Additional file 3. Table S1. Location of web-based tools. Access to web-based tools.

Additional file 4. Table S2. Recommendations for the publication and design of web-based health models. Recommendations for web-based model studies.

Author contributions

A.D. conceptualized the study. J.D.R., W.C., S.D. and A.D. performed the search, screening and extraction of the data. J.D.R., W.C., S.D., N.N., R.C., A.T.-D., F.S. and A.D. contributed to the data interpretation and revision of content. J.D.R. wrote the draft manuscript. J.D.R., W.C., S.D., N.N., A.T.-D., F.S. and A.D. contributed to the writing, review and editing of the final manuscript. All authors read and approved the final manuscript.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Ethical approval was not required for this study.

Competing interests

The authors declare no competing interests.

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