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Computational decision-support tools for urban design to improve resilience against COVID-19 and other infectious diseases: A systematic review

Liu Yang[a,b,*,1], Michiyo Iwami[c,2], Yishan Chen[d,3], Mingbo Wu[e,f,4], Koen H. van Dam[g,5]

[a] School of Architecture, Southeast University, Nanjing, China
[b] Research Center of Urban Design, Southeast University, Nanjing, China
[c] Department of Infectious Disease, Faculty of Medicine, Imperial College London, UK
[d] Architecture and Urban Design Research Center, China IPPR International Engineering CO., LTD, Beijing, China
[e] State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China
[f] University of Chinese Academy of Sciences, Beijing, China
[g] Centre for Process Systems Engineering, Department of Chemical Engineering, Imperial College London, UK

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ABSTRACT

The COVID-19 pandemic highlighted the need for decision-support tools to help cities become more resilient to infectious diseases. Through urban design and planning, non-pharmaceutical interventions can be enabled, impelling behaviour change and facilitating the construction of lower risk buildings and public spaces. Computational tools, including computer simulation, statistical models, and artificial intelligence, have been used to support responses to the current pandemic as well as to the spread of previous infectious diseases. Our multidisciplinary research group systematically reviewed state-of-the-art literature to propose a toolkit that employs computational modelling for various interventions and urban design processes. We selected 109 out of 8,737 studies retrieved from databases and analysed them based on the pathogen type, transmission mode and phase, design intervention and process, as well as modelling methodology (method, goal, motivation, focus, and indication to urban design). We also explored the relationship between infectious disease and urban design, as well as computational modelling support, including specific models and parameters. The proposed toolkit will help designers, planners, and computer modellers to select relevant approaches for evaluating design decisions depending on the target disease, geographic context, design stages, and spatial and temporal scales. The findings herein can be regarded as stand-alone tools, particularly for fighting against COVID-19, or be incorporated into broader frameworks to help cities become more resilient to future disasters.

1. Introduction

1.1. Background

Public health issues are an inherent challenge to cities (Matthew & McDonald, 2006; C. Miller, 2016). Planning has been an important means of solving such issues since the early cities of the Chaldean civilization (Frank, 1943). Until the advent of antibiotics in the 20th century, the fundamental ways to combat bacterial pandemics were restricting contact between individuals through isolation, quarantine, and lockdown. Since the 19th century, planning and design professionals have shared a common interest in infectious diseases; for example, architect Le Corbusier's Five Points of Architecture, which were derived from the Hygiene movement in the 1820s (Fezi, 2021). In the 20th

* Correspondence to: School of Architecture, Southeast University, Si-Pai-Lou 2#, Nanjing, Jiangsu Province 210096, China.
E-mail address: yangliu2020@seu.edu.cn (L. Yang).
[1] 0000-0002-3363-8620
[2] 0000-0003-3086-5921
[3] 0000-0003-3630-9192
[4] 0000-0002-1236-7091
[5] 0000-0002-4879-9259

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century, the introduction of green building certification systems and New Urbanism prevented public health problems, for example, through natural ventilation, daylighting, as well as connectivity and walkability (Iravani & Rao, 2020). In late 2019, the emergence of the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) and the subsequent Coronavirus Disease 2019 (COVID-19) pandemic became a global threat. This paper aims to investigate: 1) whether and to what extent urban design can support the fight against infectious diseases, and 2) how urban designers can consider the threat of infectious diseases while designing a healthy and resilient built environment. Professor Ann Forsyth (2020) at the Harvard Graduate School of Design reminded us that:

> "For the past decades, those looking at the intersections of planning, design, and public health have focused more on chronic disease, hazards and disasters, and the vulnerable…The pandemic brings the question of designing for infectious diseases back to the forefront."

Non-pharmaceutical interventions (NPIs) have played a significant part in mitigating and suppressing COVID-19 (Ferguson et al., 2020; Perra, 2021). Among other NPIs, urban design offers solutions with the design of buildings and the built environment. Short-term responses to COVID-19 include environmental and pandemic prevention infrastructure management (e.g. medical waste treatment), city management (e.g. individual tracking technologies), and building ventilation (Budds, 2020; Fezi, 2021; Kindervag, 2022). In the medium- and long-term responses: spatial planning can enhance public services and access to amenities; neighbourhood (re)design can satisfy both compact city development and low population density that is suggested by epidemiological studies; public spaces design is essential to support healthy activities and social interaction (Fezi, 2021; HM Government, 2021; Honey-Rosés et al., 2020; Thilakaratne, 2019; J. Wang, 2021).

Dolores Park in San Francisco and Domino Park in Brooklyn, New York City, drew social distancing circles on the grass to separate groups of people. Several museums, such as Tate Modern in London and the MoMA in New York, designed one-way visiting routes when re-opening the museum after the pandemic. The Ministry of Housing and Urban-Rural Development (MoHURD) in China announced urban residential planning and design standards in answer to COVID-19 (The World Bank, 2021).

On the other hand, the pandemic has changed public behavioural patterns and, thus, triggered a rethinking of existing urban design paradigms. As a result, there is a growing belief that urban construction needs to actively include planning against infectious diseases to pursue a healthy and resilient environment in the post-pandemic era (Desouza & Flanery, 2013; Rice, 2020). For example, some urban experts advocated for designing an "antivirus-built environment" (Megahed & Ghoneim, 2020) or a "pandemic-resilient urban environment" (Y. Yang et al., 2021). Such an environment is expected to help prevent the spread of viruses, alleviate its impacts in the short term, and improve urban resilience to infectious disease in the long term (Lai et al., 2020; Lak et al., 2020; Sharifi & Khavarian-Garmsir, 2020).

In doing so, a multi-disciplinary coalition of urban governors, policy-makers, infectious diseases scientists and urban designers is required in developing prevention and control strategies (UN-Habitat, 2020). In addition, urban design practitioners need to understand the disease mechanisms and the impact of their plans on the spread of diseases (Shearer et al., 2020) and evaluate their design against relevant indicators (L. Yang et al., 2020), which is something they may not have trained for. Decision-support tools can assist in the design process and help designers envisage what would happen if certain design interventions are applied, for example the What-if? decision support system (Pettit et al., 2015) and the MobiSim simulation platform (Tannier et al., 2016). Therefore, Professor Michael Batty from University College London highlighted the use of quantitative computer-aided technologies in urban planning (Batty, 2021).

Previous literature sought to model virus transmission, unfold the disease spreading mechanism, and predict future risks using compartment, statistical, and computer simulation models (in particular, agent-based models and artificial intelligence (AI) algorithms) (Alvarez-Pomar & Rojas-Galeano, 2021; De Las Heras et al., 2020; Hunter et al., 2017; Perra, 2021). To support urban design in response to infectious diseases, computational modelling helps designers and decision-makers analyse the status quo and evaluate possible interventions against a set of public health, resilience, and sustainability metrics.

> "Computational models can help us translate observations into anticipation of future events, act as a testbed for ideas, extract value from data and ask questions about behaviours. The answers are then used to understand, design, manage and predict the workings of complex systems and processes." (Calder et al., 2018, p. 2).

Studies in this domain have primarily focused on general guidelines for responding to outbreaks or pandemics, and this is the bulk of research on COVID-19 (D'Angelo et al., 2021; Kakodkar et al., 2020; Payedimarri et al., 2021). Some scholars summarised possible NPIs for infectious diseases (Chu et al., 2020), especially focusing on social distancing (C.T. Nguyen et al., 2020), use of face masks (Coclite et al., 2020), or quarantines (Brooks et al., 2020). Others discussed the ways to control and forecast the spread of a virus (Bian, 2013) and its effect on economies (Brodeur, Gray, Islam, & Bhuiyan, 2020).

Some detailed studies focused on specific urban interventions. For example, V.J. Lee et al. (2009) revisited mathematical models used to quantify the effectiveness of combination strategies for controlling influenza. In response to the COVID-19 pandemic, Sharifi and Khavarian-Garmsir (2020) reviewed the literature about the effects of pandemics on urban planning, where major issues and recommendations had been highlighted. Some scholars reviewed various technologies that can support urban planners to mitigate the pandemic. Adiga et al. (2020) summarised models used to influence COVID-19 policies in general without emphasising the role of NPIs and urban planning. Rahmani and Mirmahaleh (2020) elucidated the role of technology in dealing with the different temporal phases of the disease.

While such guidelines are useful for designers and other stakeholders, they do not provide direct input in the design process or a way to test proposed developments with these factors in mind. Modelling tools can bring these insights directly into a specific project. For example, Elavarasan et al. (2021) proposed a taxonomy tree to examine COVID-19 adaptation and mitigation methods and, specifically, the use of modelling tools in this space.

1.2. *Literature gaps and research objectives*

Previous literature has indicated the value of urban responses to infectious diseases, the importance of urban planning and design-related interventions, and the benefits of using computer-aided support tools. However, the literature also shows that some urban design interventions have uncertain effects on the spread of infectious diseases (e.g. density), and some can undermine disease control despite improving the quality and sustainability of urban spaces (e.g. public transport promotion). Thus, there is a need for a toolkit to help specialists appraise design scenarios against a range of performance indicators that prioritise public health concerns. In addition, although computer-based quantitative methods have been introduced in urban design, a collection of supportive computational models is still needed (J. Wang, 2021). In summary, there is still a lack of a state-of-the-art, comprehensive and systematic literature review on the existence and use of such computational decision-support tools.

To bridge this gap and to meet the two aims outlined at the beginning of this paper, we asked the following research questions (RQs):

RQ1: Which types of infectious diseases can be counteracted by urban design, and what are their characteristics?

RQ2: Which design interventions have been tested or proven to be effective as part of the infection prevention and control?

RQ3: Which computational modelling tools and parameters contribute to understanding infectious diseases mechanism or the impact of designs?

RQ4: How to choose suitable models and integrate them into urban design practices?

For the first time, this paper carries out a systematic literature review from a multi-disciplinary perspective to answer these questions. The novelty of this review lies in proposing elements of a toolkit that long-lists and maps i) design interventions, ii) target infectious diseases, and iii) computer modelling tools for the whole urban design process to create more resilient urban environments. Because multi-disciplinary coalitions are crucial for dealing with infectious diseases (UN-Habitat, 2020), we assembled a research team from urban design, architecture, geography, infectious disease, and computer science fields. We intend that the resulting toolkit will benefit urban designers, planners, decision-makers, and computer modellers. Such a toolkit will then empower cities to develop strategies in response to COVID-19 and prepare for future uncertain disasters in pursuit of creating healthy and resilient cities.

In this review, we defined computational modelling as including computer models and simulations, statistical models, AI algorithms, and relevant computer-aided decision-making techniques. We referred to the definition of urban design formulated by Carmona (2021), namely, the process of making better places for people, which deals with the spatial scales ranging from buildings, streets, public spaces, neighbourhoods, districts, to entire cities. The remainder of this paper is organised as follows: Section 2 describes the overall analytical framework and the methodology for the systematic review. Section 3 first shows the search results that formed the basis of the systematic review and then presents the descriptive analysis, which includes a description of the target infectious diseases. Then, urban design interventions, the risk of bias in modelling research, and computational modelling tools are summarised, followed by clarifications of the correspondence between diseases, design interventions, and modelling tools. Section 4 proposes a toolkit for answering the research questions, and the paper concludes in Section 5.

2. Methodology

2.1. Overall analytical framework

To structure the literature review and propose a toolkit, we set up an analytical framework inspired by previous research (Elavarasan et al., 2021; Megahed & Ghoneim, 2020; WHO, 2019). We refined this framework iteratively through team discussions, considering the study objectives and the insights team members generated through processing the studies included in this review. As shown in Fig. 1, the framework comprises three components: 1) infectious disease, 2) urban design, and 3) computational modelling. To answer the four research questions, this review aimed to identify the relationship between infectious disease and urban design along with the correspondence between urban design and modelling, shown as links between the three components in Fig. 1. The next subsections discuss the three components in detail, showing how this discussion led to selecting keywords for the systematic literature searches.

2.1.1. Infectious disease

Three characteristics of infectious diseases were considered for this study: 1) types of pathogens, 2) modes of transmission (e.g. human-to-human, aerosol, and droplet), and 3) phases of disease transmission.

Regarding the pathogens, we undertook a broad search strategy based on keywords related to an epidemic/pandemic to source literature on viral infections that could be analysed by computational models that, in turn, may inform the development of new urban design intervention.

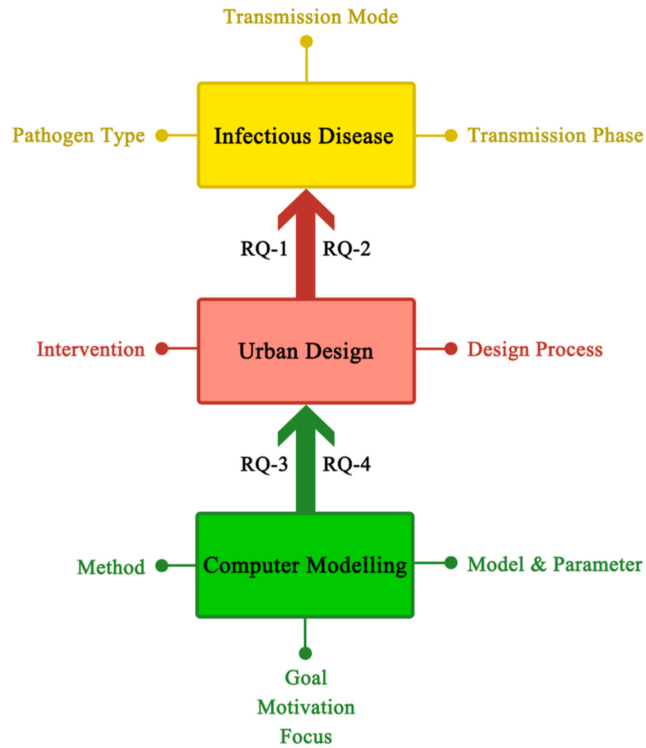

Fig. 1. Analytical framework. *Note.* This figure illustrates the analytical framework used in the systematic review to map the possible contribution areas and scope of papers identified in this study. In addition, RQ indicates the four research questions this review aims to answer.

However, our critical focus point was SARS-CoV-2 (which causes COVID-19), given the current priorities.

We made an illustrative list of similar viruses to SARS-CoV-2, where social distancing (a crucial concept in developing urban design strategies) would play an essential role in mitigating transmission. Note that this work does not attempt to provide an exhaustive list of pathogens that cover all modes of transmission. From a historical perspective, we added the following viruses to our review: SARS-CoV (SARS-CoV-1), Middle East Respiratory Syndrome (MERS)-CoV, H5N1, H1N1, H3N2, and H1N2. These viruses are either related beta coronaviruses or influenza viruses that cause respiratory viral infections and have been frequently compared with SARS-CoV-2 in research (Petersen et al., 2020). We also selected viruses causing Ebola and Hand-Foot-and-Mouth disease, known to be transmitted through direct contact or person-to-person contact, for which social distancing is also vital for cutting the chain of transmission (Richards et al., 2015). Regarding the search terms, these infectious diseases and associated viruses constituted the basis of our review, but without any weighting or preferences among these pathogens.

Dynamics of infectious disease transmission can be classified into three phases from a risk management perspective (WHO, 2017), depending on the line of action taken in case of a pandemic—from the outbreak of the disease to gaining control over the infection (Elavarasan et al., 2021; WHO, 2018). Phase 1 is the introduction or emergence of an infectious disease. In phase 2, epidemic/pandemic inflation occurs. This phase has three substages: local transmission, community transmission, and transmission amplification. In the last sub-stage, the spread of the disease speeds up rapidly, and deaths will multiply exponentially, which might ultimately lead to an epidemic in the infected regions and possibly a global pandemic. Finally, in phase 3, the transmission rates decline; the number of cases no longer rises because of effective interventions or herd immunity.

2.1.2. Urban design interventions

To prevent infectious diseases and enhance the resilience of the built environment, the World Health Organization (WHO, 2019) lists 18 NPIs. Among others, ventilation, modifying humidity, contact tracing, school and workplace measures and closures, crowding avoidance, travel advice, and internal travel restrictions closely correlate with urban design and planning. Megahed and Ghoneim (2020), for example, defined five scopes of post-pandemic architecture and urban planning: urbanism, public spaces, housing, office space, and building and construction technology. To support the prevention and mitigation of diseases, Lai et al. (2020) identified the following critical attributes of the built environment: housing (sanitation, ventilation, indoor spaces), physical morphology (density, land use, urban form, accessibility), infrastructure (transportation, workplaces, schools, public spaces), services supported (activity-friendly environment and travel facilities), and surveillance and contact tracing. Similarly, Lak et al. (2020) highlighted four physical dimensions of urban form: access, infrastructure, land use, and natural environment. They also grouped design interventions into three levels: building, neighbourhood/district/street, and city.

Apart from investigating the various design strategies, we focused on the different urban design implementation processes and examined how computational modelling could support each process. Urban design typically comprises five phases: 1) analysis of the problems, 2) design and development of design interventions, 3) prediction of the effects of interventions, 4) evaluation of the effects of interventions in a real-life setting, and 5) decision-making on the adoption of urban design interventions (Moughtin, 2003). Relevant keywords were used to retrieve studies covering these themes.

2.1.3. Computational modelling

Regarding the modelling component in the analytic framework, Table 1 reports the classification of the models used. Previous studies on modelling did not offer a precise classification that is mutually exclusive but rather provided some distinctions from multiple perspectives. Therefore, we chose to classify models according to four dimensions based on the Association for Computing Machinery's (ACM, 2012) computing classification system in combination with several classic works (Batty, 1976; Meadows & Robinson, 1985; Porgo et al., 2019). These four dimensions are "method," "goal," "motivation," and "focus." Multiple features of the models under each dimension were identified as well. Furthermore, to answer RQ 3, this review identified significant models and parameters.

Table 1
A brief definition of computational modelling categorisations.

Dimension	Categorisation	Brief definition
Method	Computer Simulation	The process of mathematical modelling, performed on a computer, for exploring the behaviour of, or the outcome of, a real-world or physical system under various input variables.
	Statistical Models	A mathematical model that embodies a set of statistical assumptions concerning the generation of sample data (and similar data from a larger population), usually specified as a mathematical relationship between one or more random variables and other non-random variables
	Artificial Intelligence	Machines mimic "cognitive" functions that humans associate with the human mind, such as learning and problem-solving, typically using large relevant datasets analysed by algorithms.
	Other Methods	Other methods cannot be categorised into the above three types.
Goal	Predictive	Forecasts future events or ranges of possible outcomes for given input data.
	Descriptive	Describes and/or explains previously observed phenomena.
Motivation	Theory-driven	Results are driven by theory/assumptions
	Data-driven	Results are inferred from data
Focus	Mechanistic	Uses mathematical terms to explicitly describe the mechanisms of infection transmission, pathogenesis and control measures.
	Phenomenological	Uses mathematical terms to describe the interrelationships between risks and outcomes without making assumptions about the underlying mechanisms.

2.2. The systematic review method

The systematic review was conducted based on the recommendations in the Preferred Reporting Item for Systematic Reviews and Meta-Analyses (PRISMA) 2020 (Page et al., 2021) and Cochrane Handbook (Higgins et al., 2019). PRISMA was devised mainly for systematic reviews on health intervention evaluation studies but has been increasingly applied to engineering disciplines, such as urban design and architecture (W. Yang & Jeon, 2020). This systematic review was conducted following seven processes: 1) preliminary searches, 2) identification of the studies, 3) screening of the title and abstracts, 4) full-text review for eligibility, 5) data extraction, 6) risk of bias assessment, and 7) data analysis and findings discussion (Page et al., 2021). Details can be found in Box 1 in the Supplementary File.

2.2.1. Data sources and search strategy

We searched the six electronic databases, namely, Web of Science, Ovid MEDLINE, Embase, PsycInfo, Scopus, and IEEE Xplore on 10–12 November 2020 ("the first round" of searching). The results were subsequently exported to an online-based systematic review management platform, Covidence (2021). We repeated these queries on 14 May 2021 ("the second round" of searching) to cover the latest literature published since the first round. This search was complemented with grey literature search and manual screening. On 8 May 2021, we scanned grey literature using the Google search engine to identify additional literature on relevant key institutional websites (e.g. government reports). Besides, we screened reference lists of the included reports using snowballing method (see Table S1 in Supplementary File for more details).

Prior to the first round, search terms were decided based on three components of the analytical framework (Fig. 1). After a search test run in October 2020 and via specialist support, the search terms were refined and finalised. For the validation purpose of the search strategy, we used 20 known relevant studies to identify whether such records appear within the databases we selected. The searches on different databases were conducted by LY and MI. The entire search strategies, including a complete list of search strings and results, are provided in the Supplementary File Table S1 and Table S2.

2.2.2. Eligibility criteria and study selection

The inclusion criteria for the searches were as follows: 1) year of dissemination: since the inception of each database; 2) setting/location: all regions in the world; 3) language: any language; 4) types of study/literature: both peer-reviewed primary research studies and grey literature (e.g. conference abstracts), especially because this rapidly growing area of research is frequently embedded in these kinds of sources. The exclusion criteria used for the title and abstract screening and the full-text review are shown in Box 2 and Box 3 in the Supplementary File.

The Covidence platform was employed for screening titles and abstracts, full-text review, as well as assessment of the risk of bias and data extraction. Pairs of researchers (LY, MI, YC, MW) simultaneously screened and selected studies independently. Any disagreements in decisions were resolved through discussion by an independent team member (KvD). Where applicable, a final consensus was achieved through team discussions. This process was repeated for the full-text review, and any conflicts, including reasons for exclusion, were resolved accordingly.

2.2.3. Data extraction

A data extraction form template was developed in Excel based on our preliminary framework and underwent a refinement process by testing it on a few included studies, followed by team discussions. The finalised data extraction form template was subsequently populated with relevant data from each report using the descriptive and analytical approaches. This mapping result was then used for the analysis of themes and gaps. Three researchers (LY, YC, and MW) independently extracted the information from each publication. Any discrepancies between their assessments were discussed and resolved through team discussions. As part of the screening process, all included papers were divided into three types: 1) general qualitative research, 2) review, and 3) computational modelling.

2.2.4. Assessment of risk of bias

We built a rating tool to guide the assessment, adapted from the existing medical and computer sciences checklists (see Table S3 in Supplementary File). This tool evaluates the study design in general and assesses the quality of review/qualitative research and modelling studies using different metrics derived from Coeytaux et al. (2014) and Wolf et al. (2019). The risk of bias for each included report was assessed by rating the quality of studies across 12 domains by LY. Uncertainties regarding quality ratings were addressed through team discussions. The quality of the studies was defined as "high," "low," or "unsure/not applicable". A full score (12 points) represented the highest quality, i.e. the lowest risk of bias. The overall rating for each paper was also shown as a proportion (%) of the full score. Consequently, we considered low bias (high quality) if the overall rate is $\geq$ 80%, moderate for $\geq$ 60% and $<$ 80%, and high bias (low quality) for $<$ 60%.

2.2.5. Synthesis methods

The final included studies were assessed using the descriptive approach to visualise temporal trends of publication and geographical distribution of case studies. We used CiteSpace software (Chen, 2006) to analyse the themes of each paper and after that grouped all papers into a few clusters. Because of the heterogeneity of the reports included in this review (e.g. discrepancies in outcome reporting), meta-analysis was not performed. The data were qualitatively synthesised by mapping onto the analytical framework (Fig. 1). The correspondence of the components was visualised using Python algorithms. Finally, we identified modelling methodologies for urban designs in the epidemic/pandemic of interest and mapped emergent themes onto a holistic toolkit.

3. Results

We systematically reviewed relevant literature at the interface of infectious diseases, urban design interventions, and computer modelling. This section presents the study results, first with a descriptive analysis of the literature, then by mapping infectious diseases and design interventions, and computational approaches used before finally presenting the results at the intersection of these themes.

3.1. Descriptive analysis

3.1.1. Search results and the PRISMA

The first and second rounds of the search yielded 4,661 and 8,737 records, respectively. A total of 6,316 records were imported to Covidence. Next, 3,500 records underwent the title and abstract screening via Covidence following the automatic removal of 2,816 duplicates. Subsequently, 2,840 records were excluded, owing to a high level of irrelevant topics. The remaining 660 records appeared relevant and were assessed through a full-text review for eligibility, after which 556 records were further excluded. Additionally, we identified seven potentially relevant records through Google search on important institutional websites and eight articles through screening reference lists of included reports. As a result, 109 distinctive eligible papers were included for analysis, including two preprints, two reports from key institutional websites and three articles through screening of references. Fig. 2 is a PRISMA flow chart that summarises the study selection process. Research aims of the included reports focused on COVID-19 were summarised in (L. Yang et al., 2022).

Among the 109 studies, 98 were quantitative computational modelling studies; apart from that, six papers documented qualitative research, and five were review papers, whose main contributions and scientific findings are presented in Appendix A.

Earlier studies on pandemic influenza and H1N1 influenza focused on using models and big data for rapid decision-making (E.K. Lee et al., 2009; Prieto et al., 2012; Van Kerkhove & Ferguson, 2012). Issues of model scalability, social behaviour representation, context-based simulation, data sharing, and stakeholders' engagement were raised. Recent research on COVID-19 has emphasised that prediction models can be built by data-driven or causal (theory-driven) methods, and timely forecasts along with modelling uncertainties are key factors to consider in model development (Adiga et al., 2020; Tang et al., 2020). Besides, it has been shown that technology advancements, such as AI (Adly et al., 2020) and wireless technologies (C.T. Nguyen et al., 2020), played a part in preventing the spread of COVID-19, especially in social distancing surveillance.

3.1.2. Temporal analysis

A change over time in the number of included studies over time and the main infectious diseases studied in each timeframe is shown in Fig. 3. The largest volume of literature was published between July and November in 2020, half a year after the first outbreak of COVID-19, while the analysis includes papers from the past few decades.

3.1.3. Geographical analysis

Fig. 4 illustrates the geographical mapping of the case study countries that appeared in the included studies. If a paper presented multiple case studies, all countries covered by the studies covered were mapped. The US dominates, with 25 papers published, followed by China, with 14 papers, which may be due to a lack of input data provided for model development. Other countries such as Italy, the UK, and Australia appeared in four or fewer articles.

3.2. Listing and mapping infectious diseases and design interventions

3.2.1. The infectious diseases investigated

The included literature investigated two types of viruses: human coronavirus (including SARS-CoV-2, SARS-CoV, MERS-CoV) and influenza viruses (including Influenza A[H5N1] virus, Influenza A[H1N1] virus). The former viruses led to COVID-19, SARS, and MERS outbreaks in 2019, 2003, and 2012, respectively. The latter viruses resulted in diseases of H5N1 influenza (in 1997), the 1918 influenza pandemic, the 2009 influenza pandemic, and other influenza. Table 2 summarises the characteristics and severity of each disease that allow planners and decision-makers to choose appropriate strategies in response. A list of the supporting references can be found in Table S4 in Supplementary File.

On the one hand, the transmission modes of these diseases are complex. For example, COVID-19 can spread through multiple modes, including human-to-human, droplet, aerosol, fomite, faecal-oral transmission, and animal-to-human. It is evident from Table 2 that all viruses listed can spread through droplets, which is the primary means of transmission, and the great majority can transmit via aerosol and human-to-human contact.

On the other hand, the case fatality rate and basic reproduction number (R_0) of the diseases differ significantly, which are key epidemiological parameters to understand an outbreak or epidemic (Alimohamadi et al., 2021). Note, the case fatality rate is the proportion of deaths within a defined population of interest; R_0 is an epidemiologic metric for demonstrating the transmissibility of infectious agents. A

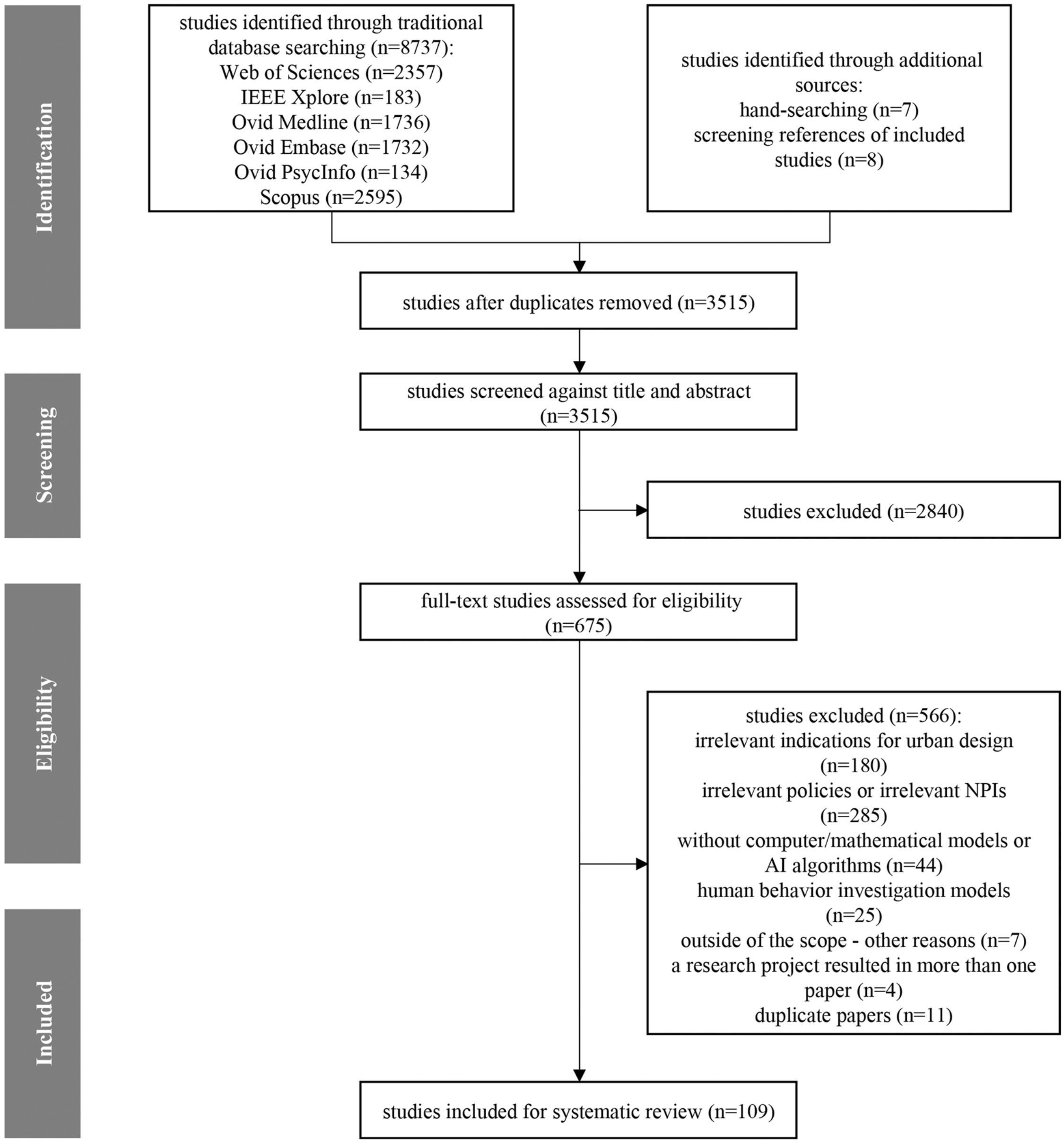

Fig. 2. PRISMA of the systematic review process undertaken in this study.

comparison between the six types of viruses shows that the human coronaviruses are more detrimental than influenza viruses, with a higher case fatality rate. Within the coronaviruses, although the case fatality rate of SARS-CoV-2 is relatively low, its R_0 is much higher than that of other viruses.

3.2.2. The urban design interventions tested and spatio-temporal scales and resolutions

We grouped the urban design interventions of the included papers into six high-level strategies (specifically, social distancing, travel-related, individual-level, building-level, neighbourhood/district-level, and city-level design interventions) and 15 detailed methods (see Table 3). Strategies outside of these six categories were tagged as "other interventions."

Appendix B longlists the type of interventions tested in each study as well as their spatial and temporal resolutions and scales. In general, studies with lower spatio-temporal resolutions tend to be larger in scales, and scales/resolutions of the papers can be classified roughly into three levels. On the national/regional scale, with spatial resolution ranging from a community to a country, and temporal resolution ranging from minutes to days, travel restrictions and city-level design interventions are primary strategies. On the city scale, neighbourhood/district-level interventions are usually tested using Global Positioning System (GPS), whose spatial resolution is around several metres. At the building scale, papers focused on building-level methods, with a spatial accuracy that varies from a few millimetres to a room and a temporal resolution from microseconds to minutes. Finally, social distancing and individual-level interventions were applied across all three scales.

To summarise, social distancing attracted the most attention among the six high-level interventions, examined by 78% of the studies (see Table S5 in Supplementary File). Specifically, facilitating to keep a defined social distance is the most potent strategy for not only COVID-19 but also other infectious diseases encountered. Next, building-level design interventions appeared in 43% of the papers, and design/redesign of indoor spaces is the major detailed method. This is followed by city-level design interventions investigated by 32% of the literature examined, with density being the most crucial detailed approach.

Fig. 5 shows that, during the outbreak and spread of COVID-19,

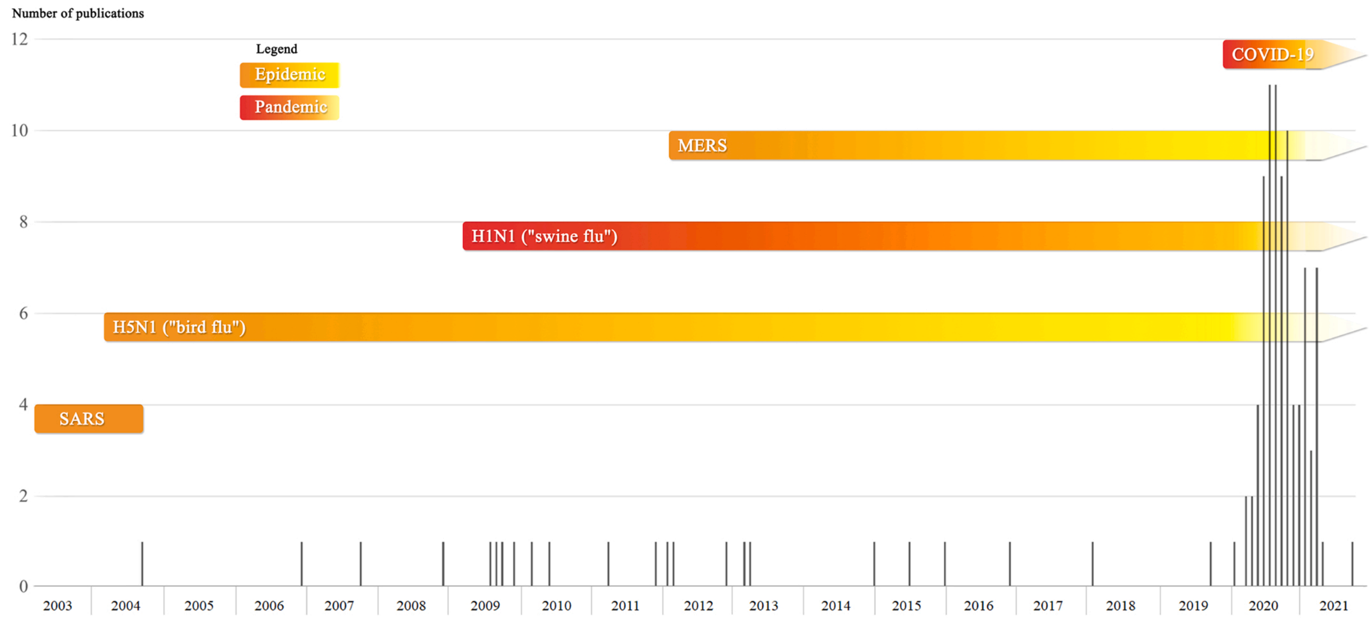

Fig. 3. Publication date of the included papers (online date) and a timeline of active outbreaks of infectious diseases covered in the literature. *Note.* The horizontal axis shows the month the report appears in the database queried, and the vertical axis shows the number of included papers in each of these periods.

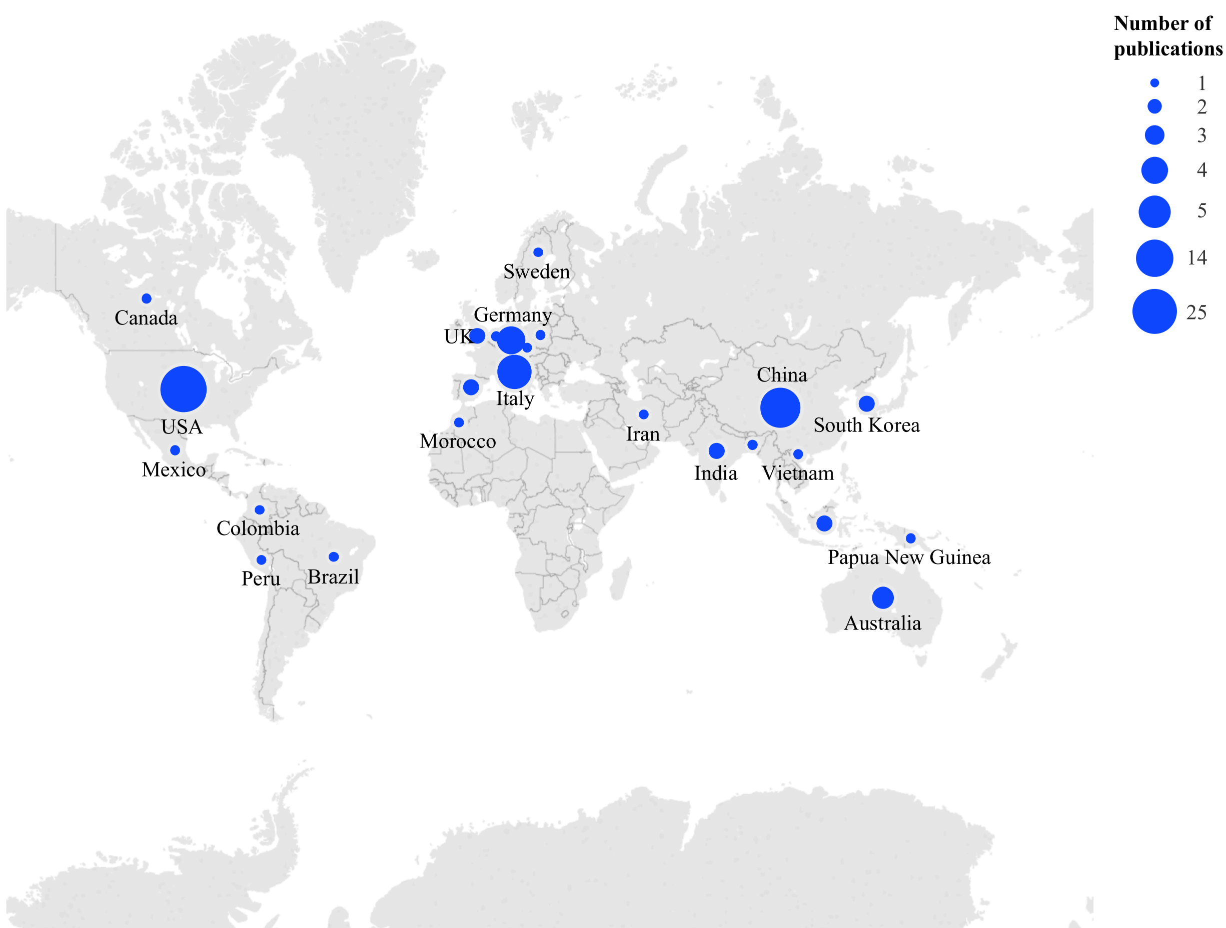

Fig. 4. Case study countries of the included papers.

building-level, social distancing, and travel-related interventions were introduced first to mitigate the disease, followed by the individual-, neighbourhood- and city-level interventions. Thus, there seems to be an increase in the spatial scale of urban design and planning over time, as the response changes from short-term to long-term strategies. Overall, we can see increased interest from researchers in exploring the

Table 2
Relevant information of the infectious diseases investigated in included papers.

Virus		Epidemic/Pandemic	Year, Place*	Transmission mode	Case fatality rate	Basic reproduction number
Human coronaviruses	SARS-CoV-2	COVID-19	2019, China	Human-to-human** (including asymptomatic); Droplet; Aerosol; Fomite; Faecal-oral (low risk); Animal-to-human (low risk); [Human-to-animal]	10%	4.08
	SARS-CoV	SARS	2003, China	Human-to-human (including asymptomatic?); Droplet; Fomite; Faecal-oral; Animal-to-human; Aerosol	11%	2.4
	MERS-CoV	MERS	2012, Saudi Arabia	Human-to-human (including asymptomatic?); Animal-to-human; Droplet; Aerosol (potentially); Fomite (potentially); Faecal-oral (potentially)	34.4%	0.9
Influenza viruses	Influenza A (H5N1) virus	H5N1 influenza (avian influenza/"bird flu")	1997, China (Hong Kong)	Animal-to-human; Droplet; Aerosol; Fomite; Faecal-oral (potentially) Human-to-human (potentially)	14–33%	<1.8
	Influenza A (H1N1) virus	The 1918 influenza pandemic The 2009 influenza pandemic ("swine flu")	1918, USA 2009, Mexico	Human-to-human (including asymptomatic); Animal-to-human; Droplet; Aerosol; Fomite; [Human-to-animal]	>2.5% (1918) 0–13.5% (2009)	2.0 (1918) 1.5 (2009)
	Influenza A (H1N1***, H3N2, H1N2) and B**** viruses	Other influenza (including seasonal influenza)		Human-to-human (including asymptomatic); Animal-to-human; Droplet; Aerosol; Fomite; [Human-to-animal]	–	–

Note. * Year and place refer to when and where the outbreak was first detected in humans. ** Human-to-human transmission indicates direct contact. *** Influenza A (H1N1) pdm09 virus is widespread worldwide and considered a currently circulating Influenza A seasonal virus. **** Influenza B viruses circulate only among humans. The transmission mode in square brackets is not our review focus and the figures for COVID-19 are subject to change.

neighbourhood and city-level interventions. In comparison, social distancing and building-level interventions had been studied and applied at consistent and significant levels before 2020.

Fig. 6 further demonstrates the relationship between different interventions. The more papers investigated a pair of interventions, the stronger the connection between them. Importantly, successful adherence to social distancing is usually connected to the (re)design of indoor spaces; the latter often makes use of ventilation means. Other highly relevant interventions are encouraging the maintenance of a defined physical distance and the avoidance of crowding, and individual behavioural changes and internal travel restrictions.

3.3. Listing and mapping computational modelling support tools

Having focused on the framework's infectious disease and planning components, we are presenting the findings of 98 computational modelling sutdies in the following sections.

3.3.1. Risk of bias in the modelling studies

The overall score of the risk of bias of the 98 modelling papers is shown in Table S6 in the Supplementary File. In short, as shown in Fig. 7, 72% of studies rated as low bias (high quality), 11% studies as high bias (low quality), and the remainder as intermediate. Assessment results show that most modelling studies examined in this review are at a low or intermediate level of risk for bias.

3.3.2. Listing, mapping, and statistical analysis of the tools

3.3.2.1. Categorisation of the modelling techniques.. First, Appendix C longlists the fundamental features of the computational models applied in each study, including its method, goal, motivation, and focus. Next, we extracted and summarised a list of specific modelling techniques used in computer simulations, statistical models, AI, and other methods that guide readers to explore relevant literature in this space (see Table 4).

3.3.2.2. Statistical analysis of the models.. In general, computer simulation is the leading method used in computational modelling research applied to urban design and NPIs (roughly 60% of the papers), followed by statistical models (used in 18% of the studies), as presented in Fig. 8 (a). It is evident from Fig. 8(b) that, overall, nearly 70% of the studies adopted models for predictive goals, while only 28% for descriptive purposes. Similarly, most papers (73%) focused on exploring the mechanism other than describing the phenomenon (27%). As for the

Table 3
Urban design-related NPIs and detailed methods.

High-level interventions	Detailed urban design methods	Examples and explanation
Social distancing interventions	Encouragement to keep a defined physical distance	
	Avoiding crowding	Avoiding crowding in communities and limiting the risk of infection
	School and workplace measures and closures	
	Contact tracing	
Travel-related interventions	Internal travel restrictions	Restrictions in neighbourhoods and public transport.
Individual-level interventions	Individual behavioural changes	Mobility pattern changes; Avoiding going outside; mobility changes in retail and recreation
Building-level design interventions	Design/Redesign of indoor spaces	Physical separators between passengers and users in airports; Design of capacity and number of servers in stores; Design of hospital isolation beds capacity; Design of vertical traffic in buildings
	Ventilation	Indoor air quality (IAQ) management
	Modifying humidity	
Neighbourhood/ District-level design interventions	Design of public/open spaces	Street greenness design; Courtyards design; Greening of the community
	Pedestrian-friendly design	The presence of crosswalks; The number of intersections
City-level design interventions	Density	Population density; Density of sidewalks; Density of general hospital and commercial facilities
	Land use mixture	
	Transport accessibility	Including the number of bus stops and transfer stations
	Spatial connectivity	
Other interventions	Public facilities provision	Locations for point-of-dispensing facility setup; Public service design; Visible utility wires; Household-scale sanitation infrastructure planning; The number of indoor sports and recreational facilities
	Transport system specific design	Transit-oriented development (TOD); Road condition
	Mapping techniques	Identification and control strategies of high-risk places; Pandemic prevention mapping; Vulnerability zoning of diseases
	Urban design and planning methods	UV-based technologies; Building type; Urban structure; development intensity; Health impact assessment; Citizen engagement

motivation in using the models, the number of theory-driven models is relatively higher than data-driven ones, with 57% and 29% records, respectively, though many studies employed both. We investigated each modelling paper's primary, secondary, and tertiary indications to urban design processes. The models are primarily developed for supporting the prediction, analysis, and evaluation processes, while few models can directly support design and decision-making.

The fundamental goal, motivation, and focus of the different methods and their contribution to urban design are also listed in Fig. 8 (b). Computer simulation is advantageous to prediction, while statistical models are profitable for description. AI algorithms have been used for both goals. Most of the computer simulation models are theory-driven and focus on exploring mechanisms. However, statistical models and AI are highly data-driven, focusing on phenomena description. Therefore, to support urban design, computer simulation built upon theories could predict the evolvement of disease transmission and assess the effects of spatial changes in the built environment. On the other hand, statistical models treated by data can be adopted to analyse the status quo of the target areas (e.g. neighbourhoods, districts, and cities). A complement to the former methods, AI algorithm can support the evaluation, prediction, and analysis processes of urban planning.

3.4. *Intersection between computational modelling, urban design, and infectious diseases*

3.4.1. *Computational models and urban design*

Fig. 9 depicts the timeline of introducing different models and their indication for supporting different urban design processes. Historically, computer simulation has been frequently used to predict urban design intervention outcomes in response to infectious diseases. In the case of COVID-19 pandemic, predictive computer simulation models were initially adopted, after which descriptive statistical models were used, and the assistance of models for urban design has covered analysis and evaluation. This transition may result from an increase in data availability. Later, AI algorithms and other methods were used, and computer simulation tools were steadily introduced for design and decision-making processes.

Fig. 10 illustrates the correlation between three computational models and high- and low-level design interventions. Computer simulation is the dominant modelling method for social distancing, travel-related, individual- and building-level interventions. In particular, building-level strategies such as ventilation were merely tested by statistical models or AI. On the other hand, statistical models and AI were more likely to be used for neighbourhood- and city-level design approaches, particularly for testing city-level planning interventions such as land use mixture and transport accessibility.

Furthermore, to support designers and computer modellers to build corresponding models, we listed the critical parameters used in the literature to examine each design strategy, as shown in Table 5.

3.4.2. *Computational models, design interventions, and diseases*

We analysed the infectious diseases, interventions, and model methodologies discussed in each paper. Fig. 11 depicts relevance among the three elements. First, droplet transmission and human-to-human transmission attracted substantial attention in urban design and planning discourse. Encouragement to keep a defined physical distance and (re)design of indoor spaces are fundamental approaches, which got substantial assistance from computer simulation. Second, prevention of aerosol and fomite transmission were tested by ventilation strategies, (re)design of indoor spaces, and incentives to keep a defined physical distance. Note that ventilation interventions were proved by computer simulation only. Finally, animal-to-human and faecal-oral transmission modes were poorly controlled through urban design approaches. Additionally, the literature is unclear about the influence of several city-level planning interventions (i.e. land use mixture, transport accessibility, and spatial connectivity) on disease transmission mode.

4. Discussions – a proposed toolkit and answers to the research questions

Building on the analysis of the literature and supported by the detailed lists of references and data extraction presented in the supplementary materials, here, we propose a toolkit to allow planners to identify relevant methodologies (and based on the review, key papers to read as part of further applications). Next, the research questions are answered.

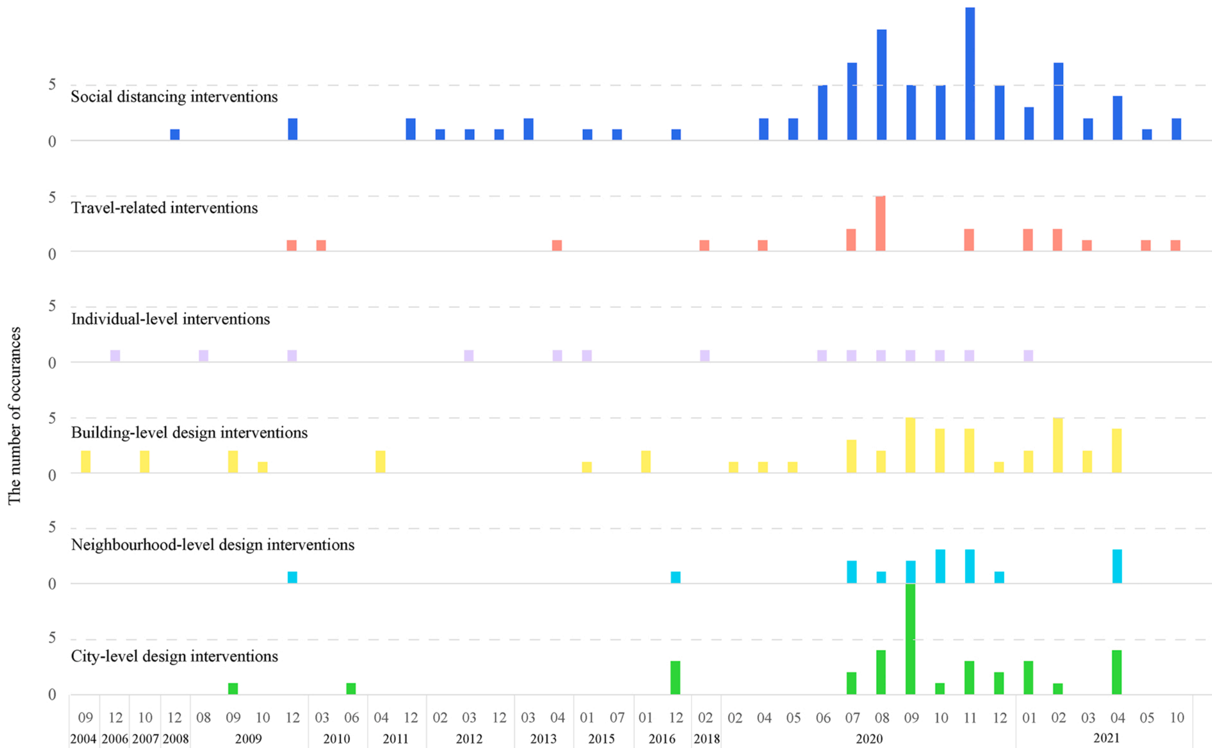

Fig. 5. The trend of the use of different urban design interventions over time.

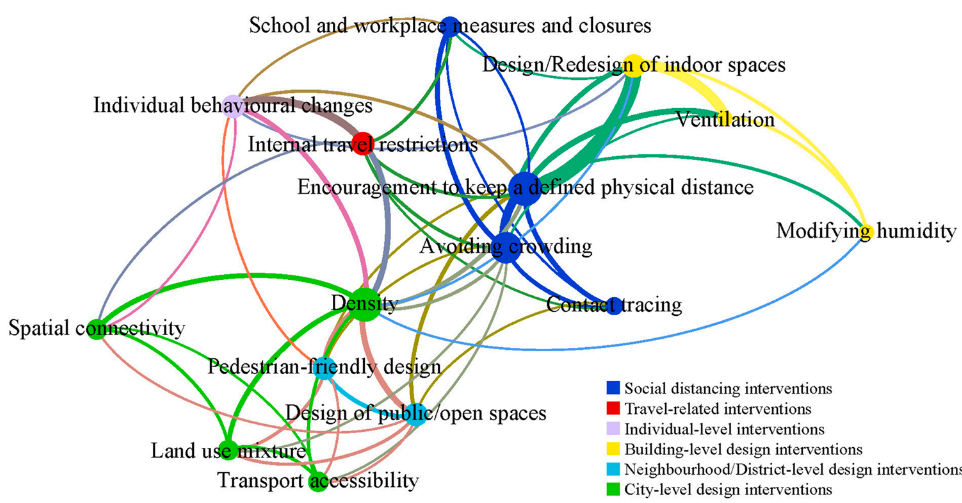

Fig. 6. The correspondence between design interventions. *Note.* The size of nodes indicates the times that this intervention appeared in all the papers, while the node colour indicates the type of high-level intervention. The width of links represents the strength of connection: the number of papers containing both interventions that the edge links.

4.1. The toolkit framework

As many countries move forward post-COVID (e.g. China, the origin country of the outbreak), the infection curve continues to flatten, and the disease comes under control. Nevertheless, to develop resilient and healthy cities, governors, researchers, and practitioners need to prepare for future public health emergencies and consider the lessons learned. This study, based on the analytical framework (Fig. 1) and the disease transmission phases (Section 2.1.1), proposes a toolkit for planning and design for responding to infectious disease epidemics/pandemics (see Fig. 12).

Taking COVID-19 as an example, this toolkit maps the various design interventions and computer modelling methods identified from the systematic review. The thickness of the lines between computational modelling methods and urban design interventions represents the number of articles that use the method to study or support the corresponding design intervention. The size of the arrows pointing from urban design interventions to infectious disease transmission phases indicates the number of studies for that intervention in the control or prevention of infectious diseases.

To respond to and prevent a pandemic effectively, interventions in urban design must be selected according to the current phase of disease transmission. Distinct interventions may be needed when the disease emerges, when widespread transmission occurs, and when effective interventions and herd immunity lead to control and a decline in transmission (WHO, 2018). By monitoring R_0 and case fatality rate to

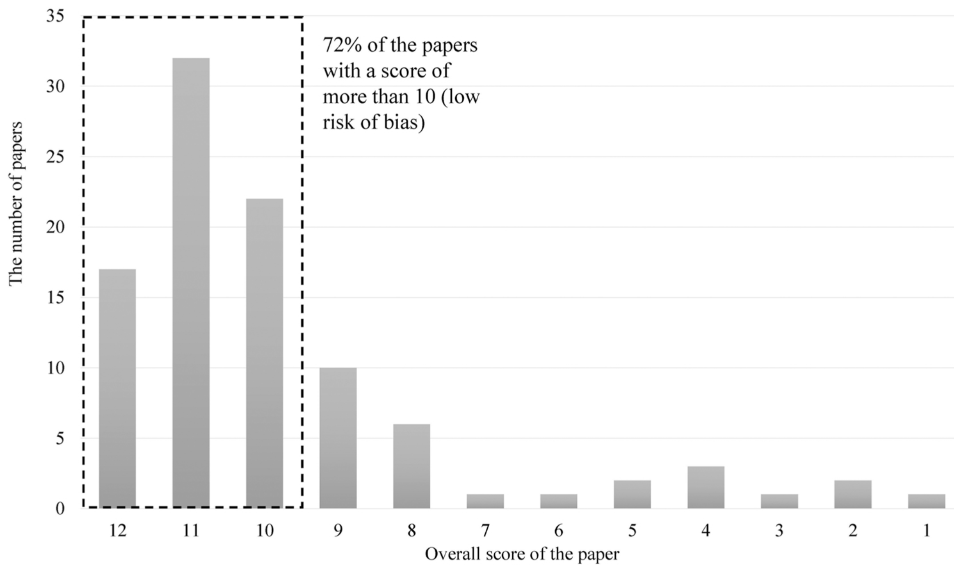

Fig. 7. The overall risk of bias of 98 modelling papers (excluding review papers and qualitative research articles) with “12” being the lowest risk and “1” the highest.

determine the current trajectory of the pandemic—and doing so on an appropriate scale for local, regional, or supra-regional interventions—decision-makers can select effective interventions from the toolkit we propose.

The tool also fits into the different stages of resilience—preparedness, response/absorption, recovery, and adaption—to assist in building resilient cities (Da Silva et al., 2011; Figueiredo et al., 2018). Before an outbreak/epidemic/pandemic is the preparedness stage when predictions of the infectious disease evolution and plans for managing such disasters are required. After an epidemic/pandemic breaks out, short-term responses can stop the chain of failures from the initial disruption. During the recovery period, cities will be reinstated, and life returns to normal with relevant adjustments. Finally, resilient cities should learn from the disaster and adapt their system to prepare for the future infectious diseases and potentially new variants of known diseases.

Simultaneously, this toolkit answers our research questions as follows.

4.2. *Urban design interventions and infectious diseases*

RQ1 & RQ2: Which types of infectious diseases can be counteracted by urban design, and what are their characteristics? Which design interventions have been tested or proven to be effective as part of the infection prevention and control?

4.2.1. *Types and transmission modes of viruses*

Urban design can limit the spread of two types of viruses, namely, human coronavirus (including SARS-CoV-2, SARS-CoV, MERS-CoV) and influenza viruses (including Influenza A[H5N1] virus, Influenza A [H1N1] virus). The former viruses are more detrimental than the latter ones. Furthermore, SARS-CoV-2 has a much higher R_0 than others within the human coronaviruses, although its case fatality rate is relatively low. These viruses then led to COVID-19, SARS, and MERS, as well as various influenza pandemics. Their transmission modes are mixed. The droplet is the primary mode, while aerosol and human-to-human transmission are secondary. Basic information on the infectious diseases investigated is concluded in Table 2.

4.2.2. *Urban design and planning interventions tested or proved to be effective*

This paper groups the urban design interventions discussed in the reviewed papers into six high-level types—namely, social distancing, travel-related, individual-level, building-level, neighbourhood/district-level, and city-level design interventionand 15 detailed methods (detailed in Table 3 and Appendix B).

First, social distancing attracted the most attention among the six high-level interventions not only during the COVID-19 but also in previous infectious diseases encountered. More specifically, maintaining a defined physical distance is the most potent strategy according to the papers reviewed. However, note that this is particularly true only in included papers where these strategies were analysed with computational models in the urban planning sphere. However, its impact remains unclear and highly dependent on the disease severity, transmission, and risk groups affected (E.K. Lee et al., 2009).

Second, building-level interventions (e.g. design/redesign of indoor spaces) and city-level design interventions (e.g. density) are significant. Some experts advocated a holistic plan for indoor air quality management in building design that includes proper ventilation, air filtration, humidity regulation, and temperature control (Megahed and Ghoneim, 2021). In city planning, the structure and organisation of cities, especially the urban transport system, proved to be essential for interfering with social distancing rates and the disease’s contagion rate (Leiva et al., 2020). Third, other research demonstrated that travel restrictions alone do not impact the overall attack rate; the pandemic and social distancing practices can alter intra-urban mobility patterns (E.K. Lee et al., 2009).

Finally, combination strategies increase the effectiveness of individual interventions and can be tailored for each scenario at organisational, community, national, and international levels. For example, several related interventions are: adherence to social distancing, (re) design of indoor spaces, and ventilation, which could be complementary strategies.

4.2.3. *Correspondence between viral transmission modes and design interventions*

Droplet transmission and human-to-human transmission received substantial attention in urban design and planning discourse. To help stop transmission, encouragement to keep a defined physical distance and (re)design of indoor spaces are fundamental approaches. Aerosol and fomite transmission tried to be controlled by ventilation strategies, (re)design of indoor spaces, and incentives to maintain a specified physical distance. Nevertheless, animal-to-human and faecal-oral transmission modes cannot be properly controlled through urban design interventions. Furthermore, the literature is unclear about the

Table 4
Specific model methods used in computer simulations, statistical models, AI, and other methods.

Method	Model	Reference
Computer Simulation	Compartment Model	Hao et al. (2020); Kain et al. (2021)
	Agent-Based Modelling	Block et al. (2020); Silva et al. (2020); Wei and Chen (2020); Hernandez-Mejia and Hernandez-Vargas (2020); Jorritsma et al. (2020); Bisset et al. (2012); Karimi et al. (2015); Gharakhanlou and Hooshangi (2020); Mao and Bian (2010); Milne et al. (2013); Novani et al. (2007); Renardy et al. (2020); Shuvo et al. (2020); Small and Cavanagh (2020); Ban et al. (2020); Vazquez-Prokopec et al. (2013); J. Wang et al. (2010); Xia et al. (2015); Zhou et al. (2006); Harweg et al. (2021); Farthing and Lanzas (2021); Patil et al. (2021); Mohammadi et al. (2021); Gomez et al. (2021); X. Li (2020); Roy et al. (2021); Fang et al. (2020); Q. Xu and Chraibi (2020)
	Micro Simulation	Ronchi and Lovreglio (2020)
	Discrete Event Simulation	Kierzkowski and Kisiel (2020); Ridenhour et al. (2011); Swinarski (2020)
	Cellular Automata	
	Monte Carlo Simulation	Dabachine et al. (2020); Larson and Nigmatulina (2010); F. Liu et al. (2021)
	System Dynamics	Lant et al. (2008)
	Particle Propagation Model	Kudryashova et al. (2021)
	Computational Fluid Dynamics	Leng et al. (2020); Miller et al. (2020); Satheesan et al. (2020); C. Sun and Zhai (2020); Yu et al. (2017); Domino (2021); H. Li et al. (2021); Yamakawa et al. (2021); Komperda et al. (2021); Z. Li et al. (2021); Sen and Singh (2021); Lim et al. (2011); Y. Li, Duan et al. (2005); Gao et al. (2008)
	Building Information Modelling	Pavon et al. (2020)
	Transient Systems Simulation	Balocco and Leoncini (2020)
Statistical Model	Applied Probability Model	Kaplan (2020); Tupper et al. (2020)
	Linear Regression	Cartenì et al. (2021); Hong et al. (2021)
	Multilevel Linear Modelling	Hamidi and Zandiatashbar (2021)
	Logistic Regression	Spencer et al. (2020)
	Negative Binomial Regression	Badr et al. (2020); Klompmaker et al. (2020); Rader et al. (2020)
	Ordinal Regression	Campisi et al. (2020)
	Path Modelling	Sung and Kwak (2016)
	Structural Equation Modelling	Hamidi et al. (2020); M.M. Rahman et al. (2020)
	Difference-in-Difference Regression	Y. Yang et al. (2021)
	Geographically Weighted Regression	X. Li et al. (2020); Ye and Qiu (2021)
	Getis-Ord Gi* Statistics	M.R. Rahman et al. (2020)
	Wells-Riley Related Model	Bazant and Bush (2021)
	Principal Component Analysis	Ye and Qiu (2021)
	Analytic Hierarchy Process	W. Xu, Xiang et al. (2021)
Artificial Intelligence	Machine Learning	Maghdid and Ghafoor (2020); Scarpone et al. (2020)
	Deep Neural Network	Q.C. Nguyen et al. (2020); Ramchandani et al. (2020); Rezaei and Azarmi (2020); Q.C. Sun et al. (2020); Selvakarthi et al. (2021); Shorfuzzaman et al. (2021)
	Deep Reinforcement Learning	Fang et al. (2020)
	Federated Learning	Pang et al. (2021)
Other Methods	Conceptual Frameworks	Dragoicea et al. (2020); Elavarasan et al. (2021); Qiu et al. (2020); UN-Habitat China, 2020; UN-Habitat and WHO (2020)
	Optimisation Methods (e.g. Nonlinear Mixed Integer Programming; Circle Packing)	Kudela (2020); E.K. Lee et al. (2009); Ugail et al. (2020); Gkiotsalitis and Cats (2021)
	Queueing Model	Perlman and Yechiali (2020)
	Graph-Based Mathematical Model (e.g. Routing Algorithm)	Subahi (2021); Klinker et al. (2021)
	Assessment Index (e.g. Level of Service Calculation; Distance- Cumulative Deficit Index)	Blečić et al. (2020); Di Mascio et al. (2020); Silalahi et al. (2020)

correspondence between several city-level planning interventions (i.e. land use mixture, transport accessibility, and spatial connectivity) and transmission modes.

4.2.4. Correspondence between disease transmission phases and design interventions

Taking COVID-19 as an example, this research finds that as the response varies from short to long term, the spatial scale of design interventions increases over time. After the infectious disease outbreak, social distancing, building-level designs, and travel-related and individual-level interventions can quickly mitigate the infection inflation at an early stage, usually during local transmission. With the disease spreading from local areas to communities, neighbourhood- and city-level interventions are needed to help cities recover from and adapt to the disaster. Finally, as the disease continues to amplify (when the epidemic/pandemic begins), national and international interventions such as lockdowns and air travel restrictions are required.

4.3. Computational modelling tools and design interventions

RQ3: Which computational modelling tools and parameters contribute to understanding infectious diseases mechanism or the impact of designs?

4.3.1. Longlisting and characteristics of the modelling tools

The dominant method (computer simulation, statistical models, AI, or other methods), goal (predictive, descriptive, or hybrid), motivation (theory-driven, data-driven, or hybrid), and focus (mechanistic, phenomenological, or hybrid) of these models are longlisted in Appendix C. A set of specific modelling techniques used in each modelling method and supporting references are summarised in Table 4 and Fig. 8. Table 5 presents critical parameters for the examination of each design strategy.

Computer simulation is the leading computational modelling method applied to analysing the effect of urban interventions on the spread of infectious diseases, followed by statistical models. Models were developed mainly for mechanism exploration and prediction in addition to phenomenon description, being primarily driven by theories or data, even though several models employed both. Computer simulation is particularly advantageous for prediction, while statistical models are profitable for description. AI algorithms have been used for both goals. Most computer simulation models are theory-driven with a focus on exploring mechanisms. However, statistical models and AI are highly data-driven, targeted at describing phenomena.

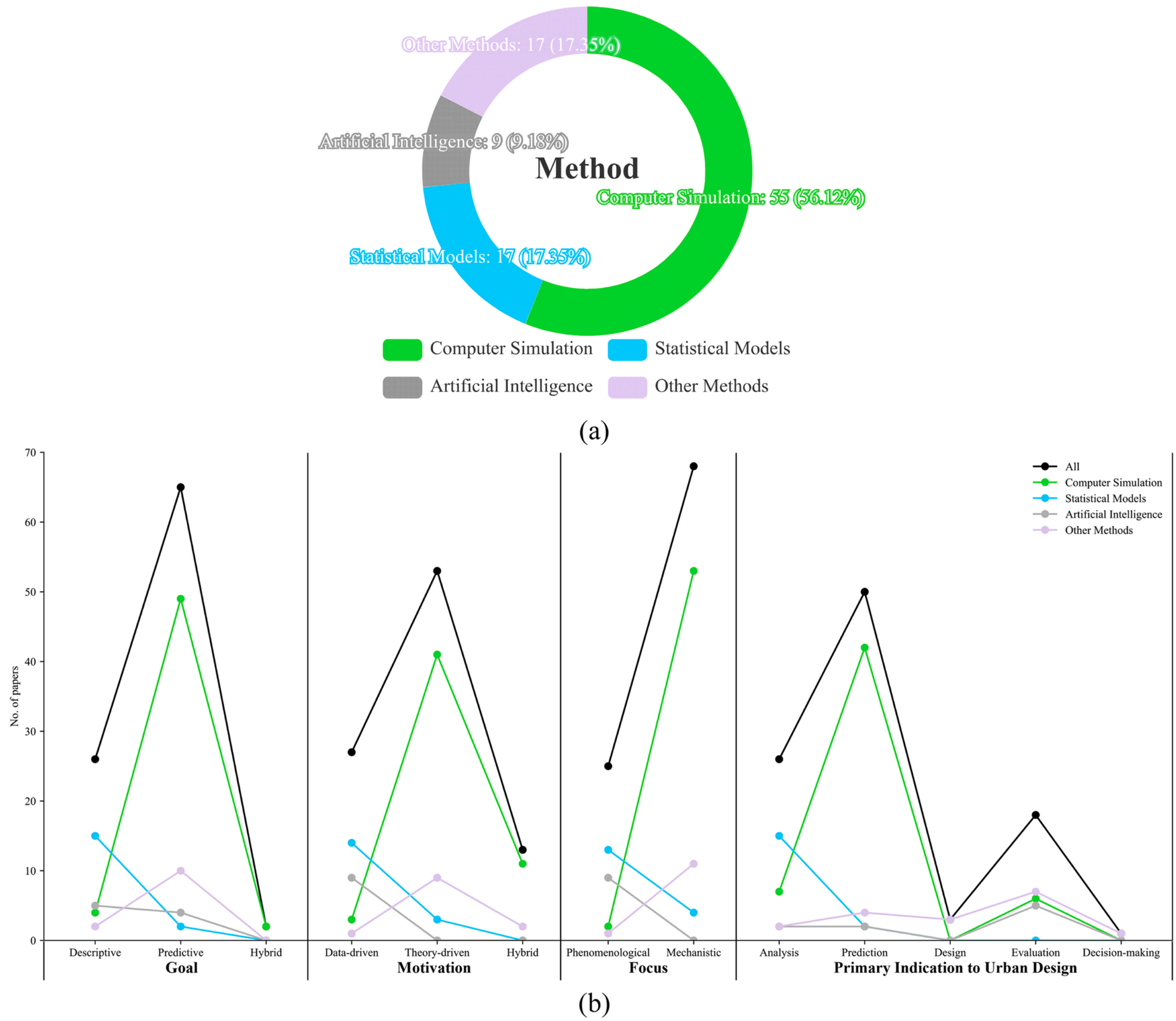

Fig. 8. Statistical analysis of (a) the method used and (b) the goal, motivation, focus, and the primary indication to urban design of the included 98 papers.

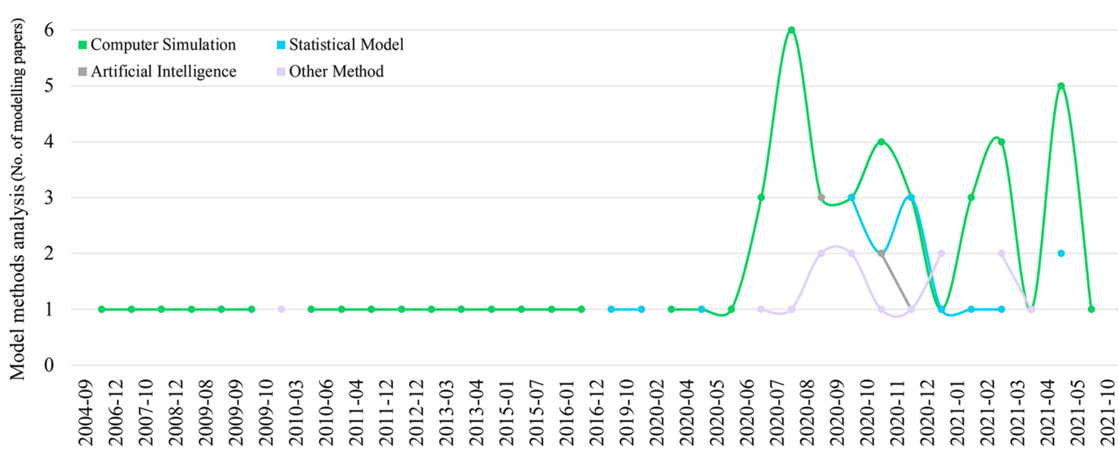

Fig. 9. Temporary analysis of the method of the models.

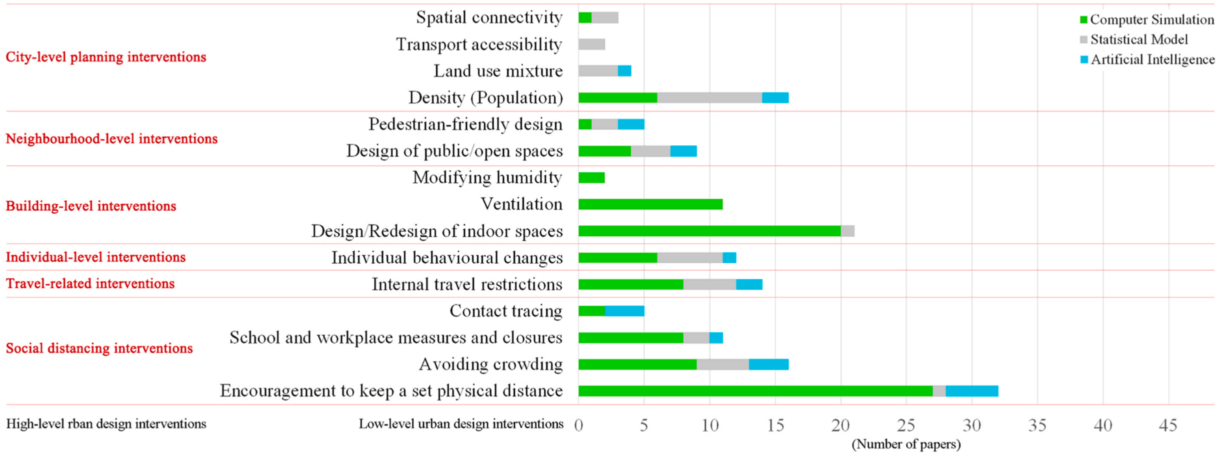

Fig. 10. The correspondence between urban design interventions and the computer modelling types.

4.3.2. Relationship between model types and design interventions

Computer simulation is commonly used to support social distancing, travel-related, and individual- and building-level interventions. In particular, building-level strategies such as ventilation were simply tested using computer simulation models. On the other hand, regarding neighbourhood/city-level design approaches, statistical models and AI are more likely to be used, particularly for testing city-level planning interventions such as land use mixture and transport accessibility.

4.3.3. Development of statistical models

Research (Tang et al., 2020) demonstrated that the following features should be considered in the development of statistical models: 1) the ability to make predictions and quantify prediction uncertainties and risk; 2) the ability to consider building sampling uncertainties in the modelling of infectious diseases; 3) the complexity of a model used for prediction should be aligned with the issue of parameter identifiability; 4) the ability to deliver an open-source software package that enables replication and wide-spread adoption.

4.3.4. Available AI techniques

AI algorithms were mainly used to assist in social distancing strategies such as contact tracing and encouragement to keep a defined physical distance which was spotted in the literature just after 2020. AI approaches include detection of suspected cases, large-scale screening, monitoring, interactions with experimental therapies, pneumonia screening, the Internet of Things (IoT) for data and information gathering and integration, resource allocation, predictions, modelling and simulation, and robotics for medical quarantine. These methods hold the potential to provide the best solutions for maximising safety and preventing the spread of infectious diseases (Adly et al., 2020). In particular, enabling wireless technologies (Wi-Fi, cellular, Bluetooth, Ultra-wideband, Global Navigation Satellite System (GNSS), Zigbee, and radio frequency identification (RFID)) has been increasingly used in symptom prediction, detection, monitorisation of quarantined people, and contact tracing (C. T. Nguyen et al., 2020).

4.4. Ways to integrate modelling into design processes

RQ4: How to choose suitable models and integrate them into urban design practices?

4.4.1. Choice of computational models

The most commonly used simulation models are compartment models, agent-based models, and computational fluid dynamics. Deterministic or simple stochastic compartment models such as the Susceptible-Exposed-Infectious-Recovered (SEIR) model are relatively easy to build and provide rapid policy-making results but lack heterogeneity. In contrast, agent-based models can simulate the interaction of disease, society, transportation, and the environment. They can, thus, generate system-level behaviour from the interaction and decisions of individuals in the population within a given environment (Hunter et al., 2017). Inevitably, agent-based simulation is more computationally intensive and requires good quality data to instantiate. Furthermore, using agent-based models for long-term forecasting is challenging and likely to lead to misleading results due to adaptive human behaviour and lack of data input (Adiga et al., 2020).

4.4.2. Indication of modelling to the urban design processes

The reviewed models were developed primarily to support prediction, analysis and evaluation, while few can directly support design and decision-making. More specifically, computer simulation built upon theories could predict disease transmission and assess the effects of spatial change on the built environment. Statistical models driven by data can be adopted to analyse the status quo of the target areas (e.g. neighbourhoods, districts, and cities). AI algorithms, a complement to the former methods, can support the evaluation, prediction, and analysis processes.

4.4.3. Gaps and challenges

There are, however, some gaps and challenges for the design and use of the previously mentioned models. There is a need to adopt AI and the IoT for examining infectious disease interactions with experimental therapies, patient resource allocation, epidemic/pandemic data gathering/integration, and medical quarantine (Adly et al., 2020).

4.4.3.1. Challenges for model input.. On the one hand, real-time data on behavioural adaptation and compliance (e.g. mobile phone data) remains very hard to obtain and this is one of the major modelling challenges. Data gaps early in the pandemic, especially on population infection rates over time, make it very difficult to accurately assess its impact and the disease severity (Van Kerkhove and Ferguson, 2012). To overcome this obstacle, surveillance systems should be improved (Adiga et al., 2020), while the population's privacy needs to be protected simultaneously. In addition, resource-rich countries should consider redistributing their resources for a greater global benefit if they are yet to be affected by the pandemic (E.K. Lee et al., 2009). On the other hand, though the epidemiological data supporting the models appear adequate in some cases, it should be validated through as many updates as possible during an outbreak. In addition, demographical datasets must improve its interfaces for access, retrieval, and translation into model parameters (Prieto et al., 2012).

Table 5
Urban design interventions and parameters used for modelling.

High-level interventions	Detailed urban design strategies	Parameters
Social distancing interventions	Encouragement to keep a defined physical distance	Interpersonal distance; Distance from source; Contact threshold distance; Distancing rule threshold; Different strategies of choosing contact partners; Distance between students and teacher; Fraction of transmission opportunities; The transmission probability; The threshold for edge cutting; long-range parameter; The safety distance; The proportion of people that heed the social distancing; The probabilities of social distancing; The maximum node degree threshold to truncate the scale-free network
	Avoiding crowding	Interpersonal distance; Population density; Exposure density (a measure of both the localised volume of activity in a defined area and the proportion of activity occurring in non-residential and outdoor land uses); Lloyd's index of mean crowding
	School and workplace measures and closures	The number of people avoiding going outside, crowded places, visiting hospitals, using public transport, going to work, and going to school; Workplace closing
	Contact tracing	
Travel-related interventions	Internal travel restrictions	Stringency index; Traffic restriction rate; Control-threshold and adjusting-frequency; Reduction factor of interpersonal contact
Individual-level interventions	Individual behavioural changes	Mobility ratio quantifying the change in mobility patterns; Ridership; Percentage change of mobility in retail and recreation trips, in transit stations trips, in workplaces trips, in residential trips; Travel habits trend after lockdown, public transport habits trend; Trip reduction to groceries/pharmacies, parks, and transit stations; Variations in neighbourhood activity; The mean value of the exponential distribution of the time spent at a given location; The frequency of individual travels
Building-level design interventions	Design/Redesign of indoor spaces	The area, depth and volume of a room; The configuration of a nursing facility and the implementation of negative pressure isolation spaces
	Ventilation	Air changes per hour; Air distribution effectiveness; Wind speed; Wind direction; Ventilation in the vicinity of doors, the extent of doors opening; With/without exhaust grilles, exhausting air rate; The opening of doors and windows, the functioning of bathroom exhaust fans; The locations of vents related to patients undergoing an aerosol-generating procedure
	Modifying humidity	Relative humidity
Neighbourhood/ District-level design interventions	Design of public/open spaces	Compactness Index; Contagion Index; Landscape Division Index; Shannon' Diversity Index; Shannon's Evenness Index; Dilapidated building, visible utility wires; Non-single family home; Sanitation coherence index
	Pedestrian-friendly design	Presence of crosswalks and sidewalks; Single-lane road; Street greenness
City-level design interventions	Density	Metropolitan population; Density of general hospital and commercial facilities; Percentage of urban land; The number of indoor sports and recreational facilities; Total building area, residential building area, commercial building area, and land use diversity; Variations in neighbourhood activity
	Land use mixture	Land use mix index
	Transport accessibility	Transport accessibility; Rail-based transport accessibility; Road and subway station density; The number of bus stops and transfer stations; The shortest distance to Central Business Districts (CBDs); The number of intersections
	Spatial connectivity	Street connectivity

4.4.3.2. Challenges for model development and validation.. The models often simplify reality to reduce the computational burden. Nevertheless, such simplification should not interfere with the performance assessment of the mitigation strategies. Existing models consider only a few social, behavioural aspects such as contact rates and compliance to social distancing; next-generation models need to explore more aspects. Finally, from a user's perspective, policymakers would prefer models scalable to any population size that can be downloadable and operable on personal computers.

Nevertheless, scaling models to larger populations often implies computational needs. Balancing between the scalability and computational demands is thus another challenge (Prieto et al., 2012). In addition, local epidemiological and modelling studies are needed to validate efficacy and feasibility (E.K. Lee et al., 2009).

4.4.3.3. Challenges for model dissemination and user engagement.. To provide insightful and timely information to policymakers, long-term forecasts of urban systems are not appropriate. Besides, assumptions underlying the models in line with what modelling can and cannot deliver should be stated as clearly as possible to set realistic expectations. Additionally, it should be admitted that the forecasts are provisional (Adiga et al., 2020). It is also vital to effectively communicate how prediction differs from scenario modelling. The failure to communicate uncertainty may lead to a misunderstanding of the modelling results (Van Kerkhove & Ferguson, 2012).

4.4.4. Implementation in real-world cases

At the early stage of an outbreak, research mainly focuses on figuring out the characteristics of the disease, predicting interactions between people, and exploring individual behaviour. Transmission modes and R_0

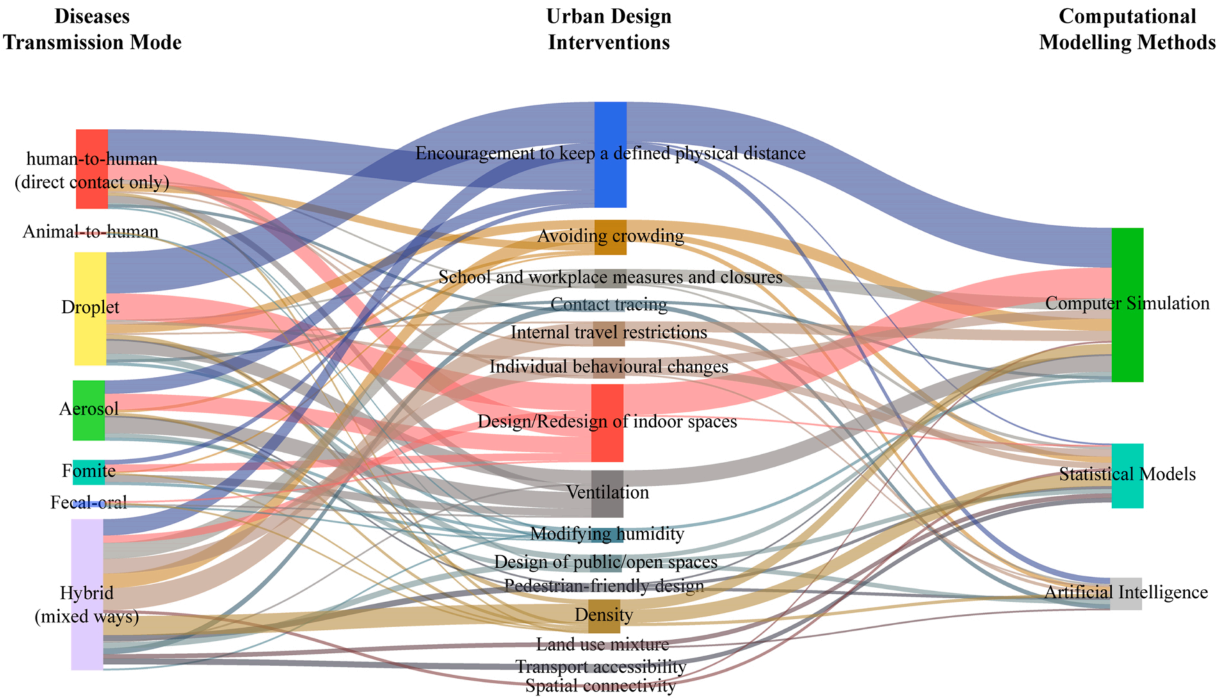

Fig. 11. The association among disease transmission modes, design interventions, and computational modelling methods. *Note.* The lines pointing to the left from "urban design interventions" represent the number of studies using each intervention to intervene in different modes of disease transmission. Lines directing to the right from "urban design interventions" mean the extent to which various computational modelling methods support each intervention, and the number of articles determines the width of the line.

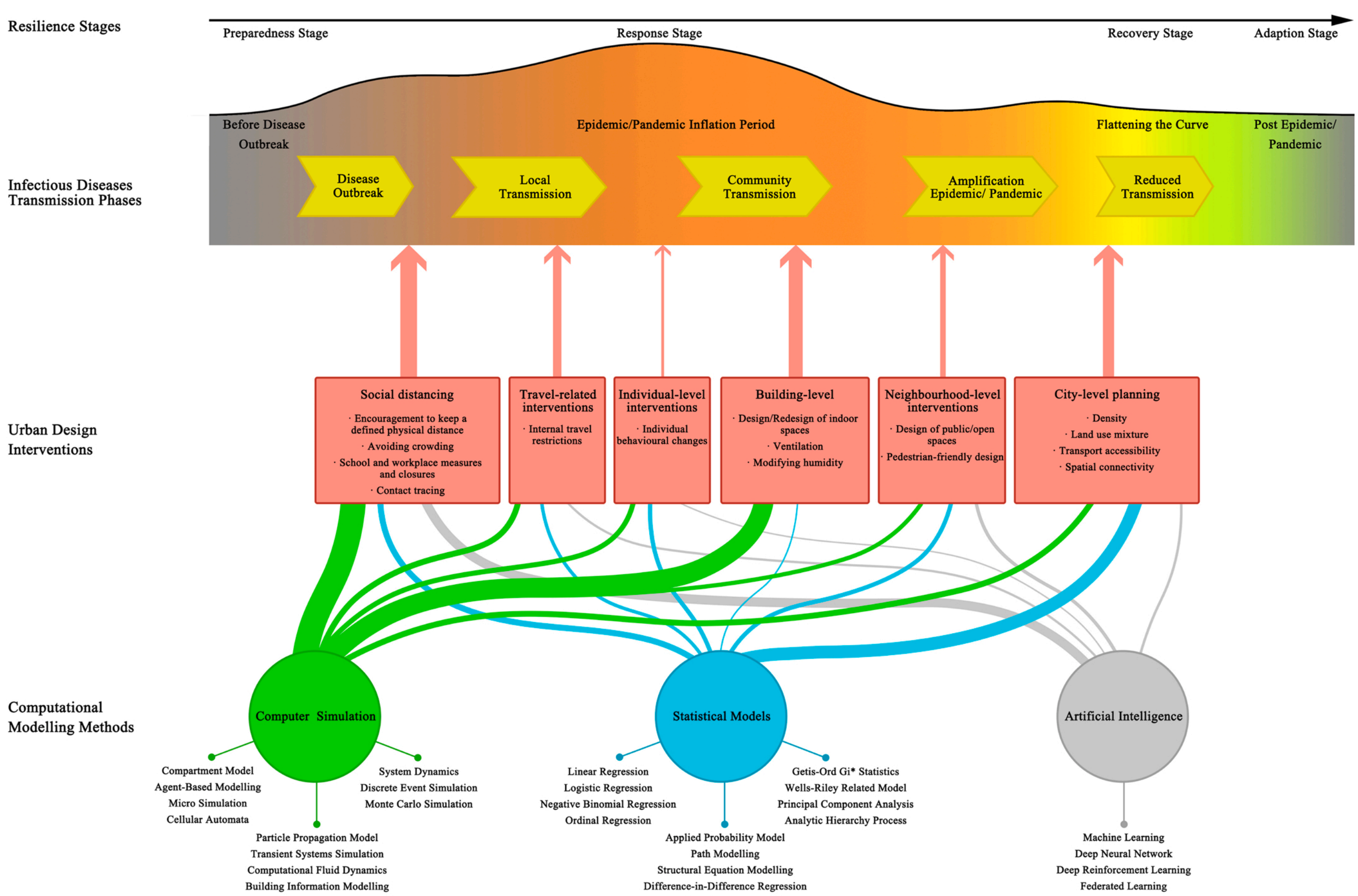

Fig. 12. A toolkit of computational modelling methods for urban design against infectious diseases.

are significant features of infectious diseases. Establishing computer simulation models and even some simple agent-based models are handy tools to predict disease progression and explore human behaviour due to a lack of data and a need for prompt responses.

Shortly after an outbreak, urban designers and planners respond to the disaster by proposing a set of physical interventions before vaccines, or other pharmaceutical interventions are developed. Therefore, research demands consist of identifying temporary (short-term) and permanent (long-term) interventions in the physical world and their spatial and temporal scales, and assessing the potential effects of design measures in terms of epidemic/pandemic mitigation and behavioural changes. Afterwards, models need to be built with adequate data collected. In this step, urban designers and modellers should engage with relevant stakeholders, e.g. governors, professionals, and citizens, to get feedback on a couple of shortlisted scenarios and collect ideas for additional scenarios to test. The modelling results then can be integrated into the decision-making process so that all stakeholders will decide on a final plan. Then, the steps for implementation and evaluation in the real world built environment should be identified, including monitoring of the effects over relevant longer time horizons. In doing so, cities hold the potential for adapting to infectious diseases and getting prepared for future epidemics/pandemics.

The toolkit presented in this paper is intended to be used as a guide to help raise the right questions, identify relevant academic literature, and suggest suitable modelling methods to be included in the development and application of decision-making support tools.

4.5. Other contributions and limitations

4.5.1. Contribution to multidisciplinary systematic review

The contribution of this systematic review also includes our collaborative, multidisciplinary approach to the systematic review process and this venture as a whole. We held team meetings regularly throughout the collaboration led by the first author and discussed the progress and task allocations. This led to the transparency of each activity, shared learnings across the disciplines, and the co-generation of strategies to address the emergent issues in the process. Moreover, this study built a rating tool to guide the risk of bias assessment, which could be used as a benchmark for future research design and model development.

4.5.2. Limitations of the review method

In this review, the literature on major known epidemics/pandemics in history was captured. This approach inevitably led to a limitation to cover different types of pathogens other than only viruses (that caused the significant pandemics) in our search. HIV/AIDS, for instance, was part of our exclusion criteria and omitted because the established interventions to prevent it are often geared towards individual sexual behaviour rather than changes in the built environment.

Our systematic review is limited by not using databases that explicitly cover dissertations and preprints. However, the remainder of grey literature was gathered through important organisational websites and by hand-searching of reference lists of the included studies. As the review topic is an emerging field, exclusion of preprint databases may lead to a limitation because scientific preprint servers would have guaranteed rapid and free access to the audience worldwide. Nevertheless, given our stepwise approach to peer-reviewed literature (two searches run in November 2020 and May 2021), we consider that this limitation was minimised. We also covered the dynamic periods of the outbreak and the full swing of the COVID-19 pandemic, as well as the emergence of new variants across the globe, where modelling results were used to predict the following wave and inform high-level decisions on NPIs.

4.5.3. Limitation of urban design and computational modelling in response to diseases

In response to infectious disease epidemics or pandemics, epidemiology, microbiology, and public health policy are fundamental disciplines, and the development of pharmaceutical interventions is essential. In comparison, the influence of architecture, urban design, and planning is limited in controlling the spread of infectious diseases. Although NPIs can break the chain of transmission, their effectiveness needs to be evaluated further and cannot replace pharmaceutical interventions. For example, after vaccines were developed, many cities lifted their social distancing regulations and travel restrictions. As a result, urban design and planning strategies against infectious diseases should be considered before disasters occur to prepare cities for risks in pursuit of resilience. For example, improving the ventilation system of buildings and flexible design of indoor and outdoor public spaces at the preparedness stage will strengthen cities' capability to resist infectious diseases transmission. The proposed toolkit can help identify relevant strategies and evaluation models.

Furthermore, the effect of urban design on disease mitigation is limited because controlling the spread of infectious diseases is simply one of the key performance indicators in the decision-making process of urban design and engineering construction. Decision-makers must balance various indicators covering environmental, economic, and social sustainability aspects. Such design and engineering implementation characteristics also indicate that the quantitative results generated by computer models provide partial support for designers and decision-makers who need to consider both quantitative and qualitative facts (e.g. aesthetics, cultural impacts).

5. Conclusion

This study began by recognising a lack of a coherent computer support toolkit that allows urban designers to evaluate the impacts of urban design interventions on the transmission of infectious diseases, including COVID-19, and incorporate public health recommendations in design decisions. To address this gap, a multidisciplinary systematic review of the state-of-the-art literature was conducted exploring the research at the interface of infectious diseases, urban design-related interventions, and computational decision-supports. This review initially found 8,737 papers in a broad selection of databases, 109 of which were included and analysed; these 109 papers used computational models to provide decision support for various interventions in the built environment. In addition, lessons from how research and applications worldwide dealt with COVID-19 and previous outbreaks of other infectious diseases were learned, highlighting where interventions at the building, urban, and national scale are of interest.

Consequently, we proposed a toolkit for urban designers, planners, and computer modellers by answering the four research questions raised at the beginning of our study. The toolkit longlists and maps various design interventions, targeting infectious diseases, and computer modelling tools for the whole urban design process in the infectious disease epidemic/pandemic context. The summaries allow experts to identify key strategies and literature sources depending on the type of the target infectious disease, geographic or medical context, design stages, and suitable spatio-temporal scales and resolutions. Furthermore, this toolkit can help designers find suitable models and metrics to evaluate the effects of various NPIs on, for example, the public space, transport infrastructure, work environment, homes, and to influence design decisions. The toolkit can also be incorporated into broader frameworks to promote resilient and healthy cities by preparing for, responding to, recovering from, and adapting to outbreaks of infectious diseases. At the same time, the models listed herein can be used as standalone tools specifically for post-COVID designs or as the complement of other models that assess key performance indicators related to environmental, economic, and social sustainability.

Admittedly, there is no universal solution or silver bullet solution to assist urban designers and decision-makers in rendering cities more resilient to COVID-19 and beyond. The discrepancies in the COVID-19 burden across the countries or within a country show the value of models that can be used in specific cases by providing context-dependent input data. At the same time, more fundamental changes might be required in a new location and design criteria. Urban design solutions can be part of integrated intersectoral solutions to respond to infectious diseases and help make design decisions to increase resilience.

Registration and protocol

The review was not registered. However, a brief review protocol was prepared in advance. The only amendment we made to this protocol during the systematic review was to conduct the second round of search six months after the first round of search to complement the results with newly accumulated evidence.

CRediT authorship contribution statement

Liu Yang: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Michiyo Iwami:** Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Yishan Chen:** Data Curation, Formal analysis, Investigation, Visualization. **Mingbo Wu:** Data Curation, Formal analysis, Investigation, Visualization. **Koen H. van Dam:** Conceptualization, Investigation, Resources, Writing – review & editing.

Competing interests

None.

Data availability

We will open our data to the audience once accepted.

Acknowledgments

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Appendix A

Characteristics of the qualitative research and review papers.

Author (Year)/ Diseases	Main contributions, key findings, and research gaps of the studies
Qualitative research	
Adiga et al. (2020)/COVID-19	A summary of key computational models for COVID was provided, finding that: 1) The susceptible-exposed-infectious-removed (SEIR) model lacked heterogeneity but are simple to programme and analysed. The agent-based model (ABM) is more computationally intensive, requires a fair bit of data to instantiate but captures the heterogeneity of the underlying countries. By now, it is clear that the use of such models for long term forecasting is challenging and likely to lead to misleading results due to adaptive human behaviour and lack of data about it. 2) Forecasting models use data-driven methods as well as causal methods. Given the intense interest in the pandemic, much data is also becoming available for researchers to use, which helps in validating some of the models further. Even so, real-time data on behavioural adaptation and compliance remains very hard to get and is one of the central modelling challenges. 3) To provide valuable and timely information to the policy-makers, it is not prudent to provide long term forecasts for such systems. However, assumptions underlying the models should be stated as clearly as possible. Besides, it should be admitted that the forecasts are provisional, and they will be revised as new data comes in. 4) Surveillance systems should be improved to produce data for models, and sustained investments are needed to prepare for the next pandemic's impact.
Barbosa et al. (2018)/Pandemic influenza	A comprehensive list of data sources used for empirical studies was provided. Key metrics, measures, spatio-temporal scales, and an overview of the fundamental physics behind human mobility studies were introduced. Novel models that best describe the empirical observations of human mobility were described and categorised, with some selected applications presented.
Grantz et al. (2020)/COVID-19	Best practices and potential pitfalls for directly integrating mobile phone data collection, analysis, and interpretation into public health decision-making were discussed.
Leiva et al. (2020)/COVID-19	National and regional data available from official bodies and other empirical studies on COVID-19 were analysed in the light of theoretical studies on urban mobility. Scientific findings include: 1) The urban structure and the organisation of cities interfere in social distancing rates and the disease's contagion rate. 2) Structure of the urban transport system plays a vital role in the pace of COVID-19 dissemination. 3) The pandemic and practices of physical and social distancing alter patterns of intra-urban mobility.
Tang et al. (2020)/COVID-19	The research demonstrated that statistical models should consider the following features in their design and development: 1) To make predictions and, more importantly, to quantify prediction uncertainties. 2) The consideration of building sampling uncertainties in the modelling of infectious disease is a fundamental difference of a statistical modelling approach from a mechanistic modelling approach. 3) Given the scarcity of the available data in public health surveillance systems, the complexity of a model used for prediction should be aligned with the issue of parameter identifiability. 4) To make research findings transparent and place resulting toolboxes into the hands of practitioners, an open-source software package must be deliverable.
Van Kerkhove and Ferguson (2012)/H1N1 influenza	The paper highlighted that modelling is not a substitute for data. Instead, modelling provides a means for making optimal use of the available data and determining the type of additional information needed to address policy-relevant questions. Challenges of modelling are: 1) To set realistic expectations, improved communication between policy-makers and the public (what modelling can and cannot

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Author (Year)/ Diseases	Main contributions, key findings, and research gaps of the studies
	deliver) is essential. It is also vital to effectively communicate how prediction differs from scenario modelling. 2) The failure to communicate uncertainty is problematic and led to a misunderstanding of modelling results during the 2009 pandemic. 3) The data available often failed to match the information needs of policy-makers. 4) Fundamental data gaps early in the pandemic, especially on population infection rates over time, made it very difficult to accurately assess its impact and disease severity.
Review	
Adly et al. (2020)/COVID-19	1) Ten most recent AI approaches were suggested to provide the best solutions for maximising safety and preventing the spread of COVID-19, including detection of suspected cases, large-scale screening, monitoring, interactions with experimental therapies, pneumonia screening, use of the IoT for data and information gathering and integration, resource allocation, predictions, modelling and simulation, and robotics for medical quarantine. 2) No studies were found regarding the use of AI to examine COVID-19 interactions with experimental therapies, AI for resource allocation to COVID-19 patients, or the use of AI and the IoT for COVID-19 data and information gathering/integration. 3) There is a need for the adoption of other approaches for COVID-19 prediction and the use of AI robotics for medical quarantine.
E.K. Lee et al. (2009)/Pandemic influenza	1) Deterministic or simple stochastic compartmental models are much easier to build and may provide rapid policy-making results. This is especially true in countries where the vast amounts of data required for individual-based and complex stochastic models may not be available. 2) Local epidemiological and modelling studies are needed to validate efficacy and feasibility. 3) Combination strategies increase the effectiveness of individual strategies. However, combination strategies have to be tailored for each scenario at organisational, community, national, and international levels, and more evidence is needed through targeted research. 4) Resource-rich countries should consider redistributing their resources for the more significant global benefit and their own benefit if they have yet to be affected by the pandemic. 5) Social distancing has been widely used in epidemics, but its impact remains unclear and highly dependent on the disease severity, transmission, and risk groups affected. Travel restrictions alone did not impact the overall attack rate. Reducing air travel is effective in delaying pandemic spread.
C.T. Nguyen et al. (2020)/COVID-19	Enabling wireless technologies (Wi-Fi, cellular, Bluetooth, Ultra-wideband, GNSS, Zigbee, RFID) were discussed, especially in social distancing, e.g. symptom prediction, detection, and monitoring quarantined people, and contact tracing. Seven groups of practical social distancing scenarios were identified.
Prieto et al. (2012)/Pandemic influenza	23 models published between 1990 and 2010 were identified that consider single-region outbreaks and multi-pronged mitigation strategies, finding that: 1) Though the epidemiological data supporting the models appear adequate, it should be validated through as many updates as possible during an outbreak. In addition, demographical data must improve its interfaces for access, retrieval, and translation into model parameters. 2) The models often simplify reality to reduce the computational burden, which is permissible if they do not interfere with the performance assessment of the mitigation strategies. 3) Social behaviour is inadequately represented in pandemic influenza models. 4) The models consider only a few social behaviour aspects, including contact rates, withdrawal from work or school, compliance to social distancing, vaccination, and antiviral prophylaxis. 5) Policy-makers would prefer models scalable to any population size that can be downloadable and operable in personal computers. Nevertheless, scaling models to larger populations often requires computational needs that cannot be handled with personal computers and laptops.
Megahed and Ghoneim (2021)/COVID-19	The research proposes holistic engineering solutions and conceptual models to improve IAQ based on the hierarchy of hazard control and recommendations. A conceptual framework was presented aiming at helping architecture ensure sufficient ventilation in the design process while managing the risk related to the COVID-19 pandemic. Ventilation-related interventions, UV-based technologies, and biofiltration systems were reviewed. For future human-centred designs, buildings require a holistic IAQ management plan that includes proper ventilation, air filtration, humidity regulation, and temperature control. Computer-aided design (CAD) tools have continuously improved to simulate natural ventilation and air distribution. Besides, building information modelling (BIM) and computational fluid dynamics (CFD) has made it easier for architects to access airflow simulation tools.

Appendix B

Characteristics of the studies: the type of interventions tested and spatial as well as temporal resolutions and scales.

Author (Year)	Type of interventions tested	Spatial resolution	Spatial scale	Temporal resolution	Temporal scale
Adiga et al. (2020)	Individual behavioural changes; Encouragement to keep a defined physical distance; School and workplace measures and closures	–	–	–	–
Adly et al. (2020)	Contact tracing	–	–	–	–
Badr et al. (2020)	Individual behavioural changes; Internal travel restrictions	1 county	Country scale (25 counties)	1 day	110 days (a dataset); 1 day (simulation)
Balocco and Leoncini (2020)	Ventilation Indoor air quality management Design/Redesign of indoor spaces	–	Building scale (school building)	1 hour	7 days
Barbosa et al. (2018)	Individual behavioural changes; Internal travel restrictions	–	–	Multi-resolution	–
Blečić et al. (2020)	Transport accessibility; Design of public/open spaces	1 street/neighbourhood	City scale (31 neighbourhoods)	–	–
Block et al. (2020)		–	(an ideal-type social network was used)	–	–

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Author (Year)	Type of interventions tested	Spatial resolution	Spatial scale	Temporal resolution	Temporal scale
	Individual behavioural changes; Encouragement to keep a defined physical distance				
Campisi et al. (2020)	Individual behavioural changes; Pedestrian-friendly design	1 city	Region scale (Sicily)	1 day	1 month (a dataset)
Cartenì et al. (2021)	Transport accessibility	1 province (zonal scale)	Country scale (105 administrative provinces)	1 day	60 consecutive days (a dataset)
Dabachine et al. (2020)	Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	0.001 m	Building scale (airport)	1 s (minimum); 10 minutes (buffer time)	18 hours
Di Mascio et al. (2020)	Design/Redesign of indoor spaces	1 m x 1 m	Building scale (airport)	1 s	1 hour
Dragoicea et al. (2020)	public service design	–	City scale	–	–
Silva et al. (2020)	Encouragement to keep a defined physical distance	1 m	Multi-scale: building – parcel – city block – sub-region – region	1 s	–
Grantz et al. (2020)	Contact tracing; Avoiding crowding; Internal travel restrictions	–	–	–	–
Wei and Chen (2020)	Encouragement to keep a defined physical distance	–	–	–	–
Hamidi et al. (2020)	Density; Spatial connectivity	1 county	Country scale (913 counties)	1 day	2 months (a dataset)
Hamidi and Zandiatashbar (2021)	Individual behavioural changes; Internal travel restrictions; Density	1 county	Country scale (771 counties)	1 day	5 weeks (a dataset)
Hao et al. (2020)	Internal travel restrictions; Density	1 block	City scale (675 blocks)	30 minutes	500 days
Hernandez-Mejia and Hernandez-Vargas (2020)	Encouragement to keep a defined physical distance; Avoiding crowding; Design/Redesign of indoor spaces	1 cm	Building scale (a small size supermarket)	1 minute	15~40 minutes
Jorritsma et al. (2020)	Encouragement to keep a defined physical distance; Internal travel restrictions	–	No spatial scale stated (a virtual network provided)	1 day	45~1200 days
Bisset et al. (2012)	School and workplace measures and closures	–	Region/Country scale	1 minute	–
Kain et al. (2021)	Encouragement to keep a defined physical distance	1 city	City scale (5 cities)	4 hours	1 day ~ 6 months
Kaplan (2020)	School and workplace measures and closures; Avoiding crowding; Design/ Redesign of indoor spaces	Multi-resolution: 1 hospital – 1 university campus – 1 state	Multi-scale: hospital – university – state scale	1 day	1 month ~ 1 year
Karimi et al. (2015)	Individual behavioural changes; Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	0.01 m	Neighbourhood scale (university campus)	1 minute	70 days
Kierzkowski and Kisiel (2020)	Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	1 m	Building scale (airport)	1 hour	results are averaged to 1 hour
Klompmaker et al. (2020)	Density; Design of public/open spaces	1 county	City scale (3,089 counties)	1 day	2 months (a dataset)
Kudela (2020)	Encouragement to keep a defined physical distance	–	–	1 s	24 hours
Lant et al. (2008)	School and workplace measures and closures	–	Neighbourhood scale (university campus)	1 day	12 weeks
Larson and Nigmatulina (2010)	Individual behavioural changes	1 sub-group in a community	Community scale (a few communities)	1 day	30 days
E.K. Lee et al. (2009)	Locations for point-of-dispensing facility setup; Design/Redesign of indoor spaces	1 mile x 1 mile	District scale (11 districts consisting multiple counties)	1 s	36 hours
V.J. Lee et al. (2009)	Individual behavioural changes; Avoiding crowding; Internal travel restrictions; School and workplace measures and closures; Design of public/open spaces	–	–	–	–
Leiva et al. (2020)	Density; Internal travel restrictions; Urban structure	1 city	City scale (6 cities)	1 day	5 months (a dataset)
Leng et al. (2020)	Design of public/open spaces	0.1 m x 0.2 m	Building scale (courtyard)	1 s	1 hour
X. Li et al. (2020)	Land use mixture; Urban growth; Density of general hospital and commercial facilities; Road and subway station density	1 km2 (a grid)	City scale (1025 communities)	1 day	20 days (a dataset)
Maghdid and Ghafoor (2020)	Contact tracing; Encouragement to keep a defined physical distance; Avoiding crowding	GPS accuracy	City scale	1 s	–
Gharakhanlou and Hooshangi (2020)	Encouragement to keep a defined physical distance	2 m x 2 m	City scale	15 minutes	75 days

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Author (Year)	Type of interventions tested	Spatial resolution	Spatial scale	Temporal resolution	Temporal scale
	School and workplace measures and closures				
Mao and Bian (2010)	Internal travel restrictions; Identification and control strategies of high-risk places	50 m x 50 m	City scale	1 day	120 days
S.L. Miller et al. (2020)	Design/Redesign of indoor spaces	0.1 inch	Room scale (a hall in a skilled nursing facility)	1 s	7 days
Milne et al. (2013)	School and workplace measures and closures; Avoiding crowding	–	City scale (2 cities)	7 hours	150 days
C.T. Nguyen et al. (2020)	Contact tracing; Encouragement to keep a defined physical distance; School and workplace measures and closures; Avoiding crowding; Internal travel restrictions; Density; Design of public/open spaces	–	–	–	–
Novani et al. (2007)	Modifying humidity; Density	–	City scale	1 s	–
Perlman and Yechiali (2020)	Design/Redesign of indoor spaces	1 building	Building scale (store)	1 hour	–
Prieto et al. (2012)	School and workplace measures and closures; Individual behavioural changes	–	–	–	–
Q.C. Nguyen et al. (2020)	Land use mixture; Design of public/open spaces; Pedestrian-friendly design; Single lane road; Building type; Visible utility wires	Multi-resolution: 640 pixels x 640 pixels (image resolution); 1 neighbourhood (zip code-level)	Country scale	–	1 day ~ 3 months ~ 4 years (datasets)
Rader et al. (2020)	Avoiding crowding; Density	Multi-resolution: 1 km x 1 km (a grid); 1 city	Global scale (310 cities across the world)	1 day	7~300 days
M.R. Rahman et al. (2020)	Vulnerability zoning of disease	1 district	Country scale (64 districts)	1 day	154 days (a dataset)
M.M. Rahman et al. (2020)	Individual behavioural changes; Internal travel restrictions; School and workplace measures and closures	1 country	Global scale (88 countries)	1 day	5 weeks (a dataset)
Ramchandani et al. (2020)	Individual behavioural changes; Internal travel restrictions; Density	1 county	City scale (3146 counties)	1 day	84 days
Renardy et al. (2020)	School and workplace measures and closures; Avoiding crowding	–	County scale	1 day	90 days
Rezaei and Azarmi (2020)	Contact tracing; Encouragement to keep a defined physical distance; Design of public/open spaces	–	–	1 s	–
Ridenhour et al. (2011)	Contact tracing; School and workplace measures and closures	1 m	Building scale (school)	1 s	1 day
Ronchi and Lovreglio (2020)	Encouragement to keep a defined physical distance; Avoiding crowding; Design/Redesign of indoor spaces	–	Building scale	1 s	–
Satheesan et al. (2020)	Ventilation	Multi-resolution: 0.167±0.012 μm (diameter of particles); 0.001 m (minimum length); 1.2 (mesh grid spacing)	Building scale (inpatient ward cubicle)	1 s	–
Scarpone et al. (2020)	Density	Multi-resolution: 100 m; 1 county	Country scale (401 counties)	–	2 months (a dataset)
Shuvo et al. (2020)	Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	–	Building scale (hospital)	12 hours	200 days
Small and Cavanagh (2020)	Contact tracing; Avoiding crowding	–	City scale	1 day	240~300 days
Spencer et al. (2020)	Household-scale sanitation infrastructure planning	1 commune	Country scale	–	2 years
C. Sun and Zhai (2020)	Ventilation; Encouragement to keep a defined physical distance	Multi-resolution: 1 μm (diameter of particles); 0.1 m (minimum height)	Room scale (a high speed train)	1 s	–
Q.C. Sun et al. (2020)	Heat mitigation interventions; Pedestrian-friendly design	Multi-resolution: 2 pixels x 2 pixels (google street view images dataset); 10 m (interval along streets); 30 m (satellite thermal images dataset)	Mesh block scale (the smallest spatial unit tracked in the Australian census)/ City scale	–	–
Sung and Kwak (2016)	Avoiding crowding; Density; Land use mixture; Pedestrian-friendly design; Transport accessibility; TOD design	A station area with a radius buffer of 500 m	City scale (238 railway stations)	–	1 month
Swinarski (2020)	Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	–	Building scale (a 12-floor university classroom building)	1 s	210 minutes
Ban et al. (2020)	School and workplace measures and closures	–	City scale	1 day	–
Tang et al. (2020)	Internal travel restrictions	– –	Country/Community scale –	– –	– –

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Author (Year)	Type of interventions tested	Spatial resolution	Spatial scale	Temporal resolution	Temporal scale
Van Kerkhove and Ferguson (2012)	School and workplace measures and closures				
Vazquez-Prokopec et al. (2013)	Individual behavioural changes; Internal travel restrictions	4.4 m and 10.3 m (point and line; GPS accuracy)	Neighbourhood scale (2 neighbourhoods)	2.5 minutes (minimum unit); 15 minutes (time step)	14 days
J. Wang et al. (2010)	Density	1 block	City scale	1 day	90 days (a case study)
Xia et al. (2015)	School and workplace measures and closures	Multi-resolution: 0.1 km, 1 ward (an administrative region in India)	City scale (114 wards)	5 minutes	300 days
Yu et al. (2017)	Ventilation; Design/Redesign of indoor spaces	Multi-resolution: 1 mm (mesh network), 0.0001 μm (diameter of droplets)	Room scale (a ward in a hospital building)	0.1 s	100 s
Zhou et al. (2006)	Individual behavioural changes	–	–	–	–
Domino (2021)	Encouragement to keep a defined physical distance; Design of public/open spaces	Multi-resolution: 16 μm (diameter of particles); 0.1 cm (mesh grid spacing)	An outdoor open space of 20 m x 20 m x 2.5 m	0.1 s	60 s
Bazant and Bush (2021)	Ventilation; Modifying humidity; Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	Multi-resolution: 0.1 μm (diameter of particles); 0.1 m (minimum length of the room)	Room scale (room volume 10~104 m3; a classroom and an elder care facility)	1 minute	1 day
Elavarasan et al. (2021)	Contact tracing; Encouragement to keep a defined physical distance	–	–	–	–
Subahi (2021)	Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	0.01 m	Room scale (an indoor public space, 200 m maximum distance)	0.001 s	1.176 s
Harweg et al. (2021)	Encouragement to keep a defined physical distance; Density; Design/Redesign of indoor spaces	1/8 m	Room scale (a supermarket of 80 m x 60 m)	0.5 s	15 minutes
H. Li et al. (2021)	Encouragement to keep a defined physical distance	Multi-resolution: 8~16 μm (diameter of particles); 0.1 m (minimum length)	Room scale (an indoor environment)	0.1 s	10 s
Ugail et al. (2020)	Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces; Ventilation	1 m	Room scale (a typical indoor public space of 150 m x 100 m was tested)	–	–
Farthing and Lanzas (2021)	Ventilation; Encouragement to keep a defined physical distance; Avoiding crowding	1 m x 1 m	Room scale (1 ~ ∞ m2)	1 minute	150 minutes
Patil et al. (2021)	Individual behavioural changes; Internal travel restrictions; Density; Spatial connectivity	100 m (population distribution data)	City scale (with a buffer of 1 km)	–	–
Pang et al. (2021)	Internal travel restrictions; Avoiding crowding; School and workplace measures and closures	1 city	multiple cities	1 day	21 days
Yamakawa et al. (2021)	Ventilation; Modifying humidity; Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	Multi-resolution: 0.9~1500 μm (diameter of particles); 0.005 m (minimum length)	Room scale (a classroom of 7.5 m x 8.0 m x 3.0 m)	1 s	90 minutes
Komperda et al. (2021)	Ventilation; Design/Redesign of indoor spaces	Multi-resolution: 20~220 μm (diameter of particles); 0.01 m (minimum length)	Building scale (a dentistry clinic of 24.1 m x 13.1 m x 3.0 m, consisting of 25 patient treatment cubicles)	0.001 s	several days
Mohammadi et al. (2021)	Encouragement to keep a defined physical distance; Density; Design of public/open spaces; Pedestrian-friendly design	0.1 m	Street scale (a virtual pedestrian walkway of 20 m x 3 m)	1 s	10 minutes
Z. Li et al. (2021)	Encouragement to keep a defined physical distance	Multi-resolution: 1~300 μm (diameter of particles); 0.1 m (mesh grid spacing)	Building scale (an escalator of 20 m x 3 m)	50 μs	8 s
Tupper et al. (2020)	Encouragement to keep a defined physical distance; Avoiding crowding	1 m	Room scale (an indoor public space, e.g. a place hosts a choir)	0.5 hour	hours (e.g. 30 hours)
Selvakarthi et al. (2021)	Encouragement to keep a defined physical distance	–	Room scale/Building scale (indoor transportation spaces)	–	–
Hong et al. (2021)	Individual behavioural changes; Density; Internal travel restrictions	1 m	Multi-scale: neighbourhood scale (aggregated to a 250 ×250 grid); 177 zip code tabulation areas	1 hour	3 months (a dataset)
Silalahi et al. (2020)	Transport accessibility	1 km	City scale (261 villages)	1 day	44 days (a dataset of confirmed cases)
Megahed and Ghoneim (2021)	Ventilation; UV-based technologies; Design/Redesign of indoor spaces	Building scale	Building scale	–	–

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Author (Year)	Type of interventions tested	Spatial resolution	Spatial scale	Temporal resolution	Temporal scale
Gomez et al. (2021)	Internal travel restrictions	1 district	City scale	1 hour	100 days
X. Li (2020)	Density; Encouragement to keep a defined physical distance	1 m	(a small social environment)	1 day	50 weeks
Klinker et al. (2021)	Avoiding crowding; Internal travel restrictions	1 m	Building scale (a public transport station)	0.1 minute	60 minutes
Roy et al. (2021)	Avoiding crowding; Encouragement to keep a defined physical distance	GPS accuracy (20 m)	Multi-scale: 1 indoor space (100 ft x 100 ft) – 1 city	1 minute	100 minutes
Fang et al. (2020)	Internal travel restrictions	GPS accuracy	City scale	2 hours	100 days
Q. Xu and Chraibi (2020)	Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	0.2 m x 0.2 m	Room scale (a supermarket of 34 m x 18 m)	0.05 s	1600 s
Gkiotsalitis and Cats (2021)	Encouragement to keep a defined physical distance; Internal travel restrictions	–	City scale	1 hour	1 day
Pavon et al. (2020)	Encouragement to keep a defined physical distance; Avoiding crowding; Design/Redesign of indoor spaces	1 room	Building scale (a large public building of 38,970.84 m2 in a campus)	1 hour	1 year
Kudryashova et al. (2021)	Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	Multi-resolution: 0.5~20 μm (diameter of particles); 0.1 cm (minimum length)	Room scale (a confined space)	0.001 s	minutes or hours
Qiu et al. (2020)	Density; Land use mixture; Spatial connectivity; Transport accessibility	–	1 city	–	–
Liu et al. (2021)	Encouragement to keep a defined physical distance; Design/Redesign of indoor spaces	Multi-resolution: 40 μm (diameter of particles); 0.01 (minimum length)	Room scale (an indoor environment, longer than 6 m)	1 minute	30 minutes
W. Xu et al. (2021)	Density; Design of public/open spaces; Road condition	Street/neighbourhood scale	3 communities	–	–
Shorfuzzaman et al. (2021)	Contact tracing; Encouragement to keep a defined physical distance; Avoiding crowding	1280 px x 720 px (video resolution)	–	1 s	–
Y. Yang et al. (2021)	Design of public/open spaces; Density; Land use mixture; The number of indoor sports and recreational facilities; Street connectivity	30 m	City scale	1 day	9 days (a dataset)
Ye and Qiu (2021)	Design of public/open spaces; Density; Development intensity	30 m	Multi-scale: 1 sub-district – 1 city (consisting of 161 sub-districts)	–	1 day (a dataset)
Sen and Singh (2021)	Ventilation; Design/Redesign of indoor spaces	Multi-resolution: 10 μm (diameter of particles); overall grid density 2.90 ×10(5) cells/m3; 0.5 mm and 25 mm (mesh spacing)	1 m x 1 m x 2 m	0.01 s	0.2 s
UN-Habitat China et al. (2020)	Contact tracing; Internal travel restrictions; Pandemic prevention mapping	–	City scale	–	–
UN-Habitat and WHO (2020)	Health impact assessment; Citizen engagement	–	City scale	–	–
Lim et al. (2011)	Ventilation; Design/Redesign of indoor spaces	1 m	Building scale (a high-rise hospital)	1 s	–
Y. Li et al. (2005)	Ventilation; Design/Redesign of indoor spaces	1 flat	Neighbourhood scale (7 high-rise residential buildings)	1 hour	30 hours
Gao et al. (2008)	Ventilation; Design/Redesign of indoor spaces	1 mm	Building scale (2.7 m x 3.1 m x 2.4 m)	1 s	600 s

Appendix C

Major method, goal, motivation, and focus of the models with an inclusive list of model names.

Author (Year)	Method	Goal	Motivation	Focus	Model name
Badr et al. (2020)	Stat.	Desc.	Data.	Phen.	Generalised Linear Model
Balocco and Leoncini (2020)	Comp.	Pred.	Theo.	Mech.	Transfer Function Method
Blečić et al. (2020)	Other	Desc.	Theo.	Mech.	UPGS Distance-Cumulative Deficit Index
Block et al. (2020)	Comp.	Pred.	Theo.	Mech.	SEIR Model + Relational Event Model
Campisi et al. (2020)	Stat.	Desc.	Data.	Phen.	Ordinal Regression; Nominal Regression
Cartenì et al. (2021)	Stat.	Desc.	Data.	Phen.	Linear Regression Model; Active Rail-based Gravity-type Accessibility Measure Model
Dabachine et al. (2020)	Comp.	Pred.	Theo.	Mech.	Random Non-directional Motion Model
Di Mascio et al. (2020)	Other	Pred.	Theo.	Mech.	IATA Level of Service Calculation Model
Dragoicea et al. (2020)	Other	–	–	–	4DocMod: four diamonds-of-context models for service design

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Author (Year)	Method	Goal	Motivation	Focus	Model name
Silva et al. (2020)	Comp.	Pred.	Theo.	Mech.	LODUS: urban simulation with different levels of details
Wei and Chen (2020)	Comp.	Pred.	Theo.	Mech.	ABM: a novel flocking algorithm with multiple virtual leaders
Hamidi et al. (2020)	Stat.	Desc.	Theo.	Mech.	Structural Equation Modelling
Hamidi and Zandiatashbar (2021)	Stat.	Desc.	Data.	Phen.	Multilevel Linear Modelling
Hao et al. (2020)	Comp.	Desc.	Data.	Phen.	GLEaM Structured Framework with a Compartment Model
Hernandez-Mejia and Hernandez-Vargas (2020)	Comp.	Pred.	Theo.	Mech.	ABM
Jorritsma et al. (2020)	Comp.	Pred.	Theo.	Mech.	ABM + Network-Based S-I-T-S Epidemic Model
Bisset et al. (2012)	Comp.	Pred.	Theo.	Mech.	CIEPI: Synthetic Relational Networks + Health Belief Model + Social Ecological Model + EpiSimdemics + EpiFast + Indemics + Interface to Synthetic Information Systems
Kain et al. (2021)	Comp.	Pred.	Theo.	Mech.	SEIR Model
Kaplan (2020)	Stat.	Pred.	Theo.	Mech.	Scratch Modelling
Karimi et al. (2015)	Comp.	Pred.	Theo.	Mech.	ABM + Health Belief Model
Kierzkowski and Kisiel (2020)	Comp.	Pred.	Hybr.	Mech.	Discrete Event Simulation
Klompmaker et al. (2020)	Stat.	Desc.	Data.	Phen.	Negative Binomial Mixed Models
Kudela (2020)	Other	Pred.	Theo.	Mech.	Pure Binary Compact Formulation; Decremental Clustering Method
Lant et al. (2008)	Comp.	Pred.	Theo.	Mech.	System Dynamics + SEIR Model
Larson and Nigmatulina (2010)	Comp.	Pred.	Theo.	Mech.	Multi-Community Model
V.J. Lee et al. (2009)	Other	Pred.	Theo.	Mech.	RealOpt©: Nonlinear Mixed Integer Program + Fluid Model + Greedy Adaptive Step + Minimum-Cost Network Flow Algorithm; Genetic Algorithm + Adaptive Greedy Search
Leng et al. (2020)	Comp.	Pred.	Theo.	Mech.	CFD
X. Li et al. (2020)	Stat.	Desc.	Data.	Phen.	Linear Regression + Geographically Weighted Regression Model
Maghdid and Ghafoor (2020)	AI	Pred.	Data.	Phen.	K-means Algorithm
Gharakhanlou and Hooshangi (2020)	Comp.	Pred.	Theo.	Mech.	SEIRD Model + ABM
Mao and Bian (2010)	Comp.	Pred.	Hybr.	Mech.	Individual-Based Spatially Explicit Model
S.L. Miller et al. (2020)	Comp.	Desc.	Hybr.	Mech.	CFD: Lagrangian Particle-Based Modelling
Milne et al. (2013)	Comp.	Pred.	Theo.	Mech.	SEIR Model + Madang Demographics Model; Small Community Model + Stochastic Individual-Based Spatial Simulation
Novani et al. (2007)	Comp.	Pred.	Theo.	Mech.	Disease State Transition Model + Virus Contamination and Infection Model + Virtual Human Activities Model
Perlman and Yechiali (2020)	Other	Pred.	Theo.	Mech.	Queueing Model + Game-Theoretic Model
Nguyen et al. (2020)	AI	Desc.	Data.	Phen.	Convolutional Neural Networks + Poisson Regression Model
Rader et al. (2020)	Stat.	Desc.	Data.	Phen.	Meta-Population Model + Generalised Linear Model + SIR Nested Network
M.R. Rahman et al. (2020)	Stat.	Desc.	Data.	Phen.	Getis-Ord Gi* Statistics + Analytical Hierarchy Process + Weighted Sum Method
M.M. Rahman et al. (2020)	Stat.	Desc.	Data.	Mech.	Structural Equation Modelling
Ramchandani et al. (2020)	AI	Pred.	Data.	Phen.	DeepCOVIDNet
Renardy et al. (2020)	Comp.	Pred.	Theo.	Mech.	Discrete and Stochastic Network-Based Model
Rezaei and Azarmi (2020)	AI	Pred.	Data.	Phen.	DeepSOCIAL: a YOLOv4-Based Deep Neural Network Model
Ridenhour et al. (2011)	Comp.	Pred.	Theo.	Mech.	Discrete Event Simulation
Ronchi and Lovreglio (2020)	Comp.	Pred.	Theo.	Mech.	EXPOSED: a Microscopic Crowd Model for Modelling Occupant Exposure in Confined Spaces
Satheesan et al. (2020)	Comp.	Pred.	Theo.	Mech.	CFD
Scarpone et al. (2020)	AI	Desc.	Data.	Phen.	Bayesian Additive Regression Trees
Shuvo et al. (2020)	Comp.	Pred.	Theo.	Mech.	ABM + Epidemiological Modelling
Small and Cavanagh (2020)	Comp.	Pred.	Hybr.	Mech.	SEIR Model + Network Modelling
Spencer et al. (2020)	Stat.	Desc.	Data.	Phen.	Multivariate Logistic Regressions
C. Sun and Zhai (2020)	Comp.	Pred.	Hybr.	Mech.	CFD: Modified Wells-Riley Model
Q.C. Sun et al. (2020)	AI	Desc.	Data.	Phen.	Image Segmentation Algorithm: pix2pix
Sung and Kwak (2016)	Stat.	Desc.	Data.	Phen.	Path Modelling
Swinarski (2020)	Comp.	Pred.	Theo.	Mech.	Discrete Event Simulation
Ban et al. (2020)	Comp.	Pred.	Theo.	Mech.	SEIR Model + ABM
Vazquez-Prokopec et al. (2013)	Comp.	Pred.	Hybr.	Mech.	Dynamic Contact Network Individual-Based Simulation Model
J. Wang et al. (2010)	Comp.	Pred.	Theo.	Mech.	SEITR Model + ABM
Xia et al. (2015)	Comp.	Pred.	Theo.	Mech.	Networked Computational Epidemiology
Yu et al. (2017)	Comp.	Pred.	Theo.	Mech.	CFD
Zhou et al. (2006)	Comp.	Pred.	Theo.	Mech.	Pedestrian Path Model + Human Daily Behaviour Model + SARS Transmission Model
Domino (2021)	Comp.	Pred.	Theo.	Mech.	CFD: Multi-physics Large-Eddy Simulation
Bazant and Bush (2021)	Other	Pred.	Hybr.	Mech.	The Well-Mixed Room Model
Elavarasan et al. (2021)	Other	–	–	–	A Conceptual Framework integrating various effectual approaches on pandemic management for sustainable cities
Subahi (2021)	Other	Pred.	Theo.	Mech.	Weighted Graph-Based Model + MDE Model Transformation + Discrete Event Simulation
Harweg et al. (2021)	Comp.	Pred.	Theo.	Mech.	ABM + Helbing
H. Li et al. (2021)	Comp.	Pred.	Theo.	Mech.	CFD: Droplet Dispersion Model + Eulerian-Lagrangian Model
Ugail et al. (2020)	Other	Pred.	Theo.	Mech.	Circle Packing
Farthing and Lanzas (2021)	Comp.	Pred.	Theo.	Mech.	Spatially-Explicit ABM
Patil et al. (2021)	Comp.	Pred.	Hybr.	Mech.	Gravity Model + SEIR Plus Model + Erdős-Réyni Graphs
Pang et al. (2021)	AI	Pred.	Data.	Phen.	Federated Learning + Time Convolutional Networks
Yamakawa et al. (2021)	Comp.	Pred.	Theo.	Mech.	CFD: Fluid-Particle Dynamics Simulations with the Steady-State Reynolds Average Navier-Stokes Incompressible Solver
Komperda et al. (2021)	Comp.	Pred.	Hybr.	Mech.	CFD: Reynolds Averaged Navier-Stokes Equations + Enhanced Wall Treatment Model + Discrete Phase Model + Convection/Diffusion-Controlled Evaporation Model
Mohammadi et al. (2021)	Comp.	Pred.	Theo.	Mech.	Level of Pedestrian Physical Distancing + Fuzzy Rule-Based Algorithm
Z. Li et al. (2021)	Comp.	Pred.	Theo.	Mech.	CFD: one-way coupled Eulerian-Lagrangian Approach + Reynolds-Averaged Navier-Stokes Equations
Tupper et al. (2020)	Stat.	Pred.	Theo.	Mech.	Applied Probability Models

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Author (Year)	Method	Goal	Motivation	Focus	Model name
Selvakarthi et al. (2021)	AI	Desc.	Data.	Phen.	Convolution Neural Network
Hong et al. (2021)	Stat.	Desc.	Data.	Phen.	Hierarchical Agglomerative Clustering + Bivariate and Multivariate Log-transformed Regression Models
Silalahi et al. (2020)	Other	Desc.	Data.	Phen.	Network analysis + Standard Deviational Ellipse Model + Origin-Destination Cost Matrix
Gomez et al. (2021)	Comp.	Pred.	Theo.	Mech.	INFEKTA: an ABM for Transmission of Infectious Diseases
X. Li (2020)	Comp.	Pred.	Theo.	Mech.	ABM
Klinker et al. (2021)	Other	Pred.	Theo.	Mech.	Navigation Algorithm
Roy et al. (2021)	Comp.	Pred.	Theo.	Mech.	SEIRD Model + Human Mobility Model + Social Network Theoretic Model
Fang et al. (2020)	Comp.	Pred.	Theo.	Mech.	Spatio-Temporal Dynamic Evolution Model: Finite Markov Decision Process + Navigation Algorithm + Deep-Reinforcement Learning
Q. Xu and Chraibi (2020)	Comp.	Pred.	Theo.	Mech.	Generalised Collision-free Velocity Model
Gkiotsalitis and Cats (2021)	Other	Pred.	Theo.	Mech.	Mixed-Integer Quadratic Programming Model
Pavon et al. (2020)	Comp.	Desc.	Data.	Phen.	BIM-FM: Infrastructure Facility Management Systems based on BIM
Kudryashova et al. (2021)	Comp.	Pred.	Data.	Mech.	Aerodynamic Calculations + Physical Model
Qiu et al. (2020)	Other	–	–	–	A conceptual framework integrating the dynamic grid simulation of epidemic spread with the spatial map model of city vulnerability
Liu et al. (2021)	Comp.	Pred.	Theo.	Mech.	Monte Carlo Simulation + Sobol's Sensitivity Analysis
W. Xu et al. (2021)	Other	Pred.	Hybr.	Mech.	Interpretative Structural Model + Analytic Hierarchy Process
Shorfuzzaman et al. (2021)	AI	Desc.	Data.	Phen.	Selected Object Detection Model: Faster R-CNN + YOLO + SSD
Y. Yang et al. (2021)	Stat.	Desc.	Data.	Phen.	Difference-in-Differences Regression
Ye and Qiu (2021)	Stat.	Desc.	Data.	Phen.	Geographically Weighted Regression + Principal Component Analysis
Sen and Singh (2021)	Comp.	Pred.	Theo.	Mech.	CFD: Three Dimensional Euler-Lagrangian Model + Schiller-Naumann Drag Model + Navier-Stokes Equation
UN-Habitat China et al. (2020)	Other	–	–	–	Practice Framework: Health QR Code + Population Mobility Monitoring + Pandemic Prevention Map
UN-Habitat and WHO (2020)	Other	–	–	–	Health Appraisal; Analysis and Data Tools
Lim et al. (2011)	Comp.	Hybr.	Hybr.	Mech.	CFD: Network Mathematical Model + CONTAMW Modelling
Y. Li et al. (2005)	Comp.	Desc.	Hybr.	Mech.	CFD: Multi-Zone Airflow Model + Plume Model
Gao et al. (2008)	Comp.	Hybr.	Hybr.	Mech.	CFD + Wells–Riley Model

Note. Abbreviations are as follows: Comp. for Computer simulation, Stat. for Statistical models, Desc. for Descriptive, Pred. for Predictive, Data. for Data-driven, Theo. for Theory-driven, Phen. for Phenomenal, Mech. for Mechanistic, and Hybr. for Hybrid.

Appendix D. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.progress.2022.100657.

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Liu Yang is a Research Associate in the School of Architecture, Southeast University (Nanjing, China). She is also working at the Research Center of Urban Design in Southeast University. Liu received a PhD in Human Geography from the University of Chinese Academy of Sciences and a Bachelor's degree on Architecture. She was a visiting PhD at the Centre for Transport Studies in Imperial College London from 2016 to 2017. In recent years, her research has focused on developing computational modelling tools to support sustainable and integrated urban design and planning, especially for urban transport and public space systems. Liu's research is currently funded by the National Natural Science Foundation China (5210081743), Natural Science Foundation of Jiangsu Province (BK20210260), China Postdoctoral Science Foundation (2021M690612), and China Fundamental Research Funds for the Central Universities (2242021R20003). Liu is a member of the European Social Simulation Association (ESSA), the Architectural Society of China, and Urban Planning Society of China. Her personal webpage could be found at: linkedin.com/in/liu-yang-2017christine

Michiyo Iwami is one of the three UK Network Members for the UKRI-GCRF Andean Network for Venezuelan Migrants. At Imperial College London, she contributed to national and international research projects around infection prevention and control, and decision-making in innovation adoption and implementation. This includes the EU-funded Prevention of Hospital Infections by Intervention & Training project, NIHR HS&DR programme-funded project, etc. She also contributed to the reviews of serious games as behavioural changes interventions and national action plans on antimicrobial resistance. She led the Daiwa Foundation Award international project to tackle global antimicrobial resistance through shared learning. PhD in Health and Social Studies from the University of Warwick.

Yishan Chen is an engineer at the Architecture and Urban Research Center in China IPPR International Engineering Co.,LTD. His research focuses on urban morphology evolution based on spatial and temporal data, and on the mechanism of hybrid block and urban elements assemblage. Such research can support urban regeneration and urban design practices at different stages. He currently works on a couple of urban regeneration projects in China, such as the Tongzhou Sub-central urban design project and the urban slow traffic system planning in Erdaobaihe Town. Yishan received his Master's degree on Human Geography from the University of Chinese Academy of Sciences (UCAS). He is a member of International Seminar on Urban Form (ISUF).

Mingbo Wu is a PhD candidate studying at the State Key Laboratory of Resources and Environmental Information System, Institute of Geographical Sciences and Natural Resources Research. He recieved bachelor's degree in Tsinghua University and master's degree in University of Chinese Academy of Sciences. His current research focuses on big data application in environmental behavior analysis and urban analysis.

Koen H van Dam is a Research Fellow at Imperial College London in the Urban Energy Systems group. His contributions focus on developing agent-based models of city systems based on spatial and temporal data from multiple sectors, focusing on energy and transport sectors at different scales from individual building to the national level. Such models can then be used to experiment with the impact of local interventions on system-level performance, providing valuable decision support for the design of new services, technologies and policies. He currently works on the FCDO Climate Compatible Growth (CCG) project and acts as technical lead for the COP26 Rapid Response Facility. Previous projects include the Climate-KIC projects Smart District Data Infrastructure (SDDI) and Smart Sustainable Districts (SSD), EPSRC-funded projects Digital City Exchange (DCE) and Integrated Development of Low-Carbon Energy Systems (IDLES), as well as the DFID project resilience.io. He is module leader and lecturer for SEF05 Urban Energy Systems at the Sustainable Energy Futures MSc course.