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Infectious disease modelling for SARS-CoV-2 in Africa to guide policy: A systematic review

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ABSTRACT

Applied epidemiological models have played a critical role in understanding the transmission and control of disease outbreaks. Their utility and accuracy in decision-making on appropriate responses during public health emergencies is however a factor of their calibration to local data, evidence informing model assumptions, speed of obtaining and communicating their results, ease of understanding and willingness by policymakers to use their insights. We conducted a systematic review of infectious disease models focused on SARS-CoV-2 in Africa to determine: a) spatial and temporal patterns of SARS-CoV-2 modelling in Africa, b) use of local data to calibrate the models and local expertise in modelling activities, and c) key modelling questions and policy insights. We searched PubMed, Embase, Web of Science and MedRxiv databases following the PRISMA guidelines to obtain all SARS-CoV-2 dynamic modelling papers for one or multiple African countries. We extracted data on countries studied, authors and their affiliations, modelling questions addressed, type of models used, use of local data to calibrate the models, and model insights for guiding policy decisions. A total of 74 papers met the inclusion criteria, with nearly two-thirds of these coming from 6% (3) of the African countries. Initial papers were published 2 months after the first cases were reported in Africa, with most papers published after the first wave. More than half of all papers (53, 78%) and (48, 65%) had a first and last author affiliated to an African institution respectively, and only 12% (9) used local data for model calibration. A total of 60% (46) of the papers modelled assessment of control interventions. The transmission rate parameter was found to drive the most uncertainty in the sensitivity analysis for majority of the models. The use of dynamic models to draw policy insights was crucial and therefore there is need to increase modelling capacity in the continent.

1. Introduction

The coronavirus COVID-19 pandemic has resulted in a major global health and economic crisis with significant mortality and morbidity associated with the disease, and disruptions to social and economic status associated with public health measures to minimize the spread of the disease. Public health interventions such as wearing of face masks, hand washing, physical/social distancing, curfews, and lockdowns have been shown to slow down transmission of the virus (Ferguson et al., 2020; Imai et al., 2020; Patel et al., 2020). However, the delicate decision on when to implement these measures and when to lift them has required balancing between health and economic stability making it challenging for policymakers (Moti and Goon, 2020).

Understanding and analyzing the complexity of human behavior and biology of pathogens requires tools to simplify both and use of locally generated data to best inform approaches needed to control the spread of diseases. The heterogeneity associated with transmission and severity of infectious diseases such as SARS-CoV-2, which include human

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behavior coupled with host-related risk factors such as underlying comorbidities, older age and male gender necessitate the need for use of data to plan for targeted response (Li et al., 2021). The unprecedented SARS-CoV-2 pandemic has created a critical need for use of applied epidemiological modelling as a fundamental tool to disentangle this complexity, identify rules to enable prediction of the patterns and effective control measures (Thompson, 2020).

Infectious disease models have previously been used to inform public health response on emerging and re-emerging infectious diseases. During the West Africa Ebola Virus epidemic in 2013–2016, epidemic models were used to estimate epidemiological parameters such as the basic reproduction number (Ro), predict the peak of the outbreak and evaluate control interventions (Shaman et al., 2014; Wong et al., 2021). In addition, epidemiological models have been used to forecast on Influenza epidemics and to evaluate vaccination strategies during the 2009 Influenza pandemic (Khazeni et al., 2014; Yang et al., 2015).

In Africa, more than 4 million cases and nearly 130,000 deaths due to COVID-19 have been reported as of May 2021(Ritchie et al., 2020). However, the true burden of the disease in the continent remains unknown due to sub optimal surveillance and testing (Kobia and Gitaka, 2020). A total of seventeen countries of the 55 member states had reported a test per case ratio lower than the recommended ten to thirty tests per case ratio by end of the year 2020 (Boum et al., 2021). In an ongoing pandemic, data available is imperfect and thus the use of dynamic modelling clarifies the disease dynamic, spread and control intervention. The skills to quickly develop epidemiological models are critical during health emergencies such as SARS-CoV-2 pandemic and the use of these models is critical in informing and evaluating policies. When compared to other continents, Africa has significantly less representation of SARS-CoV-2 epidemiological models, which is largely due to limited modeling capacity in Africa (Adetokunboh et al., 2021). Furthermore, in order to provide more authentic estimates and intervention strategies, local data and context must be used for model parameterization (Eggo et al., 2021).

To address the above gaps in knowledge, we conducted a systematic review of infectious disease epidemiological models specifically for SARS- CoV-2 in Africa to determine a) the spatial and temporal patterns of SARS-CoV-2 modelling for Africa during the pandemic, b) the use of local data to calibrate the models and local expertise in modelling activities, and c) the key modelling questions and policy insights from the SARS-CoV-2 models for Africa.

2. Methods

2.1. Literature search

A systematic review was done following the preferred reporting items for systematic review and meta-analysis (PRISMA) checklist (Page et al., 2021; Shamseer et al., 2015). Relevant databases such as PubMed, Embase and Web of Science for peer-reviewed literature and MedRxiv for unpublished literature were used to search for modelling papers on SARS-CoV-2. The databases were searched for modelling papers published or posted for one or multiple countries between March 2020 and April 2021.

2.2. Inclusion and exclusion criteria

The study included dynamic epidemiological modelling papers that focused on COVID-19 pandemic in the African continent. A combination of two search terms using AND was used to identify the review papers. The first search term identified the study population, which was defined as all fifty-four African countries that were member states of the United Nations while the second search term included the two exposures of interest: “mathematical model* ” AND “COVID* ”. See Table 1 below.

Each database was searched using the search terms in the article titles, abstracts, and keywords. Duplicate articles were removed, and three independent reviewers (NK,MN&LO) screened the study titles and abstracts. Inconsistencies between the reviewers were discussed and a consensus was reached on studies meeting the inclusion criteria. Studies were included for full text review if they included dynamic compartmental models of SARS-CoV-2 in one or multiple African countries.

Table 1
Search terms that were used to select studies from the different electronic databases.

Parameter	Search terms
Population	(Africa OR Cameroon OR "Central African Republic" OR "Congo Republic" OR "DR Congo" OR "Equatorial Guinea" OR Gabon OR Comoros OR Djibouti OR Eritrea OR Ethiopia OR Kenya OR Madagascar OR Mauritius OR Rwanda OR Seychelles OR Somalia OR "South Sudan" OR Sudan OR Tanzania OR Uganda OR Algeria OR Egypt OR Libya OR Mauritania OR Morocco OR "Sahrawi Republic" OR Tunisia OR Angola OR Botswana OR Eswatini OR Lesotho OR Malawi OR Mozambique OR Namibia OR "South Africa" OR Zambia OR Zimbabwe OR Benin OR "Burkina Faso" OR "Cabo Verde" OR "Côte d'Ivoire" OR Gambia OR Ghana OR Guinea OR "Guinea-Bissau" OR Liberia OR Nigeria OR Senegal OR “Sierra Leone” OR Togo OR Burundi OR “Sao Tome and Principe” OR Chad OR Niger) AND
Exposure	(“mathematical model*”) AND COVID*

Papers that used statistical modeling methods but did not include dynamic modeling were excluded. We only included dynamic compartmental models because they are population-based models that stratify the population into homogeneous sub-populations or health states and are useful in understanding disease transmission dynamics and forecasting outbreak growth. (Porgo et al., 2019). Models that did not primarily focus on COVID-19 but instead examined its impact on other diseases, studies lacking an abstract, and studies not written in English were all excluded from the review.

2.3. Study selection

Full manuscripts were obtained for all included studies where possible. Full articles review was done by three reviewers, assessed, and characterized to identify if they primarily focused on mathematical modelling of SARS-CoV-2 in Africa. An excerpt spreadsheet was developed and used to capture the extracted data in the full-text screening process that was done.

2.4. Data extraction, analysis, and presentation

Data variables that were abstracted included affiliation of the first and last author, published or unpublished status, year and month of publication or posting, when study was received in the journal, study population/country of study, type of model, model structure, number of state variables, use of local epidemiological data, model parameters most sensitive, key modelling questions, policy insights and use of the model. A summary of all variables that were extracted through the screening process is provided in Table 2. Analysis of the data was done and presented as counts and proportions to describe the trends.

3. Results

3.1. Study selection

We identified a total of 762 studies on applied epidemiological modelling for SARS-CoV-2 in Africa. Of these studies, 17% (131), 15% (111), 6% (46) and 62% (474) were extracted from PubMed, Embase, Web of Science and Med-archives (MedRxiv) databases, respectively. Of the peer reviewed articles identified, 62 (22%) were duplicates. A total of 74 (10%) papers met the inclusion criteria and were selected for full text review, of which 50 and 24 were peer-reviewed and non-peer-reviewed papers respectively. The main reasons for exclusion were

Table 2
Description of variables that were extracted from the articles included in the systematic review.

Variable	Description/Example
First author affiliation and year of publication	Name and year
Study population/ country of study	Country name
Month and year when study was received and published or posted	Month and year
Published or unpublished	Publication status
Type of model	Deterministic/Stochastic
Model structure	State variables
Number of state variables	Number
Use of local epidemiological data	Data source
Model parameter most sensitive	Parameter name
Key modelling question answered	Question
Policy insight	Policy insight
Use of model	Insight/ Estimation/Prediction/ Planning/ Assessment

lack of abstracts, the lack of primary focus on transmission dynamics of COVID-19. Fig. 1 is a flowchart of the article selection process. The emergent themes from the papers included in the review were abstracted from the study titles and are visualized in Fig. 2 as a word cloud image.

3.2. Spatial and temporal distribution of SARS-CoV2 modelling in Africa

There was geographical variation in the studies included in the review, with only 7% (4) of the African countries contributing 55% of the papers. Majority of the studies represented Western African countries (23%;17) whilst studies done in Central African countries contributed only 5% (4). A total of nine studies represented the entire African continent. Majority of the papers included were from South Africa (n = 15), Nigeria (n = 11) and Morocco (n = 8). Twenty-two countries did not have any papers on SARS-CoV2 modelling, (see Fig. 3). The first publication was done two months after the first case was detected in Africa. The number of peer and non-peer-reviewed manuscripts ranged between one and thirteen per month during the study period. Most papers were published/posted in July 2020 after the peak of the first wave which was experienced in May 2020. A total of 16 (35%) of the peer-reviewed papers were published between October and December 2020 just after the second peak which was in September 2020 (see Fig. 4). The turnaround time from when the papers were received in a journal to the time of publication was less than 3 months for 21 (39%) papers, 3–6 months for 20 (40%) papers and more than 6 months for 4 (8%) of the published papers included for review.

3.3. Model characteristics

The majority of the models (n = 56,76%) were deterministic, while the remaining 24% (n = 18) were stochastic; however, one model generated both deterministic and stochastic solutions. The main state variables included in the models were Susceptible, Exposed, Infected and Recovered compartments (SEIR models), with nearly half of the models (n = 33, 45%) having the "Exposed" compartment. Other models included compartments tracking people vaccinated, quarantined, hospitalized and compartments that inferred those that were

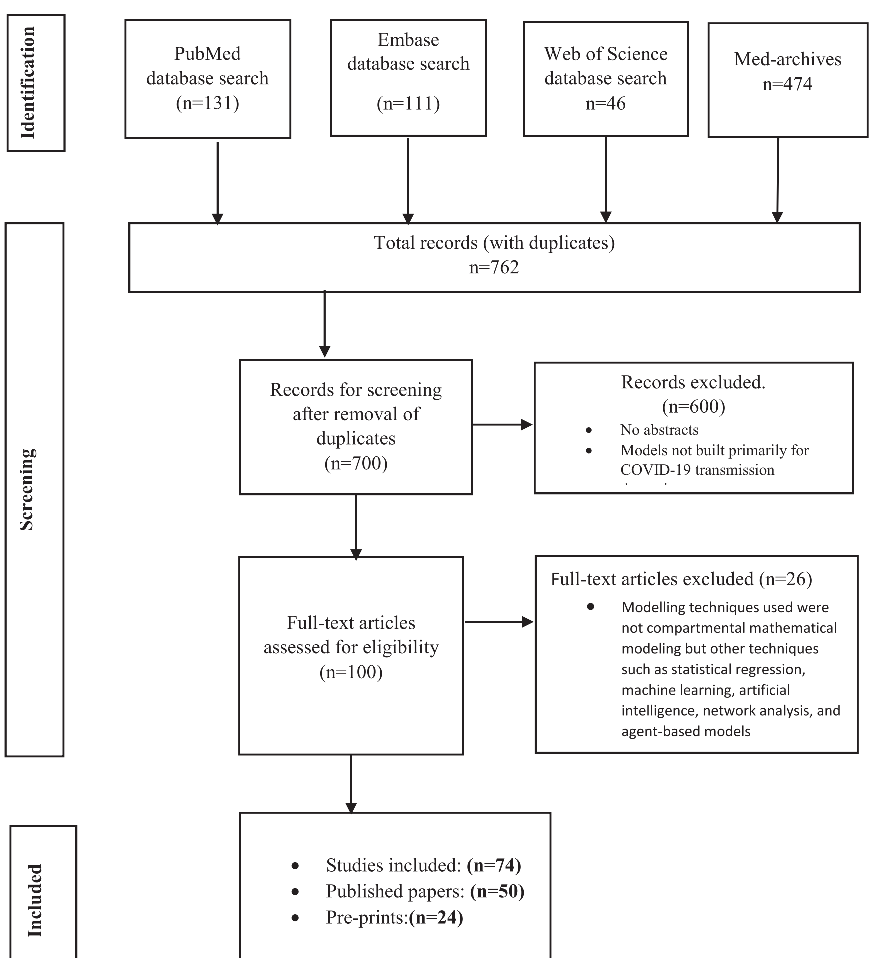

Fig. 1. PRISMA flow diagram of the selection process for including studies in the systematic review.

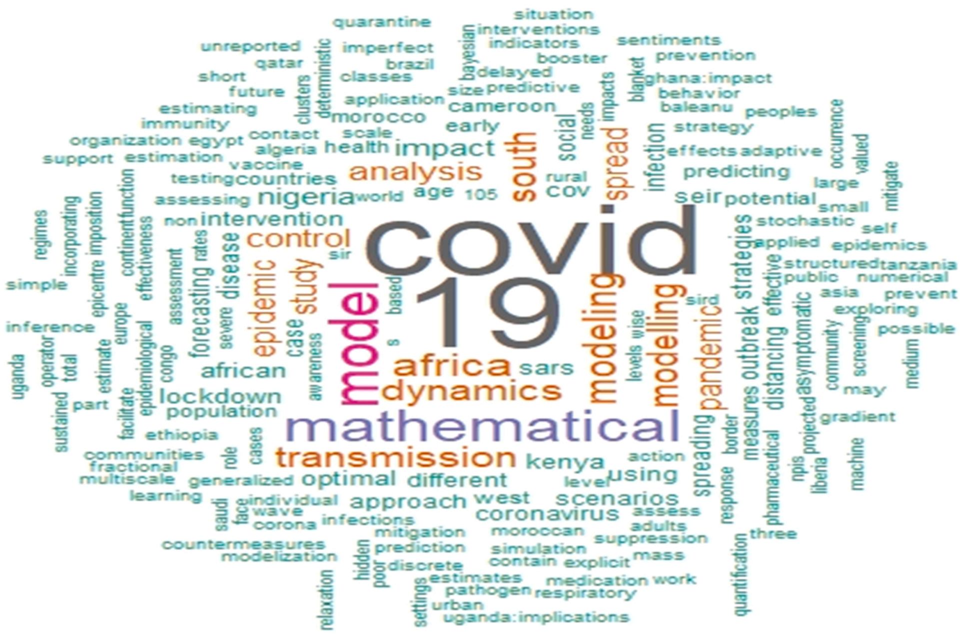

Fig. 2. A qualitative word cloud image describing emerging issues derived from the titles of the manuscript that were included in the review.

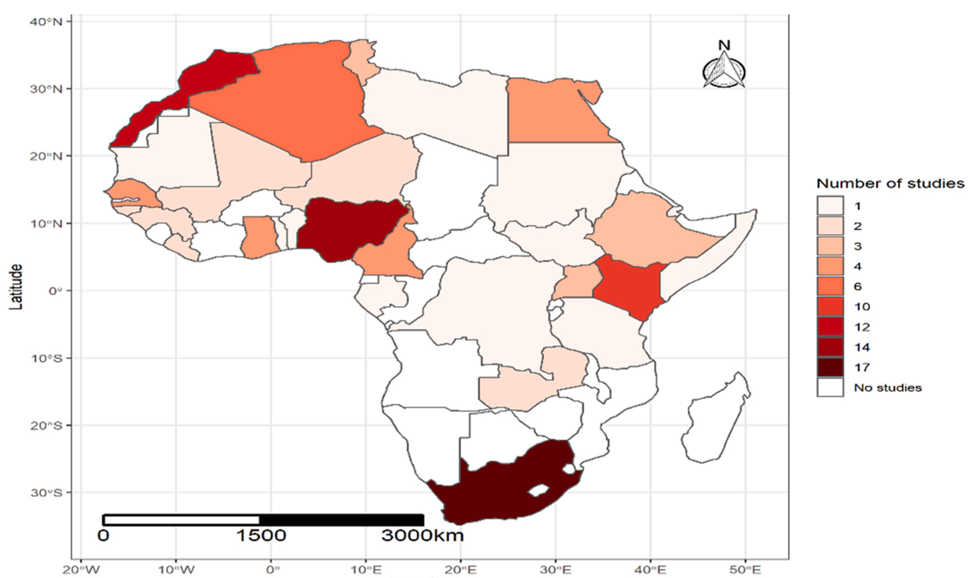

Fig. 3. : Spatial distribution of the studies included in the systematic review. Shapefile source: Database of Global Administration ("GADM," 2021).

protected through the wearing of facemasks or those adhering to lockdowns.

3.4. The use of local data to calibrate the models and local expertise in modelling activities

Only 12% (n = 9) of the models were calibrated using local data, which included demographic data to stratify the population by age, which is a risk factor for disease transmission and severity, google mobility data to estimate the number of contacts an individual had within a given population, and local sentimental data from Twitter. A total of 69 (93%) of the papers fitted their models to data on confirmed cases. Other data used to fit the models included mortality data 12% (n = 8) and hospitalization data 1% (n = 1). A total of 53 (72%) and 48 (65%) papers had a first and last author that were affiliated to an African institution respectively. The parameter for disease transmission was found to drive most uncertainty for most of the studies. Table 3 summarizes the main characteristics of the papers included in the review.

3.5. Key modelling questions and policy insights from the SARS-CoV-2 models for Africa

We classified the uses of applied epidemiological modeling into three categories: assessment and planning, prediction or forecasting and planning, and estimation and planning. The following subsections go into greater detail about the emerging issues for each theme.

3.5.1. Models used for assessment of control interventions and planning

Models that were used for purposes of assessment and planning looked at mitigation measures instituted which included non-pharmaceutical interventions such as lock downs, curfews, social distancing and wearing of face masks. The models sought to evaluate the

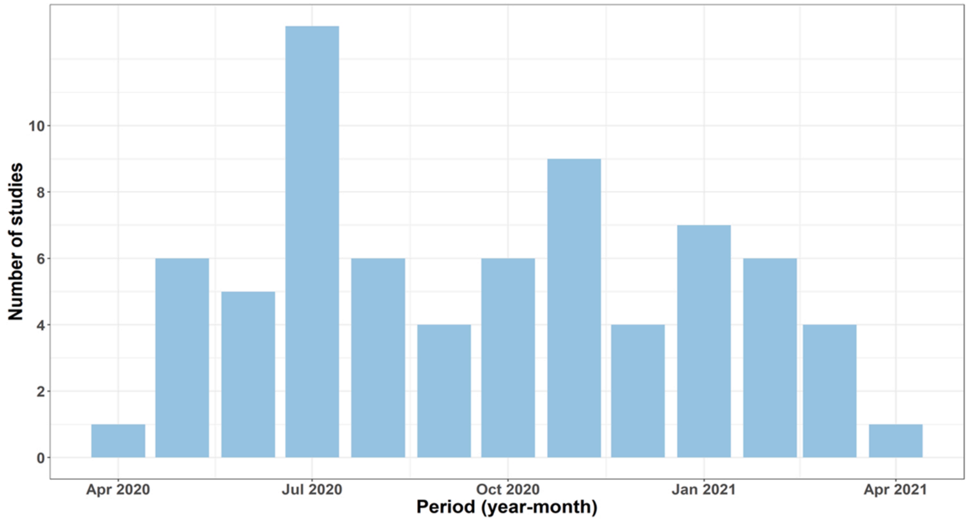

Fig. 4. : Distribution of number of studies included in the review by period of distribution between April 2020 and April 2021.

impact of these control measures on the pandemic progression. The model outputs provided insight into how best the health system should be prepared to counter a surge in number of patients requiring hospital care as well as how and when to de-escalate the confinement measures. Some models also investigated the effects of home-based and institutional isolation and quarantine. One study looked at the implication of governments facilitating and coordinating home-based isolation in informal settlements which led to a 20% reduction in community transmission (Skrip et al., n.d.).

The potential benefits of mass testing was also investigated and inspired scaling up of testing for identification and management of positive cases (Chirove et al., 2020). Furthermore, there was a study that assessed the cost-effectiveness of control interventions and found that a combination of control strategies was most cost-effective (Olaniyi et al., 2020). In addition, a few studies investigated vaccination strategies and vaccine efficacy levels for optimal control. Higher vaccine efficacy necessitated lower vaccination coverage to achieve herd immunity (Hammoumi et al., 2021; Mukandavire et al., 2020). One study used Twitter data to examine the effects of public opinions and human behaviour on the transmission of the virus, and discovered that disinformation transmitted via social media platforms contributed to the disease's spread (Agusto et al., 2021).

3.5.2. Models used for forecasting or prediction and planning

Most models predicted a second peak/wave between August and September 2020, as well as the possibility of additional waves, and advised increasing the testing rate for more precise forecasts. The models also recommended enforcement of containment measures to minimize the outbreak size and an increase in bed capacity to accommodate people with severe to critical disease (Zine et al., 2020b). One age-structured model, predicted a peak in cases in July 2020, with most infections occurring among the youth with asymptomatic or mild sickness thus reducing the disease severity in Africa (Diop et al., 2020).

3.5.3. Models used for estimation of key model outputs and for planning

Some models predicted COVID-19 related mortality and provided insight into increase in mortality in vulnerable groups, urging that vaccine administration should be prioritized for these groups (Bredan and Bakoush, 2021; Siraj et al., 2020). Moreover, there was a study that estimated the proportion of imported cases that would potentially increase community transmission and recommended enforcement of screening at all points of entry (Chevalier et al., 2021). The results on the main use of the models, key modelling questions, policy insights and sensitivity analysis of the parameters are presented in Table 4.

4. Discussion

We carried out a systematic review of 74 applied epidemiological modelling studies in Africa, which provided epidemiological insights on the current SARS-CoV-2 pandemic and had been published by April 2021. Of the 74 studies included in the review, 50 had been peer-reviewed whilst 24 were pre-prints. We found extensive geographical variation in the number of studies done with nearly half of the 54 African countries that are member states of the African Union having no peer-reviewed or non-peer-reviewed publications available. Majority of the papers included represented West African countries with nine studies representing the entire continent. Additionally, most papers included in the review focussed on assessing the impact of interventions that had been put in place on reduction of disease-related morbidity and mortality.

Most scientific journals have enabled quick publication of research and the expanding usage of preprints to provide insight into the dynamics of the COVID-19 global pandemic. A study conducted found over 30,000 preprint papers that had been hosted in a preprint server within ten months from when the first case of COVID-19 had been reported in the world (Fraser et al., 2021). Similarly, we looked at twenty-four preprints, the first of which was published two months after the African index case was reported in Egypt (CDC, 2020). It goes without saying that the pandemic has transformed the scientific landscape and necessitated quick information sharing around the globe, albeit with cautionary use of non-peer reviewed articles to inform policy.

The distribution of review papers was varied in terms of geography, with approximately a third of the papers coming from West African countries. Findings from a systematic review paper on the reliability of mathematical modelling predictions on SARS-CoV-2, which sampled 35 studies from Africa, with the bulk representing Nigeria, a country in west Africa, are similar to this (Gnanvi et al., 2020). These differences within the continent reflect the proportion of investment devoted to research by local governments; one study indicated that only three African countries, Nigeria, Egypt, and South Africa, contributed 65.7% of overall research and development funding (Simpkin et al., 2019).

Majority of the parameters used to build the models, relied on parameter extrapolation of estimates of transmissibility and age-dependent severity from Asia and Europe. This was arguably due to the virus's early and advanced establishment in those regions prior to seeding into Africa. Because the models developed ignored Africa's socio-ecological makeup, disease progression has been slower and less severe compared to what the models predicted (Okuonzi, 2020). Nonetheless, African countries benefited from early interventions that

Table 3
Characteristics of the 74 papers included in the systematic review.

Parameter	Frequency (N = 74)	Manuscripts included in the review
Publication Turnaround time (n = 50)		
< 3 months	21 (42%)	(Nkwayep et al., 2020; Bredan and Bakoush, 2021; Siraj et al., 2020; Cabore et al., 2020; Olaniyi et al., 2020; Mushayabasa, Ngarakana-gwasira, and Mushanyu, 2020; H. B.Taboe et al., 2020;Ben and Chérif, 2020;Djilali et al., 2020, 2020;Baba and Baleanu, 2020; Ifguis et al., 2020;Nadim and Chattopadhyay, 2020; Peter et al. 2020; mohamed Lounis 2021;Okuonghae and Omame, 2020;Zahra Diop et al., 2020; Adekunle et al., n.d.; Skrip et al., n.d.)
3–6 months	21 (42%)	(Mugisha et al., 2021; Iboi et al., 2020; Mwalili et al., 2020; Baba and Baleanu, 2020; S. S. Musa et al. 2020;Lmater et al., 2020;Serhani and Labbardi, 2020; Mukandavire et al., 2020;Djaoue et al., 2020;Ndondo et al., 2020;Kong et al., 2021;Kimathi et al., 2021;Kada et al., 2020; Zine, Boukhouima, et al. 2020; Nyabadza et al., 2020;Mbuvha and Marwala, 2020;Sichone et al., 2021; Gounane et al., 2021;Elhia et al., 2020; Frost et al., 2021; M. Lounis and Azevedo 2020)
> 6 months	4 (8%)	(Dwomoh et al., 2021; Gathungu et al., 2020; Atangana and İğret Araz, 2021; Mbogo and Orwa, 2021)
Pre-prints	24 (32%)	(Hammoumi, Hmarrass, and Qesmi, 2021; Honfo et al., n.d.;Agusto et al., 2021;Davies et al., 2020;Childs, 2020; Getz, Vissat, and Salter, 2020;Ogana, Juma, and Bulimo, 2021; Brand et al. 2020;Fahmy, El-desouky, and Mohamed, 2020; Timothy, Holla, and Meschke 2020; Ojiambo et al. 2020; Chirove et al., 2020;Thompson et al., 2020;Chevalier et al., 2021; R. Musa, Ezugwu, and Mbah 2020;Aries and Ounis, 2020;Gatyeni et al., 2021;Are and Colijn, 2021;Gu et al., 2021; Nannyonga et al. 2021;Madubueze, Akabuike, and Dachollom, 2020; B. H. Taboe et al., 2020;Kamugisha et al., 2020; (Zine et al., 2020b))
Type of model		
Stochastic	18 (24%)	(Cabore et al., 2020; Atangana and İğret Araz, 2021; Mukandavire et al., 2020; Kong et al., 2021; Zine, Boukhouima, et al. 2020;Mbuvha and Marwala, 2020; Adekunle et al., n.d.; Skrip et al., n.d.; Davies et al., 2020;Getz, Vissat, and Salter, 2020;Ogana, Juma, and Bulimo, 2021; Brand et al. 2020;Thompson et al., 2020;Chevalier et al., 2021;Aries and Ounis, 2020;Gatyeni et al., 2021;Are and Colijn, 2021;Gu et al., 2021)
Deterministic	57 (77%)	(Mugisha et al., 2021; Dwomoh et al., 2021; Gathungu et al., 2020; Iboi et al., 2020; Nkwayep et al., 2020; Mwalili et al., 2020; Bredan and Bakoush, 2021; Siraj et al., 2020; Baba and Baleanu, 2020, 2020; Mumbu and Hugo, 2020; S. S. Musa et al. 2020;Olaniyi et al., 2020; Mbogo and Orwa, 2021;Lmater et al., 2020;Serhani and Labbardi, 2020; Mushayabasa, Ngarakana-gwasira, and Mushanyu, 2020; H. B.Taboe et al., 2020;Ben and Chérif, 2020;Djaoue et al., 2020;Ndondo et al., 2020;Djilali et al., 2020, 2020;Kimathi et al., 2021;Kada et al., 2020;Nyabadza et al., 2020;Ifguis et al., 2020;Garba, Lubuma, and Tsanou, 2020; Zine, Boukhouima, et al. 2020; Nadim and Chattopadhyay, 2020; Peter et al. 2020;Sichone et al., 2021; mohamed Lounis 2021; Zandvoort et al. 2020;Gebremeskel, Berhe, and Atsbaha, 2021;Gounane et al., 2021;Elhia et al., 2020;Okuonghae and Omame, 2020; Frost et al., 2021;Zahra Diop et al., 2020; M. Lounis and Azevedo 2020; Hammoumi, Hmarrass, and Qesmi, 2021; Honfo et al., n.d.;Agusto et al., 2021;Childs, 2020;Getz, Vissat, and Salter, 2020;Fahmy, El-desouky, and Mohamed, 2020; Timothy, Holla, and Meschke 2020; Ojiambo et al. 2020; Chirove et al., 2020; R. Musa, Ezugwu, and Mbah 2020; Nannyonga et al. 2021; Madubueze, Akabuike, and Dachollom, 2020; B. H.Taboe et al., 2020; Kamugisha et al., 2020)
Number of state variables		
</= 4	30 (41%)	(Mugisha et al., 2021; Iboi et al., 2020; Nkwayep et al., 2020; Mwalili et al., 2020; Bredan and Bakoush, 2021; Siraj et al., 2020; Cabore et al., 2020; Lmater et al., 2020; Mukandavire et al., 2020; Djilali et al., 2020; Baba and Baleanu, 2020; Nyabadza et al., 2020; Ifguis et al., 2020; Mbuvha and Marwala, 2020; Sichone et al., 2021; mohamed Lounis 2021; Zandvoort et al. 2020; Gebremeskel, Berhe, and Atsbaha, 2021; Gounane et al., 2021;Elhia et al., 2020; Zahra Diop et al., 2020; Skrip et al., n.d.; Honfo et al., n.d.;Davies et al., 2020; Childs, 2020;Ogana, Juma, and Bulimo, 2021;Thompson et al., 2020;Chevalier et al., 2021; B. H.Taboe et al., 2020; Kamugisha et al., 2020)
5–7	33 (45%)	(Dwomoh et al., 2021; Baba and Baleanu, 2020; Mumbu and Hugo, 2020; Olaniyi et al., 2020;Mbogo and Orwa, 2021;Serhani and Labbardi, 2020; H. B. Taboe et al., 2020;Ben and Chérif, 2020; Ndondo et al., 2020;Kimathi et al., 2021; Kada et al., 2020;Garba, Lubuma, and Tsanou, 2020;Nadim and Chattopadhyay, 2020; Peter et al. 2020; Djilali et al., 2020;Okuonghae and Omame, 2020;Frost et al., 2021; M. Lounis and Azevedo 2020; Adekunle et al., n.d.;Agusto et al., 2021;Getz, Vissat, and Salter, 2020; Brand et al. 2020;Fahmy, El-desouky, and Mohamed, 2020; Timothy, Holla, and Meschke 2020; Ojiambo et al. 2020; Chirove et al., 2020;Aries and Ounis, 2020;Gatyeni et al., 2021;Are and Colijn, 2021;Gu et al., 2021;Madubueze, Akabuike, and Dachollom, 2020)
> 7	11(15%)	(Gathungu et al., 2020; Atangana and İğret Araz, 2021; S. S. Musa et al. 2020; Mushayabasa, Ngarakana-gwasira, and Mushanyu, 2020;Djaoue et al., 2020; Kong et al., 2021; Zine, Boukhouima, et al. 2020; Zine, Lotfi, et al. 2020; Hammoumi, Hmarrass, and Qesmi, 2021; R. Musa, Ezugwu, and Mbah 2020; Nannyonga et al. 2021)
Data sources for local data[†]		

(continued on next page)

Table 3 (*continued*)

Parameter	Frequency (N = 74)	Manuscripts included in the review
Confirmed cases	69 (93%)	(Mugisha et al., 2021; Dwomoh et al., 2021; Gathungu et al., 2020; Iboi et al., 2020; Nkwayep et al., 2020; Mwalili et al., 2020; Siraj et al., 2020; Cabore et al., 2020; Atangana and İğret Araz, 2021; Baba and Baleanu, 2020, 2020; Mumbu and Hugo, 2020; S. S. Musa et al. 2020;Olaniyi et al., 2020;Mbogo and Orwa, 2021;Lmater et al., 2020; Serhani and Labbardi, 2020; Mukandavire et al., 2020;Mushayabasa, Ngarakana-gwasira, and Mushanyu, 2020; H. B.Taboe et al., 2020;Ben and Chérif, 2020;Djaoue et al., 2020;Ndondo et al., 2020;Kong et al., 2021;Djilali et al., 2020, 2020;Kimathi et al., 2021; Kada et al., 2020; Zine, Boukhouima, et al. 2020;Nyabadza et al., 2020;Ifguis et al., 2020;Mbuvha and Marwala, 2020; Zine, Lotfi, et al. 2020;Nadim and Chattopadhyay, 2020; Peter et al. 2020; Sichone et al., 2021; mohamed Lounis 2021; Zandvoort et al. 2020; Gebremeskel, Berhe, and Atsbaha, 2021; Gounane et al., 2021;Elhia et al., 2020; Okuonghae and Omame, 2020;Frost et al., 2021;Zahra Diop et al., 2020; M. Lounis and Azevedo 2020; Adekunle et al., n.d.; Skrip et al., n.d.;Hammoumi, Hmarrass, and Qesmi, 2021; Honfo et al., n.d.;Agusto et al., 2021;Childs, 2020;Getz, Vissat, and Salter, 2020; Ogana, Juma, and Bulimo, 2021;Fahmy, El-desouky, and Mohamed, 2020; Timothy, Holla, and Meschke 2020; Chirove et al., 2020;Thompson et al., 2020;Chevalier et al., 2021; R. Musa, Ezugwu, and Mbah 2020;Aries and Ounis, 2020;Gatyeni et al., 2021;Are and Colijn, 2021;Gu et al., 2021; Nannyonga et al. 2021;Madubueze, Akabuike, and Dachollom, 2020; B. H. Taboe et al., 2020;Kamugisha et al., 2020)
Mortality data	8 (12%)	(Dwomoh et al., 2021; Iboi et al., 2020; Nkwayep et al., 2020; Bredan and Bakoush, 2021; Atangana and İğret Araz, 2021; Garba, Lubuma, and Tsanou, 2020; Gatyeni et al., 2021; Gu et al., 2021)
Mobility data	5 (7%)	(Cabore et al., 2020; Nyabadza et al., 2020; Djilali et al., 2020; Brand et al. 2020;Chevalier et al., 2021)
Hospitalization data	1 (1%)	(Olaniyi et al., 2020)
Demographic data	5 (7%)	(Cabore et al., 2020; Djilali et al., 2020; Davies et al., 2020; Brand et al. 2020;Are and Colijn, 2021)
Sentimental data from twitter	1 (1%)	(Agusto et al., 2021)

† Some studies had more than one data source

were informed by early modelling activities from outside the continent, and following relaxation, most African countries experienced multiple subsequent waves.

The complexities of infectious diseases, which are influenced by demographic, geographical, and socioeconomic factors, highlight the need to strengthen local data structures that can be used to calibrate model parameters and generate meaningful projections and policy insights (Eggo et al., 2021). Surveillance data, demographic data, human behaviour mixing patterns, mobility, and sentimental/opinion data are all valuable local data inputs in model development because they contextualize the outputs to local populations. According to one study from Kenya in the review, the basic reproductive number during the study period ranged between 1.78 and 3.46, with the epidemic spreading rapidly due to asymptomatic infected people. When compared to other models that used data from China, this model that included local population census data revealed significantly different age-related disease symptomatic rates (Brand et al., 2020). Furthermore, data on social behaviour is important to be included in the dynamic models to capture pandemic trends. For example, in a paper that used positive and negative opinions on COVID-19 tweets to predict the epidemic trajectory, showed that positive tweets reduced disease burden within the community (Agusto et al., 2021). However, currently, the local outbreak data structures are disjointed. It is critical to create common data spaces at the national, regional, and continental levels, with standardized data collection and transmission pathways that integrate multiple data sources which are easily accessible. This data investment would be useful for assisting in the rapid development of epidemiological models based on an interconnected knowledge ecosystem that reflects regional realities.

Although the reviewed studies lacked information directly linking most of the modelling work done to policy briefs developed, there is evidence policymakers were keen to have predictions of the pandemic trajectory. Governments' use and adoption of modelling has been facilitated by close collaboration with academic institutions with modelling expertise. An example is the South African COVID-19 modelling consortium, which was a government initiative, that linked epidemiological and costing models to help the government plan and budget for COVID-19 healthcare resources (Silal et al., 2021). Throughout the pandemic, governments' primary requirement has been to quantify health resources such as beds and supplemental oxygen, which have been identified as the primary cost driver during the response (Barasa et al., 2021b; Zine et al., 2020b). Furthermore, multidisciplinary modelling consortiums cultivate localized model outputs that capture unique population attributes, increasing the use of modelling during public health emergencies (Grant et al., 2016). The UK Scientific Advisory Group for Emergencies (SAGE) is also an example of a consortium that synthesizes evidence from various modelling groups and advises the government using sound evidence-based strategies after reaching a consensus (Government Office for Science and Cabinet Office, 2021). To determine the extent to which model findings were used to make decisions on the pandemic responses, qualitative studies that interview program managers, ministry of health officials, political leaders and modellers would be required.

It is important to note that because dynamic epidemiological models capture ongoing trends such as the current pandemic and are subject to changing assumptions over time, they provide projections with a wide range of uncertainties (James et al., 2021). Data abstracted on sensitivity analysis, in our review discovered that the rate of disease transmission (movement from susceptible to infected compartment) calculated as a function of the parameter beta (effective contact rate) contributed the most uncertainty.

Our study was however limited in the number of models developed to address the impact of vaccination, which has been a breakthrough in the control of the pandemic. This limitation resulted from the review time period. Another limitation of our study is the lack of a clear link between the reviewed modelling literature and policy implementation. The policy briefs available in some of the databases we searched, such as the World Health Organization and the Africa CDC, did not contain summaries of Africa-specific modelling literature (Africa CDC, 2020; WHO Integrated African Health Observatory, 2020). This, however, highlights a potential area for further research.

In conclusion, dynamic models have been critical in evidence-based decision making and guiding policy makers. The relevance of models is most important in understanding infectious disease outbreaks and therefore they should be quickly developed to offer insight during public health emergencies. However, there is need for collaboration between policymakers and modellers for both to understand the desired

Table 4
An overview of the of the key uses of the models for the manuscripts included in the systematic review. The table captures the main use of the models, key questions, policy insights and sensitivity analysis carried out.

Use of the model‡	Key modelling questions	Policy insights	Sensitivity analysis of parameters	Manuscripts included in the review
Assessment and planning	a) Assess the pandemic progression with institution of containment measures b) Implication of deconfinement strategies e.g., easing of lockdown. c) Assess the impact of the pandemic on the health system d) Assessment of impact of non-pharmaceutical interventions to control COVID-19 spread at both governmental and individual level. e) To assess impact of home-based quarantine and isolation in informal settlements f) Assessment of vaccine efficacy g) Assessment of vaccination strategies for optimal disease control h) Assess cost-effectiveness of control measures i) To assess the effects of public sentiments and human behavior on the spread of COVID-19 j) To assess potential benefits of mass testing	• Phased out lifting of lock downs. • Containment measures delay peak time and magnitude of pandemic and allow for ample preparation. • Increased adherence and combination of NPIs is most effective, need for more stringent containment measures • Enhanced contact tracing • Increase case ascertainment through increased testing/ scaling up of mass testing • Need to increase health system capacities; ICU beds, human resource and increase health care financing • Improve community awareness through risk communication and community engagement. Misinformation and negative message increase spread of disease • Increase supply of PPEs to reduce hospital acquired disease transmission. • Improved case management to reduce duration of infectiousness and enforce home quarantine/isolation of cases. • Provision of support to facilitate self-isolation in poor communities resulted in reduction of 20% of cases • Higher vaccine efficacy required lower vaccination coverage to achieve adequate herd immunity. • Combination of prevention and case management strategies was more cost-effective.	• Rate of transmission • Recovery rate • Confinement rate • Proportion of people adhering to NPIs. • Rate of detection of asymptomatic cases • Rate of progression of cases to quarantine/ isolation	(Adekunle et al., n.d.;Agusto et al., 2021; Baba and Baleanu, 2020;Ben and Chérif, 2020;Brand et al., 2021;Chirove et al., 2020;Davies et al., 2020;Djaoue et al., 2020;Djilali et al., 2020;Dwomoh et al., 2021;Elhia et al., 2020;Garba et al., 2020; Gatyeni et al., 2021;Gebremeskel et al., 2021;Getz et al., 2020;Gounane et al., 2021; Hammoumi et al., 2021;Iboi et al., 2020; Kada et al., 2020;Kamugisha et al., 2020; Kimathi et al., 2021;Kong et al., 2021; Lmater et al., 2020; Lounis and Azevedo, 2020;Madubueze et al., 2020;Mbabazi et al., 2020;Mbogo and Orwa, 2021; Mbuvha and Marwala, 2020;Mugisha et al., 2021;Mukandavire et al., 2020; Mumbu and Hugo, 2020; Musa et al., n.d.; Mushayabasa et al., 2020;Mwalili et al., 2020;Nadim and Chattopadhyay, 2020; Nannyonga et al., n.d.;Ndondo et al., 2020; Neil M et al., 2020;Nyabadza et al., 2020; Ogana et al., 2021;Okuonghae and Omame, 2020;Olaniyi et al., 2020;Quaife et al., 2020;Serhani and Labbardi, 2020;Sichone et al., 2021; Skrip et al., n.d.; Taboe et al., n.d.;Thompson et al., 2020;van Zandvoort et al., 2020a;Walker et al., 2020;Zine et al., 2020a)
Forecasting/ prediction and planning	a) Forecast peak of the epidemic. b) What is the effect of widespread community transmission? c) How best to prepare for the worst-case scenario d) Predict spread of disease by demographic patterns and urbanization	• Increase case ascertainment for more accurate forecasting; peak estimated to be in August/ September 2020 • Increased likelihood of subsequent waves/ second wave • Enhanced containment measures reduce peak time and magnitude of the pandemic. • Increase bed capacity for severe and critically ill patients • The peak of the first wave would be experienced in July, with many infections among the youth. The clinical presentation would be mostly asymptomatic or mild	• Rate of transmission • Rate of progression from exposed to infected. • Rate of recovery	(Are and Colijn, 2021; Aries and Ounis, 2020; Atangana and İğret Araz, 2021; Cabore et al., 2020; Djilali et al., 2020; Fahmy et al., 2020; Gathungu et al., 2020; Gebremeskel et al., 2021; Gu et al., 2021; Honfo et al., n.d.;Ifguis et al., 2020;Lmater et al., 2020; lounis, 2021; Lounis and Azevedo, 2020;Mwalili et al., 2020; Nkwayep et al., 2020; B. H.Taboe et al., 2020; H. B.Taboe et al., 2020;van Zandvoort et al., 2020b;Zahra Diop et al., 2020;Zine et al., 2020b)
Estimation and planning	a) To estimate the size of the pandemic and the effect on mortality b) Estimation of morbidity looking at different lock down scenarios c) To estimate the size of the pandemic factoring different socio-demographic groups d) To estimate the proportion of imported cases that would increase community transmission	• Prioritization of protection of high-risk groups and prioritize vaccination of high-risk groups to reduce mortality. • Strict lockdowns slow down viral progression • Enhance use NPIs in both urban and rural settings • Enforce screening at all points of entry	• Rate of transmission • Rate of disease progression • Proportion of lock down and social distancing adherence • Testing rate	(Bredan and Bakoush, 2021; Chevalier et al., 2021; Childs, 2020; Frost et al., 2021; Siraj et al., 2020)

‡ Some studies had more than one use

objectives for modelling (Hadley et al., 2021). These relationships can be realized by increasing the alignment of academic research with policy creation and decision making through ongoing engagement and updates between research institutions and governments.

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CRediT authorship contribution statement

Teresia Njoki Kimani: Conceptualization, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft preparation, Writing – review & editing, **Mutono Nyamai:** Data curation, Investigation, Validation, Visualization, Writing – review & editing, **Lillian Owino:** Data curation, Validation, **Anita Makori:**

Review & editing, **Loice Achieng Ombajo:** Review & editing, **MaryBeth Maritim:** Review & editing, **Omu Anzala:** Review & editing, **Samuel Mwangi Thumbi:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors have declared no competing interest.

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