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Infectious disease outbreak controllability: biological, social and public health factors

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Early in an infectious disease outbreak, key policy questions include whether and how the outbreak can be brought under control. In the epidemiological modelling literature, analyses of outbreak controllability have often focused on metrics such as reproduction numbers (which quantify the number of infections generated by each infected individual). However, whether an outbreak can be controlled is a complex question, depending on both the precise definition of 'under control' used and numerous factors affecting decision-makers' ability to implement transmission-reducing measures. Here, based on discussions at the Isaac Newton Institute's 'Modelling and inference for pandemic preparedness' programme (5–30 August 2024), we describe a wide range of factors affecting outbreak controllability in practice. Programme participants came from institutions in ten countries, enabling discussions to reflect experiences of using models to inform policy in different settings. We divide the factors according to whether they relate predominantly to characteristics of the pathogen, host population or available interventions, and describe policy considerations when assessing whether an outbreak is controllable.

1. Introduction

The impacts of infectious disease outbreaks on host populations vary substantially. For example, the 2002–2004 SARS epidemic was responsible for around 800 deaths before it was contained, while the COVID-19 pandemic led to millions of deaths and the causative virus (SARS-CoV-2) continues to circulate [1].

The varying impacts of different outbreaks have led epidemiological modellers to consider a key question: Which factors affect whether or not an infectious disease outbreak is controllable [2–5]? While this question might at first seem straightforward to understand, if not to answer, there is considerable nuance in precisely what is meant by the term 'controllable'. For example, a controllable outbreak could be defined to be an outbreak in which public health measures such as contact tracing and isolation of detected cases can bring the effective reproduction number (R; the expected number of infections generated by each infected individual, accounting for factors such as interventions and population immunity) below one quickly [6,7]. If R can be maintained below one, then the pathogen would eventually be eliminated. Alternatively, a controllable outbreak could be defined as one in which the pathogen can be eliminated without a threshold number of infections, hospitalizations or deaths being exceeded, or without a threshold outbreak duration being reached [8–10]. If controllability is deemed to require pathogen elimination, then it should be noted that an outbreak may fade out itself due to stochastic effects [11]; this can occur even in the absence of public health measures and represents a fundamentally different outcome to an outbreak being brought under control [12]. Another possible definition of a controllable outbreak is one in which interventions can bring the outbreak's public health impact into an acceptable range (e.g. SARS-CoV-2 might now be deemed to be under control in populations in which vaccination has reduced the risk of severe COVID-19 outcomes). As such, the choice of definition may be influenced by the set of feasible outcomes in the scenario under consideration.

In 2004, Fraser *et al.* [2] investigated some of the factors that affect outbreak controllability. Besides the basic reproduction number (R_0; i.e. the value of R in the absence of interventions and in a fully susceptible population), which has been a central concept in the field of mathematical epidemiology for decades [13–17], Fraser *et al.* [2] identified a second key factor affecting outbreak controllability. Specifically, they demonstrated that the proportion of transmissions arising from infectors who are not displaying symptoms (θ), including both presymptomatic and asymptomatic infected individuals, is central to the success of a public health strategy focusing on isolation of symptomatic hosts followed by tracing and quarantining their contacts. For example, a key reason that SARS-CoV-2 continues to circulate, whereas the 2002–2004 SARS epidemic was contained, is that a substantial proportion of SARS-CoV-2 infections arise from infectors who are not symptomatic. Fraser *et al.* [2] provided a structured way to quantify controllability in the context of isolation strategies in terms of R_0 and θ, similarly to frameworks for assessing the likely impact of a novel outbreak based on measurements of transmissibility and the clinical severity of infections [18]. Together, assessments of an outbreak's potential impact and its controllability are key to designing an appropriate public health response to an emerging pathogen, enabling the selection and timing of control measures to be determined in an informed fashion [19–23].

The values of R_0 and θ provide a useful indication as to whether it might be possible to bring an outbreak into decline using a public health strategy based on isolation and contact tracing. Similarly, R_0 is critical to the success of other control strategies. For example, its value affects the critical proportion of the population that must be vaccinated for a pathogen to be driven to elimination [24,25]. However, authors of previous studies, including Fraser *et al.* [2], have not attempted to provide an exhaustive appraisal of the wide range of factors affecting the ability of interventions to reduce pathogen transmission in real-world outbreaks. Here, we therefore document and discuss many of the factors that affect outbreak controllability in practice. Our thinking is informed by recent infectious disease outbreaks around the world, particularly the COVID-19 pandemic, that have substantially changed how we evaluate pathogen control and the implementation of public health measures. We focus predominantly on directly transmitted pathogens (rather than vector-borne or water-borne diseases), which are likely to be acute zoonotic viruses, since they have been responsible for many recent outbreaks (of diseases including COVID-19, influenza, Ebola and mpox) and represent a substantial future pandemic threat. We divide the factors (figure 1) according to whether they principally relate to the pathogen (§2), to characteristics of the host population (§3) or to the interventions used to mitigate transmission (§4), although inevitably there are overlaps between these areas. Our aim is not to develop a single model that encompasses all these factors, and indeed we note that many of the factors we describe have been included previously in different models in the literature. Rather, we aim to encourage consideration of factors that may be appropriate to include in some models that are used to guide infectious disease outbreak control policy, depending on the specific outbreak context.

We argue that, when attempting to assess outbreak controllability, the precise definition of controllable used must take the outbreak context into account. Assessments must consider the availability and quality of epidemiological data [26] and uncertainty about the impacts of available interventions [27,28]. We provide three example definitions of 'under control' in table 1 and describe scenarios in which those definitions may have been relevant, although as described above we note that a wide range of alternative definitions exist. Once an appropriate definition has been agreed, policy advisors should consider whether the factors described here are relevant to the controllability of the specific outbreak being analysed. In addition to being useful considerations for public health decision-makers, the factors outlined here should be considered by epidemiological modellers in quantitative analyses used to guide interventions, and by other scientists involved in outbreak responses.

2. Pathogen

(a) Natural history of infection

In addition to R_0 and θ, many characteristics relating to the natural history of infection affect whether targeted interventions can bring an outbreak under control (depending on the precise definition of 'under control' adopted). As Fraser *et al.* [2] noted, the clinical definition of symptoms affects the value of θ. More generally, the severity and specificity of symptoms are important factors determining outbreak controllability. If a substantial proportion of infections lead to symptoms that are non-specific or sufficiently mild not to require healthcare, then identifying cases and applying measures such as isolation are more challenging [23]. This is problematic if individuals with no or few symptoms play a substantial role in transmission. On the other hand, if symptoms are severe and/or distinctive, public awareness is likely to be greater, and case finding will be more straightforward (this relates to the so-called 'visibility' of the outbreak [4]). Despite this, for pathogens that generate infections with no or mild symptoms, widespread diagnostic testing provides an opportunity to identify infected individuals, as demonstrated in an unprecedented fashion during the COVID-19 pandemic [37]. This can improve the controllability of outbreaks in scenarios in which θ is larger than and not close to zero [38,39].

One simple way to characterize an outbreak is via its strength and speed [40]. The strength of an outbreak can be measured by R_0, and its speed can be characterized by the generation time (the period between infection times in infector-infectee transmission pairs) [41]. In addition to R_0, the generation time is a key determinant of controllability. Even in outbreaks with similar values of R_0 and θ, combatting 'faster' spreading pathogens such as influenza or SARS-CoV-2 requires different public health measures compared with 'slower' spreading pathogens such as HIV. For a given value of R_0 that is greater than one, short generation times lead to rapidly growing outbreaks, which makes timely intervention more difficult ([42]; see also §4). The efficacy of measures such as forwards contact tracing (i.e. identifying people who could potentially have been infected by a given case) and subsequent quarantine is then limited, since individuals may have already transmitted the pathogen before being identified by contact tracers. A large variance in generation times can also reduce contact tracing effectiveness [43]. The problem of short generation times can partly be addressed by tracing contacts more quickly; this can be facilitated by digital contact tracing [44], for example through mobile phone applications, as was undertaken during the COVID-19 pandemic with varying uptake and success [45,46].

Furthermore, heterogeneity in disease progression and transmission between infected individuals affects outbreak controllability and the interventions that might be expected to be effective. For a range of pathogens, a relatively small proportion of infected individuals generate a high proportion of secondary infections [47–49]. This is often incorporated in epidemiological models by allowing the number of infections generated by each infected host (the offspring distribution) [48,50], or the number of infections each day [29,51], to be drawn from an over-dispersed probability distribution (such as a negative binomial distribution with a small value of the dispersion parameter). Alternatively, transmission heterogeneity can be incorporated by explicitly modelling the social contact network with a heavy-tailed degree distribution, representing high variance in the number of contacts per individual [52,53]. Interventions that target individuals or settings corresponding to a high transmission risk may be most effective. However, identifying the individuals or settings corresponding to the greatest transmission risks can be challenging, in part because transmission risks are determined by a combination of individual-based factors (e.g. individuals' adoption of transmission-reducing measures [54] or their underlying health conditions [55]) and setting-based factors (e.g. numbers of attendees at events [56,57]). Backwards contact tracing (i.e. attempting to trace the sources of infections) can be a useful approach for identifying superspreaders or high transmission settings, enabling individuals who may have become infected to be quarantined [58].

While characterizing outbreak controllability based on R_0 and θ provides a useful rule of thumb, the factors described here, alongside other features relating to the natural history of infection, affect the success of outbreak control measures.

(b) Pathogen emergence setting

The controllability of an outbreak in its earliest stages depends on where and when the initial phase of the outbreak occurs (i.e. the location of early epidemic growth). We note that this can be different from the location of zoonotic spillover (if applicable), which may be unknown. There is substantial geographical heterogeneity in the locations of the initial stages of infectious disease outbreaks. For example, the early phase of the 2014–2016 Ebola epidemic took place in rural areas of southeast Guinea [59], whereas early epidemic growth of SARS-CoV-2 arose in the city of Wuhan, China [60,61]. If transmission at the

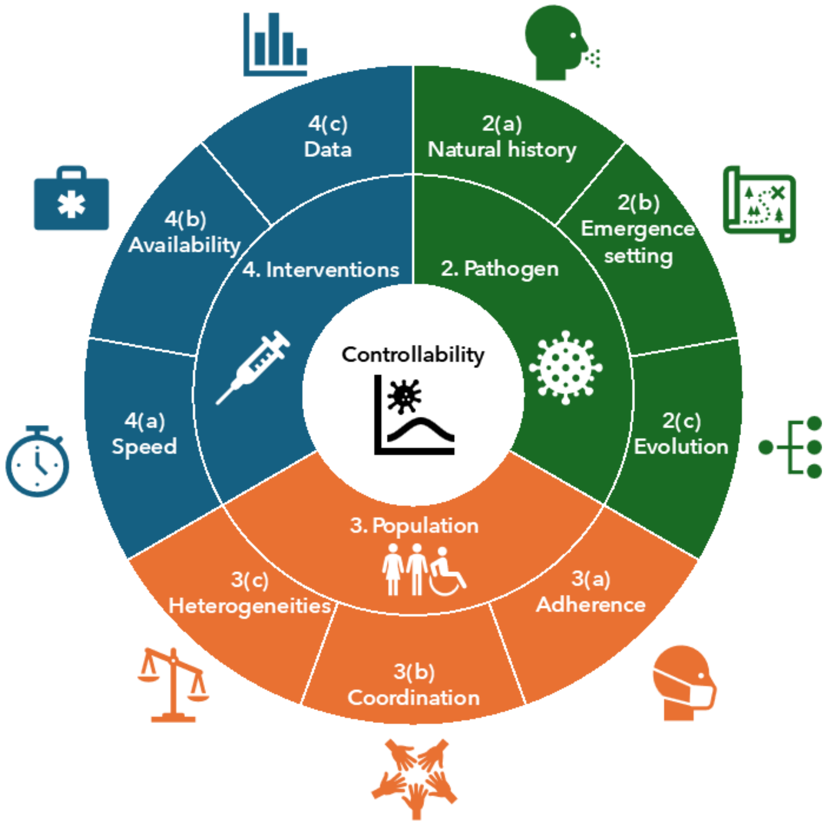

Figure 1. Schematic depicting the factors affecting outbreak controllability that are discussed in this manuscript. Numbers in this figure relate to the relevant section numbers in the manuscript.

Table 1. Three example definitions of 'under control' that might be applicable for policy in different scenarios, and case studies in which these definitions may have applied. We emphasize, however, that numerous possible definitions exist, and a bespoke definition may be most appropriate for a specific outbreak.

control objective	definition of 'controllable'	relevant examples
local elimination of the pathogen	possible to use public health measures to achieve no transmission within a defined geographical area	Ebola virus disease outbreaks in sub-Saharan Africa [29,30]
		mass vaccination programmes that aim to prevent transmission (e.g. for measles [31])
		SARS-CoV-2 elimination strategies implemented in countries including Australia, New Zealand, South Korea and China during the COVID-19 pandemic [32,33]
prevention of epidemic growth	possible to use public health measures to suppress $R < 1$	government strategy to control mpox in the UK in 2022–2023, since local elimination was deemed impossible in that timeframe [34]
manageable impact	possible to use public health measures to maintain incidence of severe cases below a specified threshold	introduction of highly restrictive non-pharmaceutical interventions (informally termed 'lockdowns') in different countries to protect healthcare services during the COVID-19 pandemic [35,36]

beginning of an outbreak is predominantly in urban environments, outbreak control may be challenging; pathogens tend to spread faster in cities due to high population densities and high connectivity. On the other hand, access to healthcare can be more straightforward in cities than in rural locations, meaning that infections may be diagnosed more quickly, with potential benefits in terms of outbreak control. As a result, there may be location-specific variables affecting the potential for an outbreak to be controlled rapidly.

Similarly, the timing of the early outbreak phase plays a crucial role in the potential for interventions to reduce transmission. Many pathogens exhibit seasonal dynamics, for example due to environmental variations [62–64] or temporally varying human mobility [65], and rapid control may be more achievable at times of year when there is only limited transmission [66]. The potential to detect an emerging outbreak quickly may also vary seasonally; for example, if an outbreak begins at a time of year when infections by other pathogens lead to similar symptoms, then outbreak detection may be more challenging. Relatedly, pathogen interference has been shown to operate across disease systems via various immune mechanisms [67–69], potentially driving time-dependent variations in susceptibility to infection and the risk of severe disease. While the location and timing of the initial outbreak phase affect the potential for both early detection and rapid containment, it should be noted that, once widespread human-to-human transmission has been established, the location of the early stage of the outbreak is unlikely to affect the efficacy of control measures.

(c) Extent of pathogen evolution

During individual infections, mutations can occur within the genome of a pathogen that alter its intrinsic transmissibility, the natural history of infection, clinical severity and immune properties (e.g. evasion of host immunity). Consequently, the rate and nature of pathogen evolution can fundamentally influence outbreak controllability.

For zoonotic pathogens, in the early stages of an outbreak (soon after zoonotic spillover), there is a strong selection pressure favouring mutations that increase pathogen transmissibility. Therefore, a pathogen that is initially controllable with relatively few interventions might evolve into a fitter phenotype as it adapts to its new host population, besetting outbreak control [70–72]. Changes in transmissibility can also occur after the initial outbreak stages. For example, the emergence of the SARS-CoV-2 Alpha variant led to a surge of COVID-19 cases in the UK [73,74], requiring stringent non-pharmaceutical interventions to limit its spread.

Pathogens may evolve to evade existing immunity, increasing the pool of susceptible individuals and reducing the effectiveness of pharmaceutical interventions. For example, influenza A antigenic drift necessitates regular vaccine updates [75]. During the COVID-19 pandemic, some emerging variants were associated with decreased effectiveness of monoclonal antibody therapies [76], restricting the choice of available interventions. The Omicron SARS-CoV-2 variant exhibited high levels of evasion of neutralizing antibodies from vaccination or prior infection [77], requiring booster vaccination to mitigate its adverse impacts [78]. Therapeutics may also create selective pressures that act to reduce their effectiveness [79], and non-pharmaceutical interventions can affect pathogen evolution [80].

Feedback loops between pathogen evolution, outbreak dynamics and controllability may be hard to anticipate. Nonetheless, in some scenarios, pathogen evolution should be accounted for when analysing outbreak controllability; for instance, by assessing whether interventions may select for mutations that enhance transmissibility or facilitate immune evasion. This is likely to require the consideration of 'what-if' scenarios and will introduce additional uncertainty that may affect the objectives of policy-makers when implementing public health measures.

3. Population

(a) Adherence to interventions

Outbreak controllability depends crucially on whether or not, and to what extent, communities follow public health measures [81]. As Fraser *et al.* [2] showed, even for fixed values of R_0 and θ, the proportion of symptomatic cases who isolate and the proportion of contacts who are traced and quarantined are crucial in determining whether R is brought below one. The degree of community adoption of measures is affected both by the characteristics of the pathogen and by the local situation, including the public health infrastructure and the economic environment. Furthermore, adherence to interventions can change during an outbreak, including in response to different public health policies [46] and based on individuals' awareness of the risk of infection [82]. Engaging the public when formulating public health policy, and clear and consistent messaging, can increase trust in public health authorities, with implications for adherence to interventions [83].

As well as affecting case identification (§2(a)), the severity of infections also affects individuals' adherence to public health measures. Pathogens that are viewed as more likely to lead to severe outcomes, such as Ebola virus, provide higher incentives for avoiding infection and can therefore prompt infection-avoidance behaviours. Perceived risks are influenced by multiple factors, including traditional and social media, with differing risks of misinformation. Nonetheless, through clear and accurate communication of the rationale for interventions, public health authorities may build trust and increase the chance of successful outbreak control. Strong surveillance systems are crucial [84], as are methods and metrics for tracking pathogen transmissibility, the effectiveness of implemented control measures and behavioural attributes (e.g. trends in test-seeking behaviour [85,86]). Combined, these help to ensure that the state of the outbreak can be measured and communicated to the public accurately and in real-time [87,88]. In addition, measures that are aligned with population characteristics and lifestyle may prove more effective than those that require substantial behavioural changes. If interventions impose a financial burden, such as quarantine leading to loss of income, government support may be required to promote uptake. Responses to recent outbreaks, for example the global mpox epidemic that began in 2022, have shown how interventions may be hindered when infection is stigmatized, highlighting the importance of inclusive actions to counter stigmatization of affected communities [89–91].

(b) Coordination of the outbreak response

Once a pathogen has invaded a host population, control measures are more likely to be successful if public health decision-makers work in a coordinated and consistent fashion. This applies both within countries (e.g. co-operation between policy specialists at the state and national level in the USA) and internationally (see §3(c)). An important aspect of response coordination and decision-making is analysis of counterfactual scenarios (i.e. possible outcomes in the presence or absence of a given intervention at a particular time) [92,93]. This is useful to ensure that interventions are proportionate and to develop a clear rationale for the response (which in turn, if communicated clearly, enhances public trust; see §3(a)).

A proportionate response may differ between pathogens, even for fixed values of R_0 and θ. For example, a large-scale response might be harder to justify for a pathogen that is associated with less severe infection outcomes, even if such a pathogen might be controllable in principle (depending on the definition of 'controllable' used). Modelling plays a crucial role in anticipating how different interventions may affect the trajectory of an outbreak, and modellers should consider the robustness of public health measures to details of their implementation [94]. However, it is crucial that modelling investigations are complementary to other expert activity. Optimal outbreak responses can only be achieved using multi-disciplinary expertise, so policy-makers must ensure that their decisions are guided by evidence provided by experts from multiple fields (epidemiological modellers, behavioural scientists, public health experts, virologists and economists, among others). Similarly, modellers can conduct the most useful possible analyses by working closely with individuals from other relevant disciplines.

(c) Population heterogeneities and disparities

Differences in healthcare access, income and social status affect health outcomes [95] and the impacts of public health measures. Reduced healthcare access delays diagnosis and treatment, leading to higher transmission rates in certain sub-populations. Higher vulnerability in marginalized groups due to comorbidities, poor living conditions or chronic stress may make them more susceptible to severe outcomes of infection. When behavioural interventions (e.g. social distancing, travel restrictions or school and workplace closures) are put in place, vulnerable populations may be less able to adopt and adhere to those measures due to structural barriers, putting individuals in those groups at higher risk and reducing the effectiveness of those interventions [96–98]. Cultures and beliefs can affect controllability in different communities (e.g. due to vaccine hesitancy [99] or cultural practices that promote transmission [100,101]), and there may be different infection risk perceptions between host populations.

At the global scale, heterogeneities in social structure and attitudes affect the outcomes of control measures in different countries. For example, acceptance of mass testing and contact tracing reduced transmission (and therefore limited COVID-19 mortality) in South Korea in the early stages of the COVID-19 pandemic, whereas more stringent measures were required to limit transmission in western countries such as Italy and the UK [102].

Inequalities between countries can hinder outbreak control. For example, benefits of COVID-19 vaccination have tended to be concentrated in high-income countries [103], but epidemiological modelling has demonstrated that increased vaccine sharing between countries could have reduced global COVID-19 burden [104]. Similarly, access to effective and low-cost diagnostic tests was more limited in many low- and middle-income countries than in high-income countries. Given this variability, it should be noted that an outbreak may be controllable in a high-resource setting but not in a low-resource setting, and this could compromise global containment efforts. Disparities in control resources can prolong the duration of an outbreak, as uncontrolled spread in one region or population group can lead to resurgence elsewhere. Successful control often involves ensuring that resources are distributed and public health measures are applied appropriately everywhere (and withdrawn in a coordinated fashion [105]), reducing the effects of population heterogeneities and inequalities.

4. Interventions

(a) Speed of response

The timeliness of public health measures is central to their effectiveness [94,106,107]. For example, delays in isolating cases or quarantining contacts can substantially reduce the effectiveness of these measures [39,108,109], particularly for pathogens with short generation times. Outbreak control becomes substantially more challenging if healthcare or control resources are stretched or exceeded. This could include, for example, the number of active Ebola cases exceeding the availability of secure isolation rooms, the number of cases increasing beyond contact tracing teams' capacity to conduct case interviews and advise contacts to quarantine, or insufficient availability of diagnostic tests or laboratory capacity. During the COVID-19 pandemic, studies were undertaken to assess the risk that the number of individuals requiring intensive care would exceed the number of beds in intensive care units [35,110]. We note, however, that assessing the capacity of healthcare systems is a challenging problem [111], generating uncertainty when analysing whether public health measures can prevent healthcare resources being exceeded.

The effectiveness of some measures depends on the stage of the outbreak. For example, outbreak containment may be possible through case isolation and contact tracing if this is implemented while the number of cases is small, but containment may become infeasible if case numbers exceed testing or tracing capacity [112,113]. In contrast, the effectiveness of other measures may be less sensitive to the size of the outbreak (e.g. population-wide measures such as mask wearing or limiting mass gatherings) [4]. The latter interventions often have high societal costs, precisely because they are applied widely, and therefore may not be desirable even if they can reduce transmission substantially.

Emerging pathogens usually require interventions to be evaluated and revised as new information is acquired. This is difficult when a pathogen spreads quickly, particularly when the delays between infection and observed severe outcomes such as hospitalization and death are substantial compared to the speed of transmission. For example, early in the COVID-19 pandemic, the combination of fast transmission [44,114–116] and delays between infection and hospitalization [117] meant that, even when effective controls were in place, the total disease burden and demand for healthcare services increased substantially before the impacts of the measures were detected [118]. A related consequence is that decisions about the interventions that are likely to lead to successful control may need to be made relatively early in an outbreak. For example, in a fast-growing outbreak with large numbers of severe cases, to maintain the number of individuals requiring hospitalization below a specified threshold, it is necessary to implement public health measures well before that level is reached [119].

As described in §3(b), an effective response to an emerging outbreak is more likely if decisions are informed by evidence provided by experts from different fields. In the UK, for example, discipline-specific subgroups of the Scientific Advisory Group for Emergencies were mobilized during the COVID-19 pandemic so that scientists with different expertise could provide information to guide UK government policy. These included groups with expertise in infectious disease modelling (Scientific Pandemic Influenza Group on Modelling; SPI-M), behavioural science (Scientific Pandemic Insights Group on Behaviours; SPI-B) and environmental modelling (Environmental Modelling Group; EMG). To ensure a fast response, a network of experts would ideally be in place prior to an outbreak, enabling the relevant scientific expertise to be called on when required.

Related to this, it is essential for scientists to consider how to contribute to policy when an outbreak is ongoing. A fast outbreak response may be best informed by conclusions obtained from relatively simple epidemiological models with transparent assumptions and appropriate uncertainty quantification, rather than complex models that are challenging to validate when policy decisions are required quickly. Similarly, when many scientists are qualified to advise policy-makers, greater benefits may be achieved if some scientists direct their expertise towards settings with limited scientific capacity. For example, during the COVID-19 pandemic, while many epidemiological modellers were concentrated in (typically high-income) countries such as the UK, numerous other countries lacked such expertise, creating valuable opportunities for international collaboration and knowledge sharing. Alternatively, scientists may make important contributions by applying their specialist knowledge in other ways, such as through public communication of the scientific evidence informing policy decisions or by reviewing the analyses of others, rather than attempting to contribute original analyses directly to the local outbreak response [120].

(b) Outbreak preparedness and availability of interventions

Linked to the requirement for fast responses to emerging outbreaks (§4(a)), preparedness is essential. The limited availability of personal protective equipment for healthcare workers and patients hampered the response to the early stages of the COVID-19 pandemic in many countries. Strategies such as 'test-and-isolate' or 'test-and-treat' aimed to identify infected individuals and use targeted measures to prevent onwards transmission. These strategies require timely availability of accurate diagnostic tests in sufficient quantities and quick turnaround times [39] to curb outbreaks effectively. We note a potential trade-off between factors such as test sensitivity and result processing times; when available, rapid antigen tests are typically cheaper and faster, but less sensitive, than laboratory-based PCR tests. Alternative testing strategies have different costs, but also have varying implications in terms of the likelihood of an outbreak being brought under control [121]. For example, in the presence of transmission from both symptomatic and asymptomatic cases, only testing symptomatic individuals is cheaper than population-wide testing but may be less likely to lead to successful outbreak control (depending on the objectives of policy-makers).

Delays or unavailability of treatments that reduce transmission (e.g. antiretrovirals for HIV) can make outbreak control challenging. The trajectory of the HIV pandemic was changed partly by the introduction of universal test-and-treat (i.e. treatment as prevention) strategies that aimed for viral suppression immediately on testing positive, both to improve individual outcomes and to reduce transmission risks.

As noted in §3(c), the availability of interventions often differs substantially between low-resource and high-resource settings. Ensuring that resources are distributed efficiently at the global scale is challenging when a public health emergency is ongoing. Instead, outbreak preparedness plans must ensure that interventions are widely available and can be deployed when and where they are needed. For example, the development of an effective system to facilitate global sharing of vaccines and other resources must be undertaken before epidemics occur [122], so that it can be leveraged in low- and middle-income countries as soon as it is required. As a positive step, in May 2025, member states of the World Health Organization adopted the world's first 'Pandemic Agreement' [123], including committing to ensuring that diagnostics, therapeutics or vaccines are procured during pandemics for use in countries facing challenges in meeting public health needs.

(c) Data streams

Inferring whether an outbreak is likely to be controllable is a dynamic process, requiring frequently updated data and quantitative analyses. While the values of R_0 and θ provide a useful indication of the likelihood of controlling an outbreak using case-targeted public health measures, estimating the realized and required speed and coverage of interventions is also important. This requires relevant data and quantitative methods to estimate the distribution of epidemiological delays [124], such as the periods from symptom onset to isolation and from case notification to quarantine of the case's traced contacts. Furthermore, the values of key parameters may change during an outbreak. For example, as public awareness of an outbreak increases, symptomatic individuals may be more likely to isolate, increasing the value of θ [125]. Therefore, although higher θ values in the absence of public health measures are associated with outbreak control being more challenging, an increasing value of θ during an outbreak may indicate that interventions targeting symptomatic cases are effective. Up-to-date data are required to infer epidemiological parameter values and to assess their temporal variations in real-time during an outbreak.

As outlined throughout this article, there are many factors determining whether or not an outbreak can be controlled. Data are needed to inform the structures and parameterizations of epidemiological models used to assess possible future scenarios, and a range of modelling approaches is required to analyse different data types [126,127]. Availability of testing affects how readily new cases are detected, but many forms of data are needed to gain a complete picture of an unfolding outbreak. As two of many examples, mobility and connectivity data may be needed to evaluate whether a pathogen can be contained locally, and data that facilitate quantification of temporal changes in infectiousness during each infection are useful to assess the population-scale effects of reducing transmission at different infection stages (e.g. pre- or post-symptoms).

Fast determination and communication of interventions that can reduce transmission successfully, and which interventions are ineffective, are essential during an emerging outbreak. Disentangling the causal factors driving changes in transmission from wider confounding factors poses methodological challenges [128,129]. While randomized-controlled trials represent the ideal approach for overcoming confounding factors and making unbiased evaluations of intervention effectiveness, there are often ethical and practical barriers to conducting these trials in an outbreak context. Robust methods that can be applied to observational data are therefore needed, while leveraging opportunities for randomization (e.g. natural experiments) when they arise. Careful recording of implemented interventions and their coverage at appropriate spatial and temporal resolutions is key for such evaluations.

As well as data availability, data quality is crucial. For example, reliable surveillance data are required for epidemiologically important changes (e.g. early warning signals of resurgence [130,131]) to be detected quickly and accurately, with clear implications for assessments of outbreak controllability [26,132].

In summary, the ability to determine which interventions are likely to bring an outbreak under control successfully, and to evaluate their effectiveness once introduced, relies on the timely availability of relevant and reliable data. The development of frameworks for data collection, sharing and analysis must be prioritized in advance of future infectious disease epidemics.

5. Summary and discussion

In this article, we have highlighted that a wide range of factors affect outbreak controllability. While the factors that we have discussed here do not represent an exhaustive list, they are some of the most important considerations for public health policy specialists when attempting to determine whether an outbreak can be brought under control.

We do not suggest that epidemiological modellers should attempt to include all the factors described here in a single model. In many scenarios, simple models with transparent assumptions are appropriate tools for contributing to public health policy advice during an outbreak. Furthermore, simple models are useful to demonstrate key epidemiological principles. In a real-time outbreak response, we contend that epidemiological modellers should consider whether each of the factors described here is relevant to the scenario under consideration and include only necessary factors in models used to guide public health measures. Ideally, multiple models would be used in combination to assess whether an outbreak is controllable. Ensembles of models, in which outputs from multiple models are combined, have been shown to provide more robust conclusions than individual models in epidemiological modelling analyses [133–135]. We note that some of the factors described here could, in principle, be accounted for in adapted versions of the model by Fraser *et al.* [2]. For example, measures that increase adherence to interventions could be included in the analyses of Fraser *et al.* [2] in a similar fashion to their consideration of isolation strategies with different efficacy. In contrast, accounting for some of the other factors that we have described may require entirely different modelling approaches.

Overall, three key points were evident in our discussions of the factors affecting outbreak controllability. First, the extent to which specific factors influence controllability depends critically on the precise definition of 'under control' used. It is therefore essential for policy-makers to formulate their objectives clearly and for scientists to conduct analyses that are aligned with those objectives. We note that setting policy objectives often requires careful consideration and may need to be done iteratively while assessing the feasibility and implications of different choices. This means that policy advisors, including modellers, also have a role to play in assisting policy-makers to define the criteria for successful outbreak control. Policy-makers' objectives are often affected by the cost-effectiveness of available measures and are likely to change during an outbreak. It may therefore be necessary to consider both short-term and long-term goals when assessing outbreak controllability. After the emergence of a novel pathogen, it may be appropriate to use highly restrictive non-pharmaceutical interventions (combinations of which were referred to informally as 'lockdowns' during the COVID-19 pandemic) to ensure case numbers remain low in the short-term, if the long-term strategy is to develop and deploy an effective vaccine [28,136].

Second, many sources of heterogeneity affect outbreak controllability and must be considered by scientists and policy-makers. These include variability in the timing and setting of early epidemic growth between outbreaks (§2(b)), variations in exposure to infection and the risk of severe disease for different demographic and socioeconomic groups, disparities in cultural norms and access to crucial control resources (§3(c)), to name a few. As part of this, requirements to respond to outbreaks in resource-limited settings must be considered, including sharing knowledge and resources as required; inequalities both within and between countries were all too evident during the COVID-19 pandemic.

Third, associated with many of the factors discussed here is the need to prepare in advance of future public health emergencies. On the one hand, some factors affecting outbreak controllability may be hard to assess in advance (e.g. the precise properties of a newly emerging pathogen; §2(a)). On the other hand, some factors can be influenced prior to an outbreak (e.g. data availability can be improved by strengthening surveillance systems and developing networks for sharing data or expertise that are often required during outbreak responses [137]). These latter factors cannot typically be addressed quickly and effectively during an outbreak, highlighting the need for advanced coordination. As well as the development of generalizable tools and procedures, plans for interventions must be made for outbreaks with different characteristics. The optimal responses to pathogens transmitted via different routes (e.g. respiratory, sexually transmitted, vector-borne and so on) are likely to be very different, requiring planning for a wide range of possible scenarios, drawing on the knowledge of different experts.

Many infectious disease threats are currently at different stages worldwide: the acute phase of the COVID-19 pandemic is over yet transmission is ongoing; multiple clades of mpox are driving outbreaks; substantial outbreaks of haemorrhagic fevers have occurred recently in African countries; the number of human cases of H5N1 influenza is increasing but frequent human-to-human transmission has not been documented; low or declining childhood vaccination rates are increasing the risk of large outbreaks of vaccine-preventable diseases; and the danger of newly emerging zoonotic diseases is ever-present. With many different infectious disease threats globally, the topic of outbreak controllability is particularly relevant now. Consideration of the nuance in this topic, extending analyses undertaken previously, is of critical importance to improve responses to future outbreaks of emerging infectious diseases.

Ethics. This work did not require ethical approval from a human subject or animal welfare committee.

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