Deploying wearable sensors for pandemic mitigation

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Abstract

Wearable sensors can detect potential respiratory infections before or absent symptoms through continuous, passive monitoring of pathogen-elicited physiological changes. While numerous efforts have been made to develop wearable sensor-based infection detection algorithms, the population-level impact of deploying such technology during a pandemic has not been explored. In this thesis, we used mathematical modelling to study wearable sensor-based pandemic mitigation strategies. Using SARS-CoV-2 as an illustrative example, we constructed a compartmental model of Canada's second COVID-19 wave, simulated counterfactual wearable sensor deployment scenarios, and systematically investigated the role of detection algorithm accuracy, uptake, and adherence. With currently available detection algorithms and 4% uptake, we observed a 16% reduction in the second wave burden of infection; however, 22% of this reduction was attributed to incorrectly quarantining uninfected device users. Improving detection specificity and offering confirmatory rapid tests each minimised unnecessary quarantines and lab-based tests. With a sufficiently low false positive rate, increasing uptake and adherence became effective strategies for scaling averted infections. We concluded that wearable sensors capable of detecting presymptomatic or asymptomatic infections have potential to help reduce the burden of infection during pandemics. In the case of COVID-19, technology improvements or supporting measures are required to keep social and resource costs sustainable.

Résumé Scientifique

Les capteurs portables peuvent détecter les infections respiratoires potentielles avant ou en l'absence de symptômes grâce à une surveillance passive et continue des changements physiologiques provoqués par les agents pathogènes. Bien que de nombreux efforts aient été déployés pour développer des algorithmes de détection d'infections basés sur des capteurs portables, l'impact du déploiement d'une telle technologie au niveau de la population pendant une pandémie n'a pas été exploré. Dans cette thèse, nous avons utilisé la modélisation mathématique pour étudier les stratégies d'atténuation des pandémies basées sur des capteurs portables. En utilisant le SRAS-CoV-2 comme exemple, nous avons construit un modèle compartimental de la deuxième vague de COVID-19 au Canada. Nous avons simulé des scénarios contrefactuels de déploiement de capteurs portables et étudié systématiquement le rôle de la précision des algorithmes de détection, de leur adoption, et de leur adhésion. Avec les algorithmes de détection disponibles et un taux d'adoption de 4%, nous avons observé une réduction de 16% de la charge d'infection de la deuxième vague de COVID-19. Toutefois, 22% de cette réduction a été attribuée à la mise en quarantaine incorrecte d'utilisateurs de dispositifs non infectés. L'amélioration de la spécificité de la détection et l'offre de tests rapides de confirmation ont permis de réduire les quarantaines et les tests de laboratoire inutiles. Avec un taux de faux positifs suffisamment faible, l'augmentation de l'adoption et de l'adhésion est devenue une stratégie efficace pour éviter les infections. Nous avons conclu que les capteurs portables capables de détecter les infections présymptomatiques ou asymptomatiques peuvent contribuer à réduire la charge d'infection pendant les pandémies. Dans le cas de COVID-19, des améliorations technologiques ou des mesures de soutien sont nécessaires pour assurer que les coûts sociaux et les coûts des ressources restent viables.

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All models are wrong, but some are useful.

– George Box

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Introduction

The uncontrolled transmission of infectious pathogens can have catastrophic public health and socioeconomic consequences [1]. The recent COVID-19 (coronavirus disease 2019) pandemic, caused by the rapid spread of SARS-CoV-2 (severe acute respiratory syndrome coronavirus 2), sheds light on the potential for harm: over 630 million confirmed cases and 6.6 million deaths were reported as of November 29, 2022 [2, 3]. Importantly, pathogens with pandemic potential have regularly appeared throughout history, and will continue to do so with an accelerating pace driven by climate change, biosecurity threats, and other such factors [4–6]. Minimising the damage these infectious diseases could cause will require robust public health responses that optimally deploy tools and resources available.

There are a variety of public health interventions one can implement to mitigate viral spread [7]. Identifying the best intervention (or set of interventions) for a particular scenario requires decision-makers to balance multiple factors including the projected effectiveness, costs, feasibility, social acceptability, and higher-order consequences of different options. A lockdown, for example, might be a useful policy to reduce short-term transmission; however, it would also constrain economic activity and harm mental health, among other negative ramifications [8, 9].

Mathematical models of infectious disease spread are critical tools that help public health officials understand trade-offs associated with different interventions and make decisions [10]. The use of infectious disease models is essential for three reasons. First, emergency scenarios at hand have likely never been faced before, demanding a systematic and principled approach to applying established epidemiological frameworks to an often-evolving understanding of the present situation. Second, the spread of infectious pathogens is an exponential and nonlinear process, and how different interventions might steer this

process can be non-intuitive [11]. Finally, public health officials are often interested in considering multiple possible epidemic trajectories, each the result of a different set of assumptions or interventions. In reality, however, only one trajectory can be realised. Models can be used to simulate a range of counterfactual and hypothetical scenarios, enabling decision-makers to assess each anticipated outcome before coming to a conclusion [12]. In this M.Sc. thesis, we construct a mathematical model to explore the potential impact of deploying wearable sensors to detect infections, strengthen Find-Test-Trace-Isolate (FTTI) systems, and improve pandemic mitigation [13].

FTTI systems are a central element of pandemic mitigation, especially in scenarios where it is important to reduce the number of infections (e.g., during the acute phase of a pandemic, prior to vaccine availability) [14, 15]. These systems aim to identify and isolate infectious individuals, however, the COVID-19 pandemic highlighted two limitations in how they are commonly implemented. First, hidden infection chains resulting from presymptomatic and asymptomatic transmission were often missed because symptoms are what usually prompt individuals to seek a test [16]. Second, slow test result turnaround times—caused by reliance on lab-based polymerase chain reaction (PCR) testing infrastructure—meant that infectious individuals could unknowingly spread the virus for a longer period of time [17, 18].

Digital contact tracing apps were promising tools to detect potential transmissions that resulted from contact with an infectious individual, irrespective of whether they presented with symptoms. However, the impact of these apps was limited by inadequate participation and concerns around privacy [19, 20]. Separately, rapid testing programs—in which individuals are supplied with a rapid antigen test (RAT), self-administer the test, receive the result almost immediately, and then self-isolate in the case of a positive result—showed promise in addressing the issue of slow turnaround of lab-based test results. While rapid testing programs eventually supplanted lab-based testing infrastructure—particularly due to the failure of such infrastructure during the Omicron wave of the COVID-19 pandemic—they have been limited by high costs, occasionally sparse supply, and concerns around the accuracy of the RATs themselves [21–23].

Wearable sensors have already been established as tools to detect deviations from users' physiological baselines, and could serve as a novel platform for infection detection with potential to strengthen FTTI systems [24]. Recent findings suggest that wearable sensors may be able to detect infections caused by respiratory pathogens such as SARS-CoV-2, before or absent symptoms [25, 26]. As one example, Alavi et al. developed an algorithm that analyses patterns in smartwatch-captured overnight resting heart rate and can provide real-time alerts of potential presymptomatic or asymptomatic SARS-CoV-2 infection [27]. If algorithms like this were widely deployed, wearable sensors could help FTTI systems more rapidly identify (and subsequently isolate) infectious individuals, including those without symptoms. As well, wearable sensor-based detection would offer the unique benefit of passive monitoring, which minimises required user engagement; could operate in privacy-preserving fashion because sensor data would not need to be shared with a centralised database; and could leverage the fact that 22–25% of the Canadian population already owns a wearable device, reducing the infrastructure costs of the intervention [28, 29].

With these potential benefits in mind, many efforts—in addition to those of Alavi et al.—have been made to develop algorithms to detect SARS-CoV-2 infections from wearable sensor data [30, 31]. We enumerate and discuss these research thrusts in Chapter 2. However, in spite of this host of efforts, the potential population-level impact of deploying wearable sensors to strengthen FTTI systems and improve pandemic mitigation has yet to be assessed. To the best of our knowledge, no studies have characterised how the technological and behavioural parameters of a wearable sensor-based intervention might influence its effectiveness, social burden, and resource costs. Moreover, practical policies that could complement and augment a wearable sensor-based intervention remain to be explored. The unfortunate result of this knowledge gap is that decision-makers are left with access to potentially impactful public health tools but without the information needed to optimally deploy them.

In this M.Sc. thesis, we construct and employ a mathematical model of infectious disease spread to address this knowledge gap. After reviewing necessary background material in Chapter 2, we present the approach and findings of the modelling exercise in Chapter 3,

drawing from the published version of this work [13]. We discuss the implications of these findings and opportunities for future study in Chapter 4. Our contributions are as follows:

1. We demonstrate that deploying wearable sensors capable of detecting infections before or absent symptoms can help reduce the burden of infection during a pandemic. We do so by estimating the number of infections that would have been averted had this technology been deployed during Canada's second COVID-19 wave.

2. We show that currently available detection algorithms would likely prompt a prohibitive volume of unnecessary quarantines and lab-based tests, but that improving detection specificity and offering confirmatory RATs were each useful strategies for bringing these social and resource costs to more feasible levels.

3. We establish that once false positive notifications are minimized, increasing uptake and adherence become effective strategies to scale the number of averted infections.

We use the example of SARS-CoV-2 throughout this modelling exercise to obtain concrete estimates of impact that are relevant to the current public health context. However, as we later detail in Chapter 3, we construct the mathematical model in such a way that we capture uncertainties around the wearable sensor-based detection technology (as opposed to uncertainties around SARS-CoV-2 epidemiology). Consequently, the intuition we generate around the trade-offs of this intervention can be applied to the acute phase of any pandemic caused by a respiratory pathogen, enabling public health decision-makers to better address infectious threats.

2

Background

In this thesis, we construct a mathematical model to explore how wearable sensors capable of detecting infections can augment Find-Test-Trace-Isolate (FTTI) systems and contribute to pandemic mitigation. This chapter presents the context and background material needed to follow this modelling effort. We segment this chapter into four components: (1) an outline of current pandemic mitigation strategies; (2) an introduction to techniques used to design mathematical models of pandemics; (3) an overview of physiological responses to SARS-CoV-2 infection; and (4) a discussion of recent efforts to develop wearable sensor-based public health tools. As mentioned in Chapter 1, we use the example of SARS-CoV-2 throughout this thesis—including while presenting background material in this chapter—to generate insights that are topical. Later, in Chapter 3, we discuss how we construct the model to derive takeaways that are generalizable beyond the COVID-19 pandemic.

2.1 Pandemic mitigation strategies

The term epidemic—which means "on the people" in Greek—was first used by Hippocrates to refer to the spread of disease within a population [32]. Today, the US Centers for Disease Control and Prevention defines an "epidemic" as "an increase, often sudden, in the number of cases of a disease above what is normally expected in that population in that area" [33]. An "outbreak" is defined similarly, though in application to a more restricted geographical area, and a "pandemic" is defined as "an epidemic that has spread over several countries or continents, usually affecting a large number of people" [33]. In this section we discuss how public health decision-makers design interventions to address pandemics of infectious pathogens. We also formally introduce the concept of FTTI systems—pandemic mitigation interventions that are relevant to this thesis.

There are several approaches to reducing the public health impact of a pandemic. Which set of strategies decision-makers choose to deploy, and how they construct policies to support this deployment, shapes an epidemic's trajectory. In Table 1, we present a taxonomy of mitigation strategies, drawing from World Health Organization guidance on mitigating pandemic influenza [7]. Each class of interventions has its own benefits and drawbacks, and, further, these trade-offs can evolve over time and vary depending on the specific public health objective being pursued. For instance, border closures can reduce imported infections and contain transmission but cause economic and humanitarian harm, and strain diplomatic relations; they represent extreme but sometimes-warranted interventions [34]. In most scenarios, deploying a carefully selected subset of interventions will be more effective than deploying any single intervention on its own. Importantly, effectiveness in achieving a public health objective is not the only factor that governs which interventions are deployed and how. Other key factors include the costs of different strategies [35, 36]; the need to optimise for multiple public health objectives at once [37]; concerns around privacy, particularly when data are collected and deployed on digital platforms [38]; public attitudes, awareness, and cultural norms [39–41]; and the impact of different strategies on health equity [42].

Table 1: Taxonomy of pandemic mitigation strategies. We draw the segmentation of non-pharmaceutical interventions and some examples of these interventions from World Health Organisation guidance on mitigating pandemic influenza [7].

Intervention Type		**Description**	**Examples**
Pharmaceutical Interventions			
	Therapeutics	Drugs designed to reduce the severity of disease within an infected individual.	Antiviral medications, monoclonal antibodies
	Vaccines	Drugs designed to reduce the risk of one or more outcomes including infection, symptomatic disease, severe disease (e.g., hospitalisation, intensive care), and death.	Several types including mRNA, viral vector, and live attenuated viruses
Non-Pharmaceutical Interventions			
	Personal Protective Measures	Individual-level action to reduce the risk of transmission, without modification of movement or social engagement patterns.	Wearing masks, hand and face hygiene
	Environmental Measures	Modification of properties of a physical location to reduce the risk of transmission in that location.	Air filtration, ventilation, surface cleaning, UV light
	Social Distancing Measures	Modification of movement and/or social engagement patterns, driven by individual-level action or broader policies, to reduce the risk of transmission.	Contact tracing, isolation of individuals with confirmed infection, school closures, social distancing
	Travel-Related Measures	Restriction of movement between larger geographical regions (e.g., provinces, states, countries) to contain pathogen circulation.	Travel screening, border closures, travel restrictions

FTTI systems were important public health tools during the COVID-19 pandemic [15]. These systems combine multiple Social Distancing Measures into a cohesive strategy for identifying infected or potentially infected individuals and isolating or quarantining them, respectively, to reduce the likelihood that they infect others. "Find" refers to the process of identifying potentially infected individuals, for example, by screening them for relevant symptoms or determining if they were in contact with others who were known to be infected. The status of these potentially infected individuals is then confirmed ("Test"). If they are indeed infected, effort is made to identify who they may have contacted ("Trace") and they themselves are asked to "Isolate" until recovery. FTTI systems are particularly useful when there is a public health imperative to reduce the number of infections (e.g., as opposed to the number of hospitalisations or the number of deaths). Certainly, the availability of vaccines or therapeutics that reduce the severity of disease might decrease the marginal impact of an averted infection because the consequences of being infected become less severe. However, FTTI systems remain particularly useful prior to the development, approval, and distribution of such pharmaceuticals; in scenarios where the longer-term consequences of infection remain unclear (e.g., with "long COVID-19") [43]; and in instances where the reduction in risk of hospitalisation is outweighed by the sheer volume of infections (e.g., if the pathogen spreads rapidly) and health system infrastructure becomes at risk of being overwhelmed.

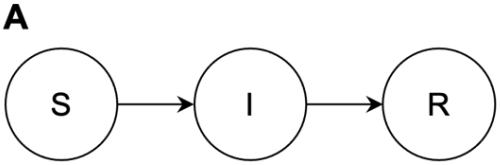
During the COVID-19 pandemic, there were myriad approaches to designing FTTI systems [15]. Yet, even with this heterogeneity, two challenges were pervasive. First, the "Find" component of these systems was often limited in its ability to identify hidden infection chains resulting from presymptomatic or asymptomatic transmission of SARS-CoV-2 [16]. Second, the "Test" component of these systems was often reliant on lab-based testing, but slow test result turnaround times increased the window in which infected individuals could unknowingly transmit the virus to their contacts [17, 18]. While these two bottlenecks are specific nodes in a larger system that represents just one of many pandemic mitigation strategies, the outcome is that society's ability to limit the number of infections is compromised. Innovative fixes—whether enabled by advances in technology, improved logistics, or other solutions—are needed to strengthen FTTI systems and thereby enhance our broader pandemic mitigation toolkit.

2.2 Mathematical models of pandemics

Mathematical models of infectious disease transmission are critical tools for public health decision-making during pandemics [10]. Well-designed models can help officials apply established epidemiological frameworks to a dynamic emergency scenario, develop intuition around the nonlinear effects an intervention might have, and consider multiple plausible epidemic trajectories before coming to a decision. In this section, we introduce and compare two infectious disease modelling frameworks: compartmental models, which are the focus of this thesis, and agent-based models (ABMs). We discuss two approaches to addressing uncertainty in modelling results and elaborate on the utility of counterfactual models.

The process of engineering a useful model involves weighing trade-offs between a model's complexity, its accuracy, the computational resources it requires, and the extent of the assumptions it makes. In the context of infectious disease control, these considerations govern whether one might choose to construct a compartmental model or an ABM to answer a particular public health question.

Compartmental models—in systems engineering terminology, "state space models"—segment the population into groups and describe flows between groups using a set of differential equations [44]. To illustrate this concept, we can consider a *Susceptible*, *Infectious*, *Removed* (SIR) model (Figure 1) that splits the population into three mutually exclusive compartments on the basis of health status. *Susceptible*, healthy individuals can get infected; *Infectious* individuals recover or die after a period of being able to infect others; and *Removed* individuals have either gained immunity (i.e., cannot become infectious again) or died. Equations 1–3 below govern the flow of individuals between compartments. $S(t)$, $I(t)$, and $R(t)$ represent the time-varying number of individuals in the *Susceptible*, *Infectious*, and *Recovered* groups, respectively. As well, N represents the number of individuals in the population; β represents the transmission rate in units of the number of transmissions per infected individual per unit of time; and γ represents the recovery rate, calculated as one divided by the number of units of time that an individual remains *Infectious*.



B

Compartment	Symbol
Susceptible	S
Infectious	I
Removed	R

Figure 1: Schematic of a *Susceptible, Infectious, Removed* (SIR) compartmental model. *Susceptible* individuals are healthy and can get infected. *Infectious* individuals can infect others for a period of time, after which they recover or die. *Removed* individuals have either died or gained immunity (i.e., cannot become infectious again).

$$\frac{d}{dt}S(t) = -\frac{\beta S(t) I(t)}{N} \quad (1)$$

$$\frac{d}{dt}I(t) = \frac{\beta S(t) I(t)}{N} - \gamma I(t) \quad (2)$$

$$\frac{d}{dt}R(t) = \gamma I(t) \quad (3)$$

Compartmental models are not typically computationally intensive, making them accessible and relatively easy to iteratively prototype [44]. They can be mathematically probed and characterised with the same established analytical toolkit that is commonly applied to other state-space models. These models are typically more straightforward to parameterise due to their small set of variables, and this simplicity enables model users to easily understand underlying assumptions in turn. Altogether, these features make compartmental models highly attractive for generating principled initial estimates to answer questions about public health interventions, however, limitations of these models must also be acknowledged [10]. The downside of being parameterised by a small set of variables is that compartmental models may not be able to capture the complicated realities of viral transmission, which can be influenced by policies, human behaviour, climate, and myriad other factors. Moreover, these models are often parameterized by mean values of variables (though it is possible to parametrise them with statistical distributions) and they assume that the population is homogenous and well-mixed. At baseline, these models cannot capture key individual-level

heterogeneities. Take the SIR model above applied to influenza as one example: children are known to be more susceptible to this virus than adults, and the transmission rate may therefore vary by age [45]. Indeed, it is possible to add compartments beyond the SIR structure, whether to capture such heterogeneities (e.g., compartments for different age or symptom groups to reflect differential susceptibility or infectiousness) or to capture other complexities of the situation at hand (e.g., compartments representing individuals in quarantine). However, each additional compartment contributes to the number of equations and parameters, making the model increasingly difficult to implement and analyse.

ABMs leverage computational capabilities to simulate each person in a population as an "agent" and thereby account for individual-level heterogeneities [10, 44]. More specifically, ABMs capture the status of each agent (e.g., susceptible, infectious, in quarantine) and track their contact networks (i.e., the list of people they interact with). Viral transmission can occur when a susceptible agent and an infectious agent encounter each other. Heterogeneities can be incorporated in a variety of ways, for example, by specifying contact networks on the basis of age or contact setting (e.g., home, school, workplace), by drawing an individual's duration of infectiousness from a probability distribution instead of using a consistent value across the population, or by varying the probability of transmission based on the contact setting.

The ability to capture individual-level heterogeneities is the preeminent advantage that ABMs have over compartmental models [10, 44]. These heterogeneities can lead to emergent behaviour on a population level and enable modellers to explore hypotheses with greater precision. The trade-off is that far more data are required—or far more assumptions must be made—to parameterise ABMs. ABMs are also more challenging to implement than compartmental models and typically require dedicated software tools and packages, making them less accessible and flexible to answer custom questions. Moreover, the computational resources ABMs require rapidly grow with the number of agents and calculations performed per time step; in many instances virtual servers and computational platforms are required to run simulations. In general, ABMs are useful when individual-level heterogeneity must be accounted for, and when sufficient data and computational resources are available.

Regardless of the modelling framework one adopts, uncertainty must be incorporated into modelling exercises to appropriately enable public health decisions [10]. The level of confidence in the anticipated outcome of each possible decision dictates which decisions are ultimately taken. Various factors can contribute to the uncertainty one might have about a modelled epidemic, for example, a limited understanding of viral characteristics (e.g., the duration of infectiousness), or an inability to anticipate the effect of an intervention (e.g., the extent to which mandating face masks might reduce the transmission rate).

There are two common approaches to capturing uncertainty in infectious disease models. First, one can define selected parameters as random variables instead of constants. In the context of compartmental models, values for these parameters can be drawn at the beginning of each simulation or values can be drawn each day, resulting in the differential equations that describe flows between compartments becoming stochastic differential equations. Then, confidence intervals can be generated with Monte Carlo simulations: the model can be run thousands of times and the range of epidemic trajectories that could result can be captured [46]. In the context of ABMs, many parameters are already specified as probability distributions to enable individual-level heterogeneity. With these models, uncertainty would be reflected in the level of confidence one has in the probability distributions being used: the parameters of these distributions could themselves be treated as random variables (e.g., as is typically the case with Bayesian statistical models), or the distributions could be wider than they would be if they were well-characterised. In any instance, Monte Carlo simulations can again be conducted to generate confidence intervals from ABM simulations. In a general sense, it is important to carefully define which sources of uncertainty are important to consider—and in turn, which parameters should be treated as random variables—to avoid the uninformative finding that any outcome could occur.

The second approach to capturing uncertainty involves performing sensitivity analyses on key parameters or, similarly, reporting multiple simulated outcomes, each obtained with a different set of assumptions [10]. As an example of when this approach might be useful, consider the case in which a policymaker is evaluating the possibility of imposing a lockdown. One could certainly model the reduction in the number of contacts per day that

results as a random variable with a wide distribution to reflect uncertainty in the effect of the intervention. However, doing so would likely lead to the finding that "most epidemic trajectories are possible". Instead, a more informed decision could be made if a few illustrative scenarios (e.g., a 10%, 25%, 50%, and 80% reduction) were defined and their outcomes presented side-by-side. In this case, the policymaker could more easily grasp what conditions would need to be true for an intervention to have the desired effect.

A final concept related to the construction and use of infectious disease models is that of counterfactual analysis. A counterfactual scenario is defined in relation to a scenario realised in the real world such that the only difference between the two is the presence of an intervention [12]. As such, any differences in outcome can be attributed to the intervention. Since both scenarios cannot occur simultaneously, decision-makers must use mathematical models to make these comparisons. It is important to carefully construct these scenarios to ensure that any side-by-side comparisons are fair and that the impact of the intervention is accurately estimated. Ideally, models should be designed so that their users can easily replicate both realized and counterfactual epidemic trajectories by including or excluding the intervention in question.

2.3 Physiological responses to SARS-CoV-2 infection

Viruses are molecular entities that leverage a host's biological machinery to replicate but can damage the host in the process, sometimes critically [47]. In response, many hosts have evolved to develop dedicated biological mechanisms—immune systems—to protect against such threats. In this section, we provide a conceptual overview of how human hosts respond to viral infections and we elaborate on the physiological responses elicited by SARS-CoV-2.

The interplay between the viral replication process and the host's immune response is mediated by complicated cellular pathways [47]. The viral replication process begins with a latent period during which the virus enters host cells and initiates replication. Once the virus has begun to replicate at sufficient levels, the host becomes infectious and can transmit the virus to others. Importantly, the host is not equally infectious throughout the infectious

period: viral replication accelerates past the threshold for being infectious, peaks at some point during the infectious window, and then begins to fall as the host's immune response begins addressing the infection (Figure 2).

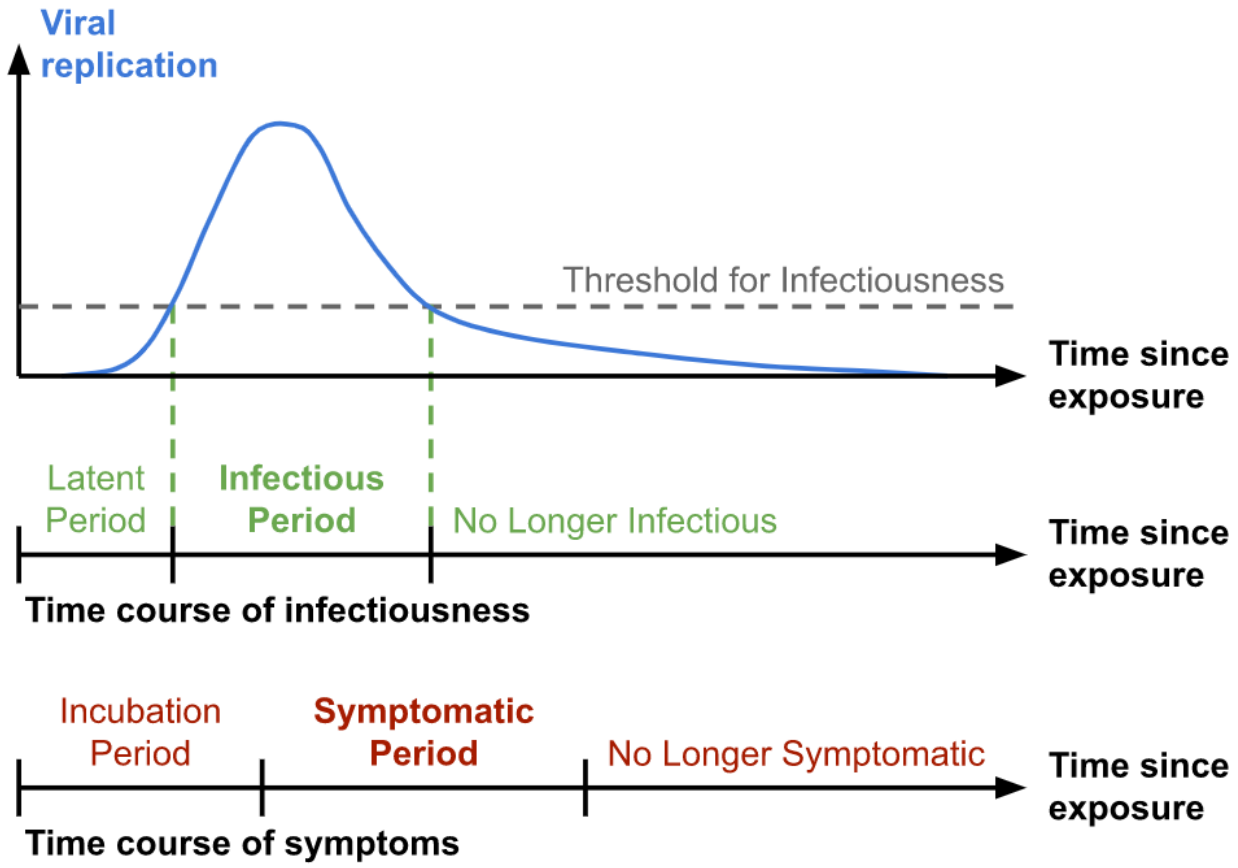


Figure 2: Schematic of the time course of infection for an individual. After exposure, viral replication accelerates, and at a certain point, the host is able to infect others. Viral replication peaks and then begins to fall as the host's immune system begins to address the viral assault. Here, we represent the latent period as one in which viral replication has not yet reached the infectious threshold and the infectious period as one in which viral replication is above this threshold. Importantly, various factors such as the duration and proximity of contact, the wearing of masks, and vaccination history can influence whether transmission actually occurs upon contact. As such, the concept of an infectious threshold is merely illustrative. In this schematic we also depict the progression of symptoms, which typically begin following an incubation period, at a time point close to peak viral replication. The duration of symptoms is highly variable.

Symptoms and physiological manifestations of disease are the result of both the virus' assault on host biology and the host's immune response [48]. For example, in scenarios where a host does not have existing immunity to a pathogen, symptoms can begin after viral replication (and infectiousness) has peaked and reflect a naive immune response [49]. In

such instances, symptom severity could be correlated to the level of infectiousness and mediated by damage caused by viral replication [49, 50]. Conversely, in scenarios where the host does have existing immunity, symptoms could begin much sooner, prior to the infectious period, and reflect a robust host response that is rapidly addressing the viral assault [51]. The window between when one is exposed to the pathogen and when they present with symptoms is called the incubation period (Figure 2). Importantly, not all infected individuals go on to present with symptoms; the fraction that remain asymptomatic depends on specific virus characteristics and pre-existing host immunity [52].

Host responses to SARS-CoV-2 are complicated and heterogenous. SARS-CoV-2 enters the host's lungs through the respiratory tract and attacks the alveoli, impairing gas exchange and triggering the release of immune cells [49, 53]. These cells release signalling molecules into the bloodstream, which in turn cause vasodilation (loosening of the blood vessels), increase capillary permeability, and prompt the hypothalamus to increase body temperature. Each of these initial effects can trigger further follow-on effects. Damage to the alveoli can induce coughing or difficulty breathing and result in hypoxemia (low blood oxygen concentration) which, in turn, could cause tachycardia (elevated heart rate). Vasodilation can decrease blood volume and peripheral resistance, which reduces blood pressure and circulation, and could cause different organs to fail.

The way in which SARS-CoV-2 infection modulates physiological parameters, particularly during its acute phases, has been well-studied over the course of the COVID-19 pandemic. First, temperature, heart rate, resting heart rate, and heart rate variability are all modulated as the hypothalamus mediates the host's inflammatory immune response. Changes in heart rate and resting heart rate are coupled with changes in temperature: on average a 1 degree Celsius increase in temperature is associated with an 8.5 beat per minute increase in heart rate [54]. Heart rate variability is influenced by autonomous nervous system activity and its modulation can reflect an ongoing immune response [55, 56]. Second, the viral replication process, in damaging the alveoli and respiratory tract, can increase respiratory rate and decrease oxygen saturation [57, 58]. Many of these physiological indicators are consistently modulated prior to the onset of symptoms, but the magnitude of physiological changes is not

necessarily associated with the severity of symptoms [26, 55, 59, 60]. As we discuss in the following section, continuous monitoring of these physiological markers—as well as behavioural markers such as sleep duration and step counts [59, 61]—could enable novel infection detection platforms.

2.4 Wearable sensor-based detection of SARS-CoV-2 infections

Wearable devices fitted with sensors that can monitor physiological signals are rapidly growing in interest and adoption [62]. Currently, 22–25% of the Canadian population owns a wearable device, examples of which include smartwatches and fitness trackers [28, 29]. The breadth and fidelity of wearable sensor-captured physiological signals are also increasing, driven by scientific advances and technology maturation. Wearable sensors could be attractive tools for detecting infections given that infectious pathogens can elicit physiological changes before or absent symptoms [25, 26]. Wearable sensor-based infection detection tools would also be capable of passive detection, minimising necessary user engagement; could operate in a privacy-preserving fashion; and could leverage existing trends in device uptake to minimise infrastructure costs [28, 29]. In this section, we review efforts to develop wearable sensor-based algorithms to detect SARS-CoV-2 infections.

Over the course of the COVID-19 pandemic, there have been several attempts to develop algorithms capable of detecting SARS-CoV-2 infections from wearable sensor-captured physiological signals. We enumerate such attempts in Table 2, restricting our focus to studies that present a specific detection algorithm, as opposed to ones that only use wearable sensors to capture and describe physiological responses to SARS-CoV-2 infection. We note that other groups have generated similar lists, albeit with slightly different objectives, for example, to describe the performance of the algorithms or the types of sensors and devices used [30, 31]. Here, in addition to restricting the scope of the studies we include, we focus on insights relevant to the translation of these algorithms into public health tools to minimise overlap with existing summaries as best as possible.

Table 2: Efforts to develop wearable sensor-based algorithms to detect SARS-CoV-2 infections. In the Detection Type column, "Retrospective" detection refers to the use of a complete time window of data, defined in relation to symptom onset,

as an algorithm input; the user would need to progress through this time period, input their data, and only then learn whether they were infected. Conversely, an "Alerting System" is designed to perform detection every day, using the last few days of data as algorithm inputs; this recurring detection can occur passively and in real time.

Authors	Date	Detection Type	Population	Physiological Biomarkers
Abir et al. [63]	2022-05-30	Retrospective	Symptomatic	Resting Heart Rate
Alavi et al. [27]	2021-11-29	Alerting System	Asymptomatic, Symptomatic	Resting Heart Rate
Bogu et al. [64]	2021-01-09	Retrospective	Symptomatic	Resting Heart Rate
Cleary et al. [65]	2021-04-22	Retrospective	Symptomatic	Resting Heart Rate, Steps, Sleep Duration
Conroy et al. [66]	2022-03-08	Alerting System	Symptomatic	Heart Rate, Heart Rate Variability, Respiratory Rate, Temperature, Oxygen Saturation, Other Activity Metrics, Other Sleep Metrics, Symptoms
D'Haese et al. [67]	2021-10-14	Retrospective	Symptomatic	Heart Rate, Heart Rate Variability, Respiratory Rate, Other Activity Metrics, Other Sleep Metrics, Temperature, Sleep Duration
Gadaleta et al. [68]	2021-12-08	Alerting System	Symptomatic	Symptoms, Steps, Calories, Other Activity Metrics, Heart Rate Variability, Sleep Duration, Other Sleep Metrics
Hassantabar et al. [69]	2021-11-24	Retrospective	Asymptomatic, Symptomatic	Galvanic Skin Response, Heart Rate, Temperature, Oxygen Saturation, Blood Pressure
Mason et al. [70]	2022-03-02	Retrospective	Symptomatic	Heart Rate, Heart Rate Variability, Respiratory Rate, Other Activity Metrics, Temperature
Mayer et al. [71]	2022-04-19	Alerting System	Asymptomatic, Symptomatic	Heart Rate, Steps
Miller et al. [72]	2020-12-10	Alerting System	Symptomatic	Respiratory Rate, Resting Heart Rate, Heart Rate Variability
Mishra et al. [26]	2020-11-18	Alerting System	Asymptomatic, Symptomatic	Resting Heart Rate, Steps
Natarajan et al. [55]	2020-11-30	Alerting System	Asymptomatic, Symptomatic	Respiratory Rate, Heart Rate, Heart Rate Variability
Nestor et al. [73]	2021-05-17	Alerting System	Symptomatic	Heart Rate, Steps, Sleep Duration
Ni et al. [74]	2021-04-23	Retrospective	Symptomatic, Hospitalised	Heart Rate, Respiratory Rate, Temperature, Cough Audio
Quer et al. [61]	2020-10-29	Retrospective	Symptomatic	Symptoms, Resting Heart Rate, Steps, Sleep Duration
Risch et al. [75]	2022-04-04	Retrospective	Symptomatic	Temperature, Respiratory Rate
Sarwar et al. [76]	2021-09-10	Retrospective	Symptomatic	Heart Rate, Steps, Sleep Duration
Skibinska et al. [77]	2021-08-18	Retrospective	Symptomatic	Heart Rate, Steps
Smarr et al. [78]	2021-02-11	Retrospective	Symptomatic	Heart Rate, Heart Rate Variability, Respiratory Rate, Other Activity Metrics, Cough Audio

Nine (45%) of the studies in Table 2 developed detection algorithms that rely on heart rate, step counts, and sleep tracking—physiological parameters that are capturable by the most commonly used consumer-grade wearable devices [31]. In many instances, studies calculated derivative measures of these basic parameters to arrive at biomarkers that reflect more specific physiological processes or to avoid capturing fluctuations caused by quotidian activities such as exercise. Mayer et al., for example, calculated six derivatives of heart rate

that each reflect a distinct physiological process, while Alavi et al. calculated overnight resting heart rate, which they posited to be more stable than heart rate throughout the day [27, 71]. The use of commonly captured parameters and their derivatives as algorithm inputs means that a larger fraction of wearable device users would be able to participate in public health interventions that leverage wearable sensor-based infection detection.

The remaining 11 (55%) studies incorporate other data including less commonly captured physiological signals (e.g., temperature, oxygen saturation, respiratory rate) or manually entered data (e.g., user-reported symptoms). In theory, these physiological signals would provide complementary information about potential infection and improve detection accuracy. Some groups attempted to explore this hypothesis. Gadaleta et al., for example, found self-reported symptoms to be the most important feature when available, and activity metrics otherwise [68]. Mason et al. considered a broader host of biomarkers and found temperature and activity metrics to have the most impact on detection accuracy [70]. More systematic comparisons beyond these within-study efforts are difficult, however, due to differences in participant cohort composition and size; in the data processing steps and detection algorithms used; and in the decision thresholds selected, which result in the final algorithms falling at different points on receiver-operator curves based on the authors' choice to prioritise detection sensitivity or specificity. Importantly, while algorithms that use biomarkers that are not yet commonly captured are unquestionably valuable, over-reliance on these algorithms could constrain the pool of wearable device users able to participate in wearable sensor-based public health interventions.

Confirmed cases of SARS-CoV-2 infection who also developed symptoms were the focus of 15 (75%) of the studies in Table 2. Many of these studies segmented their analysis of physiological signals into two time windows (or a closely related variant of this concept). One window was typically defined in relation to symptom onset (e.g., from *i* days before symptom onset to *j* days after symptom onset) to reflect an infected state, and the other window encompassed the remaining period of available data to reflect a healthy state. Then, biomarkers were extracted, labelled as "healthy" or "infected" data points, and used to train detection algorithms. This common conceptual approach led to two important trends. First,

12 (60%) of the presented algorithms could be classified as "retrospective" algorithms insofar as the user would need to progress through the $i + j$ day time window relative to symptom onset before they could then input those data into a classifier and determine whether they were infected. In theory, any $i + j$ day time window could be passed into these algorithms, but detection accuracy would likely deteriorate because the algorithms were not trained in this way. Conversely, the remaining seven (35%) algorithms could be used as "alerting systems" capable of passive detection because they can classify users on a day-to-day basis, notifying users as soon as a potential infection is detected.

The second consequence of the disproportionate focus on symptoms is that only five (25%) algorithms were developed to detect asymptomatic infections despite physiological changes occurring before or absent symptoms and despite 40–45% of SARS-CoV-2 infections being asymptomatic [52, 55]. Mason et al. explored detection of asymptomatic infections by identifying individuals who were potentially asymptomatic on the basis of a positive antibody test [70]. However, antibody tests do not provide insight as to *when* the asymptomatic infection might have occurred, and the authors also note that the antibody tests used had low sensitivity. Other studies that considered asymptomatic detection—for example, that by Mishra et al.—oriented analysis around the date on which an individual who did not experience symptoms received a positive PCR test [26].

The focus on symptomatic individuals and on retrospective detection limits the public health utility of some algorithms in Table 2. As discussed, much of the value that wearable sensors could contribute to FTTI systems stems from their potential to identify presymptomatic or asymptomatic individuals without delays. However, a more pervasive limitation applicable to *all* of these detection algorithms is that none have been tested at a population level: there is no data on how these algorithms would perform if they were deployed as a public health intervention. Such a study would be difficult to conduct as it would need a large sample size to observe an effect directly attributable to wearable sensor-based infection detection. Yet, understanding how detection accuracy, behavioral parameters, and policies can affect the utility of these tools is still important for policymakers and algorithm developers. Infectious disease models can help answer these questions, and this thesis presents such a model.

3

Methods and Findings

In this chapter, we present the core modelling exercise that is the focus of this thesis, drawing from the published version of this work [13]. We situate the study and describe our modelling approach in the first two sections and present our findings in the remaining five. We discuss and interpret these findings in Chapter 4.

3.1 Study Design

3.1.1 Objectives

In this modelling exercise, we investigated the potential for wearable sensors capable of detecting presymptomatic and asymptomatic infections to help reduce the burden of infection during the acute phase of a pandemic. To do so, we used SARS-CoV-2 as an example and explored counterfactual scenarios in which these devices were deployed to combat Canada's second COVID-19 wave (September 1, 2020 to February 20, 2021). This time window allowed us to capture the dynamics of wearable sensor deployment during an acute phase of the pandemic and at a time when the technology would have been ready and deployable. Further, it allowed us to consider scenarios prior to broad vaccine availability and before then-emerging variants of concern were dominant [79]. Potential reinfections were also likely to be negligible in this timeframe [80].

In the context of this pandemic scenario, we aimed to develop an infectious disease model in which wearable devices notify users of potential infection and prompt them to seek a confirmatory lab-based test, quarantining while waiting for the result. We aimed to use this model to answer the following questions:

1. What is the baseline impact of deploying currently available detection algorithms during Canada's second COVID-19 wave? In this baseline scenario, wearable device

users would be able to download an application that runs these detection algorithms and provides notifications of potential infection.

2. How do detection sensitivity and specificity, uptake, and adherence influence this impact? Uptake is the proportion of the population that has downloaded the detection/notification application and uses their wearable device often enough. Adherence is the proportion of users who comply with all recommended next steps after a positive notification.

3. Would providing confirmatory rapid antigen tests (RATs) to users with a positive notification be a useful complementary strategy? In this scenario, a positive RAT result would confirm that the user should proceed to seek a lab-based test and quarantine while waiting for the result.

3.1.2 Outcome measures

Reducing viral transmission is an important public health objective in a number of scenarios: some examples include instances when vaccines are not available, when vaccines are available but immune-evasive variants are circulating, and when the long-term health implications of infection are not well understood. We quantified the health impact of wearable sensor deployment by calculating the number of averted infections and the percent reduction in the burden of infection, both over the simulation timeframe. We defined the number of averted infections as the difference between the historical number of infections and the number of infections in counterfactual scenarios. We calculated the percent reduction in the burden of infection by dividing the number of averted infections by the historical number of infections.

We also measured the number of days incorrectly spent in quarantine per month per wearable device user (a consequence of false positive notifications) as the primary indicator of the strategy's social burden [81]. Finally, to assess resource consumption, we quantified

the average number of additional lab-based tests (and RATs, where applicable) required each day as a result of the intervention.

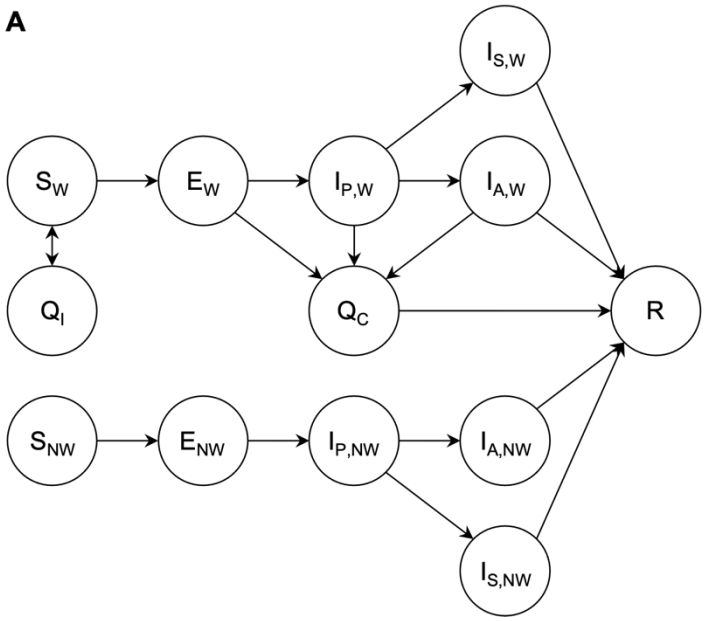
3.2 Modelling Approach

3.2.1 Modelling framework

We chose to use a compartmental modelling framework over an agent-based one. Because this modelling exercise is only an initial assessment of wearable sensor-based pandemic mitigation, we prioritised generating estimates that provide a sense of the potential scale of impact over estimates that were unnecessarily precise. A compartmental model can capture key parameters and dynamics of wearable sensor-based interventions while retaining parsimony and operating with small, clearly defined set of assumptions. Conversely, the heterogeneity and complexity afforded by agent-based models are less valuable at this stage of analysis. Using a compartmental modelling framework also allowed us to avoid the infrastructural burden of writing software on top of an existing agent-based modeling platform or setting up dedicated a computational environment for simulations.

3.2.2 Model structure

We structured the compartmental model—mathematically specified by Equations 4–17 in the following section—using a *Susceptible*, *Exposed*, *Infectious*, *Removed* (SEIR) framework (Figure 3). In this framework, the *Susceptible*, *Infectious*, and *Removed* compartments reflect the same stages of infection that they do in an SIR model, however, it was also necessary to incorporate an *Exposed* compartment to capture the latent period of SARS-CoV-2 infection [82]. *Exposed* individuals are infected but cannot yet infect others; for them, the viral replication process has begun but has not reached a level sufficient to be considered *Infectious*. We also split the *Infectious* state into three sub-states: *Presymptomatic*, *Asymptomatic*, and *Symptomatic*. All infected individuals enter the *Presymptomatic* infectious state after a latent period following exposure; some go on to develop symptoms (*Symptomatic*) while others do not (*Asymptomatic*). It was important to distinguish individuals based on symptoms to allow exploration of the capacity for wearable sensors to identify signs of infection before or absent symptoms [26].



B

Compartment	Symbol
Susceptible	S
Exposed	E
Infectious (presymptomatic)	I_p
Infectious (asymptomatic)	I_a
Infectious (symptomatic)	I_s
Removed	R
Quarantined (correctly)	Q_c
Quarantined (incorrectly)	Q_i

Figure 3: Compartmental model structure. Subscript "W" denotes a wearable device user and "NW" denotes otherwise. Model equations, parameters, and assumptions are described across Sections 3.2.2, 3.2.3, and 3.2.4.

To incorporate a counterfactual wearable sensor-based intervention, we stratified all *Susceptible*, *Exposed*, and *Infectious* states by whether individuals are participating wearable device users or not. Participating users can enter *Quarantined* states if they are notified of potential infection, and if they adhere to this notification by seeking a confirmatory lab-based test and quarantining while awaiting the result. We modelled adherence as the fraction of notified users who comply with all recommended next steps; accordingly non-adherent users ignore the notification entirely in this framework. We captured adherence in one parameter to preserve model parsimony and considered all values of this parameter (i.e., from 0% to 100%) recognizing the reality there will be great variation in the extent to which notified users are adherent. *Susceptible* wearable device users could be *Incorrectly Quarantined* due to a false positive notification and would re-enter the *Susceptible* state after receiving their lab-based test result. *Exposed* and *Infectious* device users would be *Correctly Quarantined* and would enter the *Removed* state (a longer period of isolation until recovery) after their lab-based test confirms infection.

Even though wearable sensors are capable of detecting presymptomatic, asymptomatic, *and* symptomatic SARS-CoV-2 infections, we did not include a pathway for *Symptomatic* device users to enter a *Quarantined* state [26, 61]. Historically, a meaningful yet unknown fraction of *Symptomatic* individuals would have already undergone some degree of quarantining, and this behaviour would already be accounted for in the historical transmission rate, as we later discuss. As such, preventing *Symptomatic* users from quarantining based on wearable sensor notifications enables a fairer counterfactual comparison.

In some scenarios, we also included a step where compliant wearable device users perform a confirmatory RAT after receiving a positive notification. If the RAT result is positive, we assumed they then take a lab-based test, quarantining while awaiting the result; if the RAT result is negative, we assumed they return to historical behaviour.

3.2.3 Model equations and parameterisation

We mathematically defined the compartmental model with Equations 4–17. We omit explicit specification of each compartment as a time-varying value—for example, by representing the number of *Susceptible* individuals as *S* instead of *S(t)*—to maximise equation readability. We enumerate model parameters, their values, and associated assumptions in Tables 3 and 4. Finally, for the remainder of this sub-section, we elaborate on how we estimated values of certain parameters and how we accounted for parameter uncertainty.

$$\frac{d}{dt}S_w = -\theta\pi - \psi\chi(1-\nu_w)(1-\nu_a)S_w + \frac{Q_i}{\epsilon} \quad (4)$$

$$\frac{d}{dt}E_w = \theta\pi - \psi\kappa\sigma_w\sigma_a E_w - \alpha E_w \quad (5)$$

$$\frac{d}{dt}I_{p,w} = \alpha E_w - \psi\kappa\sigma_w\sigma_a I_{p,w} - \tau I_{p,w} \quad (6)$$

$$\frac{d}{dt}I_{a,w} = \rho\tau I_{p,w} - \psi\kappa\sigma_w\sigma_a I_{a,w} - \gamma I_{a,w} \quad (7)$$

$$\frac{d}{dt}I_{s,w} = (1-\rho)\tau I_{p,w} - \gamma I_{s,w} \quad (8)$$

$$\frac{d}{dt}S_{nw} = -(1-\theta)\pi \quad (9)$$

$$\frac{d}{dt}E_{nw} = (1-\theta)\pi - \alpha E_{nw} \quad (10)$$

$$\frac{d}{dt}I_{p,nw} = \alpha E_{nw} - \tau I_{p,nw} \quad (11)$$

$$\frac{d}{dt}I_{a,nw} = \rho\tau I_{p,nw} - \gamma I_{a,nw} \quad (12)$$

$$\frac{d}{dt}I_{s,nw} = (1-\rho)\tau I_{p,nw} - \gamma I_{s,nw} \quad (13)$$

$$\frac{d}{dt}R = \gamma\left(I_{a,w} + I_{s,w} + I_{a,nw} + I_{s,nw}\right) + \frac{Q_c}{\epsilon} \quad (14)$$

$$\frac{d}{dt}Q_i = \psi\chi(1-\nu_w)(1-\nu_a)S_w - \frac{Q_i}{\epsilon} \quad (15)$$

$$\frac{d}{dt}Q_c = \psi\kappa\sigma_w\sigma_a\left(E_w + I_{p,w} + I_{a,w}\right) - \frac{Q_c}{\epsilon} \quad (16)$$

$$\pi = \frac{\beta_h}{N}\left[\lambda\left(aI_{p,w} + I_{p,nw} + aI_{a,w} + I_{a,nw}\right) + \left(I_{s,w} + I_{s,nw}\right)\right][aS_w + S_{nw}] \quad (17)$$

Table 3: SARS-CoV-2 characteristics. We assumed a mean generation time of 7 days [83–85]. We assumed a mean incubation period of 5 days [83–86]. We applied the fact that the mean generation time is equal to the sum of the mean latent period and the mean infectious period [87]. We subtracted the mean latent period from the mean incubation period to obtain the presymptomatic infectious period. We subtracted the incubation period from the mean generation time to obtain the mean asymptomatic and symptomatic infectious period. We modelled asymptomatic prevalence as a beta random variable with a mean of 0.4 and a sample size of 200; a sample size of 200 is greater than 75% of the study populations examined by Oran et al. in their analysis of the asymptomatic prevalence [52].

Parameter	Symbol	Value
Latent period	α^{-1}	3 days [83, 88, 89]
PR symptomatic infectious period	τ^{-1}	2 days [83–86, 88, 89]
Asymptomatic and symptomatic infectious period	γ^{-1}	2 days [83–86]
Asymptomatic prevalence	ρ	40% [52]
Transmission potential without symptoms relative to with symptoms	λ	50% [90–92]
Historical incidence of infection (i.e., number of new infections per day)	π_h	varies; obtained from IHME [93]
Counterfactual incidence of infection (i.e., number of new infections per day)	π	varies; calculated using Equation 17
Historical average number of transmissions per infectious person per day	β_h	varies; calculated using Equations 18–24 below

Table 4: Technology, behavioural, and policy parameters and associated assumptions.

Parameter	Symbol	Nominal Value	Notes
Uptake	θ	4%	We defined uptake as the percent of the population that owns a wearable device, has downloaded the detection/notification application, and uses the device enough to collect sufficient data for detection. We estimated uptake would range from 0.5% to 7.5% at baseline. We elaborate on how this estimate was generated below (Tables 5 and 6).

Adherence to wearable device notification	ψ	50%	We defined adherence as the proportion of wearable device users that comply with recommended next steps upon notification of potential infection. At baseline, next steps include seeking a confirmatory lab-based test, quarantining while awaiting a result, and self-isolating until recovery if the result is positive. With antigen tests, compliant users also take a confirmatory RAT prior to seeking a lab-based test. In Israel, at least ~53% of antigen test kit results were reported (~613,000 reports out of ~1,150,000 kits taken home) [94, 95]. In the UK, duration-adjusted adherence to self-isolation was 42.5% [96]. In Norway, up to 70% of those with a suspected diagnosis and up to 86% with a positive diagnostic test adhered to self-isolation [97]. However, adherence could be as low as ~14% if one considers Canada's COVID Alert contact tracing app's reporting rate in light of the number of confirmed cases as of July 27, 2021 [98]. We modeled adherence as a beta random variable with a mean of 0.5 and a sample size of 1723; 1723 was the sample size for the relevant experiment in the Norway study.
Detection algorithm sensitivity	σ_w	80%	We defined detection sensitivity as the proportion of infected yet asymptomatic device users (i.e., *Exposed*, *Presymptomatic*, and *Asymptomatic*) who receive a notification of potential infection prior to recovering and entering the *Removed* compartment. Alavi and et al.'s NightSignal algorithm achieved a sensitivity of ~80%, which is a plausible value based on other efforts to develop similar algorithms [27, 68, 70]. We modeled sensitivity as a beta random variable with a mean of 0.80 and a sample size of 84; 84 was the size of the sample used to calculate NightSignal algorithm sensitivity.
Detection algorithm specificity	ν_w	92%	We defined specificity as the probability that, on a given day, a healthy (i.e., *Susceptible*) wearable device user does not receive a notification of potential infection. Alavi et al.'s NightSignal algorithm gave potentially healthy users 0.0819 false positive notifications ("red alerts") per day on average, corresponding to a specificity of ~92% [27]. We modeled specificity as a beta random variable with a mean of 0.92 and a sample size of 818; alarm data from 818 potentially healthy users in Alavi et al.'s dataset were used to calculate the false positive rate.
Detection algorithm sensitivity adjustment factor	κ	$(\alpha^{-1} + \tau^{-1} + \lambda^{-1})^{-1}$ $days^{-1}$	We assumed that σ_w is applied uniformly across *Exposed*, *Presymptomatic*, and *Asymptomatic* states such that by the time infectiousness ends, σ_w of infected users without symptoms have been notified.
Detection algorithm specificity adjustment factor	χ	$(1)^{-1}$ $days^{-1}$	We assumed that ν_w is applied over one day such that on a given day, *Susceptible* users receive an incorrect (i.e., false positive) notification of potential infection with probability $(1-\nu_w)$.
Rapid antigen test sensitivity	σ_a	91.1%	We used the worst performance reported for Abbot's Panbio RAT [99]. Independent evaluations of this test suggest lower sensitivity in presymptomatic and asymptomatic individuals [100, 101]. However, we reasoned that the receipt of a wearable sensor-based notification of potential infection raised the pretest probability of infection, thereby improving the negative predictive value (NPV) of the RATs [102].
Rapid antigen test specificity	ν_a	99.7%	We used the lowest performance reported for Abbot's Panbio RAT [99]. Independent evaluations suggest that this test's specificity is even higher [100, 101].

Lab-based test result turnaround time	ε	2 days	ε generally ranges between 1–3 days based on Health Canada reporting [103]. We assumed perfect lab-based test accuracy.
Relative contribution to transmission	*a*	1	*a* is used to study scenarios in which wearable device users who do not receive a positive notification or who ignore a positive notification act in a riskier or more cautious fashion, respectively [65]. See Equation 17 above.

During the COVID-19 pandemic, low adoption of digital tools for pandemic mitigation resulted in these tools delivering less impact than had been hoped for [19, 20]. To obtain a realistic estimate of uptake of wearable sensor-based infection detection tools, we considered device ownership, the anticipated application download rate, and the level of utilisation of the wearable devices themselves. We first multiplied the proportion of the population that owns a wearable device by the anticipated download rate to obtain a plausible range for the proportion of the population that would own the detection/notification application (Table 5). Estimates from 2018 placed wearable device ownership in Canada between 22% and 25% [28, 29]. Separate, a study found that the baseline download rate of Germany's national contact tracing application was between ~8% and ~11%, and that incentives could increase this rate [104]. Paré et al. also found that 57% of owners regularly track their health with their wearable device [28]. We ultimately considered download rates ranging from 10% to 60%.

Table 5: Estimating detection/notification application ownership.

Application Ownership	*Device Ownership*		
Download Rate	22.0%	23.5%	25.0%
10.0%	2.2%	2.4%	2.5%
35.0%	7.7%	8.2%	8.8%
60.0%	13.2%	14.1%	15.0%

We then calculated a range for uptake by multiplying the proportion of individuals that own the detection/notification application by expected levels of utilization (Table 6). Accounting for utilization was a necessary step because not all individuals who download the application to their device will use it enough to provide sufficient data for the algorithm to function correctly. In research studies where wearable devices were used to track health, usage rates ranged from as low as 24%, to 50% in the long run [105, 106]. We ultimately concluded that in a baseline scenario, uptake would likely range from 0.5% to 7.5%.

We used the performance of Alavi et al.'s NightSignal algorithm to obtain nominal values for the sensitivity and specificity of wearable sensor-based detection [27]. NightSignal is the second iteration of detection algorithms published by Mishra et al. [26]. Together, this team's algorithm development efforts represent two of the seven algorithms in Section 2.4 that were "alerting systems" capable of passive infection detection, as well as and two of the five algorithms developed to detect asymptomatic SARS-CoV-2 infections. Beyond possessing these important attributes, the NightSignal algorithm was also amenable to being modelled because its developers were receptive and enthusiastic to collaborate on appropriately capturing its performance in this exercise.

Table 6: Estimating uptake. Uptake is the proportion of individuals who own the detection/notification application and use their wearable device enough to collect sufficient data.

Uptake	*Application Ownership*		
Utilisation	2.2%	8.6%	15.0%
24.0%	0.5%	2.1%	3.6%
37.0%	0.8%	3.2%	5.6%
50.0%	1.1%	4.3%	7.5%

Detection algorithm sensitivity (σ_w) and specificity (ν_w), the asymptomatic prevalence (ρ), and adherence (ψ) were important sources of uncertainty in our assessment of wearable sensors as pandemic mitigation tools. To account for uncertainty stemming from how values for these parameters were measured (e.g., with a small sample size), we modelled them as beta-distributed random variables, as specified in Table 4. We sampled these variables at the start of each simulation, using the resulting values to generate an epidemic trajectory, and ran 5,000 Monte Carlo simulations to obtain confidence intervals [46].

We also conducted various sensitivity analyses to isolate the influence of parameters beyond detection accuracy, uptake, and adherence. To explore the notion that adherence may not be "all or nothing" in practice, we considered the possibility that non-adherent users who do not take any recommended next steps still act more cautiously (e.g., limiting contacts, wearing a more protective mask) due to the notification. We also considered the possibility that device users who are not notified of potential infection act in a riskier fashion (e.g.,

increasing contacts) relative to historical behaviour [65]. We modulated *a* in Equation 17—a parameter nominally set to 1 (Table 4)—to explore these possibilities. When *a* is above 1, the average device user in the *Susceptible*, *Presymptomatic Infectious*, and *Asymptomatic Infectious* compartments acts in a riskier fashion relative to historical behaviour; when *a* is below 1, the average user in these groups acts more cautiously. Finally, we explored a range of values for the prevalence of infected individuals that remain asymptomatic, lab-based test turnaround time, and RAT sensitivity.

3.2.4 Simulation approach

To perform counterfactual simulations, we needed to obtain the historical time-varying transmission rate (β_h) and apply it in the context of Equations 4–17 specified above. We first extracted β_h from the historical incidence of infection (π_h) using Equations 18–24 below. These equations define the same compartmental model presented above, absent the counterfactual wearable sensor-based intervention. Using the true incidence of infection, rather than a time series of incompletely ascertained PCR-confirmed COVID-19 cases, was crucial to appropriately capture the extent of historical viral spread [107]. Because estimating π_h is challenging and was not itself an objective of the present work, we drew from the Institute for Health Metrics and Evaluation (IHME) infection model, a time series nowcasting model that is widely used to understand the historical extent of infection [108–110]. The IHME model estimates π_h from confirmed cases, hospitalizations, and deaths, and validates results against seroprevalence data. We downloaded these data from the IHME website on December 7, 2021. To ensure our findings were robust to the underlying infection model, we replicated core analyses using estimates of π_h from the Imperial College London (ICL) infection model [111].

$$\beta_h = \frac{\pi_h N}{S(\lambda I_p + \lambda I_a + I_s)} \tag{18}$$

$$\frac{d}{dt} S = -\pi_h \tag{19}$$

$$\frac{d}{dt} E = \pi_h - \alpha E \tag{20}$$

$$\frac{d}{dt} I_p = \alpha E - \tau I_p \quad (21)$$

$$\frac{d}{dt} I_a = \rho\tau I_p - \gamma I_a \quad (22)$$

$$\frac{d}{dt} I_s = (1-\rho)\tau I_p - \gamma I_s \quad (23)$$

$$\frac{d}{dt} R = \gamma I_a + \gamma I_s \quad (24)$$

Next, we applied β_h according to Equation 17 in the context of the counterfactual model defined above. The time series for β_h that results from Equation 18 incorporates all historical policy measures (e.g., restrictions, business closures, testing availability) and behaviour (e.g., adherence to restrictions, quarantines) that occurred. However, because some *Susceptible*, *Exposed*, and *Infectious* device users now quarantine in simulations, the counterfactual incidence of infection (i.e., the π obtained from Equation 17) decreases relative to historical levels (i.e., π_h).

3.2.5 Model implementation

We implemented the compartmental model in Python 3.10 using the following packages: *numpy*, *pandas*, and *scipy*. On a 2019 MacBook Pro with a 2.8 GHz Quad-Core Intel Core i7 processor, we were able to run ~35 simulations per second. Our code is publicly available at https://github.com/nathanduarte/wearables_for_pandemic_mitigation.git [13].

3.3 Baseline impact of wearable sensor deployment

We first investigated the baseline scenario in which detection algorithms that currently exist are made publicly available for wearable device users to download and use (Figure 4) [27]. Upon notification of potential presymptomatic or asymptomatic infection, users are prompted to seek a confirmatory lab-based test, quarantine while awaiting the result, and self-isolate until recovery if positive. We used the nominal values outlined in Table 4, setting uptake, adherence, detection sensitivity, and detection specificity to 4%, 50%, 80%, and 92%, respectively.

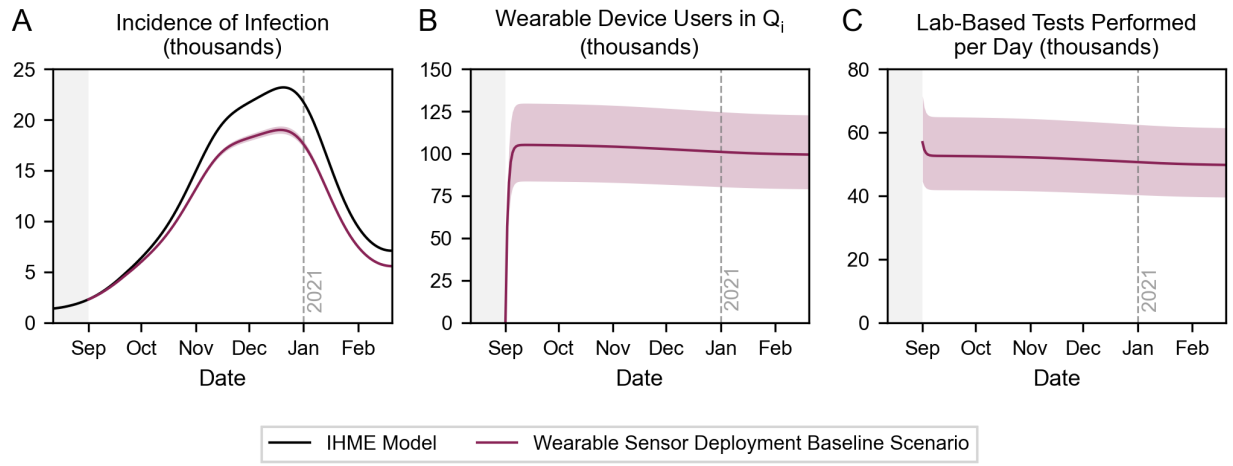


Figure 4: Baseline impact of wearable sensor deployment. Time series depiction of (A) the incidence of infection, (B) the number of wearable device users incorrectly in quarantine, and (C) the daily demand for lab-based tests. Uptake, adherence, detection sensitivity, and detection specificity are set to 4%, 50%, 80%, and 92%, respectively.

We observed that in a baseline scenario, 366,143 (95% CI: 333,242–396,944) infections could have been averted during Canada's second COVID-19 wave—a 15.6% (95% CI: 14.2–16.9%) reduction in the burden of infection (Figure 4A). However, the social costs were high: between ~75,000 and ~125,000 device users were incorrectly quarantining on any given day (Figure 4B). Moreover, between ~40,000 and ~65,000 additional lab-based tests were required each day (Figure 4C), corresponding to a 51.6% (95% CI: 41.1–63.6%) increase in demand relative to historical volumes. Historically, ~101,000 lab-based tests were performed each day, on average, during the simulation timeframe [109, 112]. The number of individuals incorrectly in quarantine and daily demand for lab-based tests were generally steady over time because they largely depend on the number of *Susceptible* device users, adherence, and detection specificity; the gradual decrease can be attributed to the flow of users into the *Removed* state.

To ensure our findings were robust to the underlying infection model, we replicated core analyses using estimates of π_h from the ICL infection model (Figure 5) [111]. ICL and IHME estimates of π_h expectedly differ greatly, however, we confirmed that the *relative* public health impact of wearable sensor deployment remained consistent. In the same baseline scenario (4% uptake, 50% adherence, 80% detection sensitivity, 92% detection specificity),

we observed a 15.8% (95% CI: 14.5–17.2%) reduction in the burden of infection when the ICL infection model was used. The number of device users incorrectly in quarantine on any given day and the number of additional lab-based tests required each day were largely consistent between the two infection models because the relative change in the number of *Susceptible* individuals across the models was marginal.

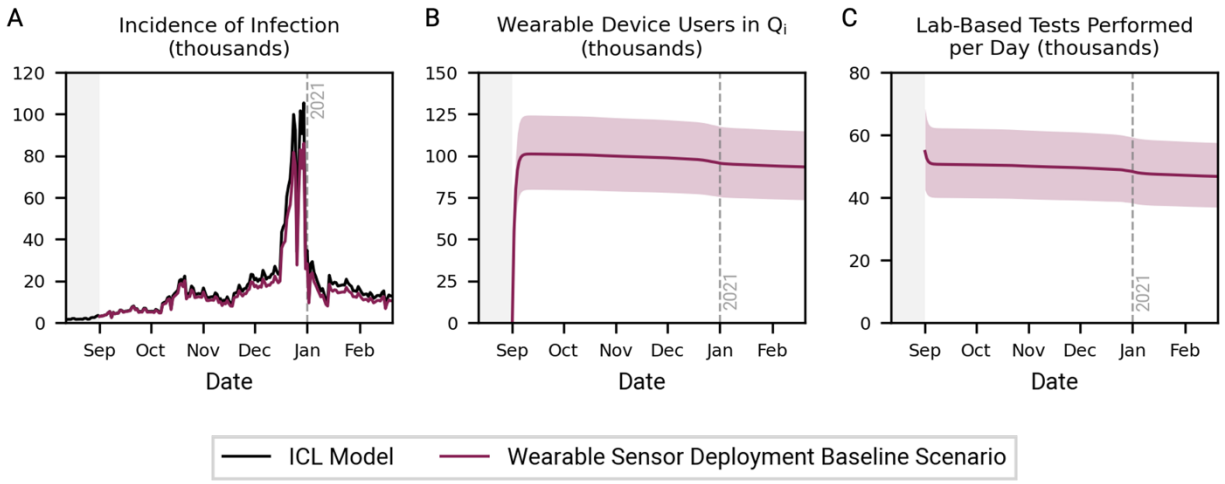


Figure 5: Baseline impact of wearable sensor deployment using Imperial College London's infection model. Time series depiction of (A) the incidence of infection, (B) the number of wearable device users incorrectly in quarantine, and (C) the daily demand for lab-based tests. Uptake, adherence, detection sensitivity, and detection specificity are set to 4%, 50%, 80%, and 92%, respectively.

3.4 Influence of detection sensitivity and specificity

After their initial release on technology platforms, health detection algorithms can be updated and improved as more real-world data are collected. However, it is often challenging to dramatically raise detection sensitivity and specificity at the same time. We explored the implications of this trade-off (Figure 6), varying detection sensitivity and specificity while keeping uptake and adherence constant at 4% and 50%, respectively.

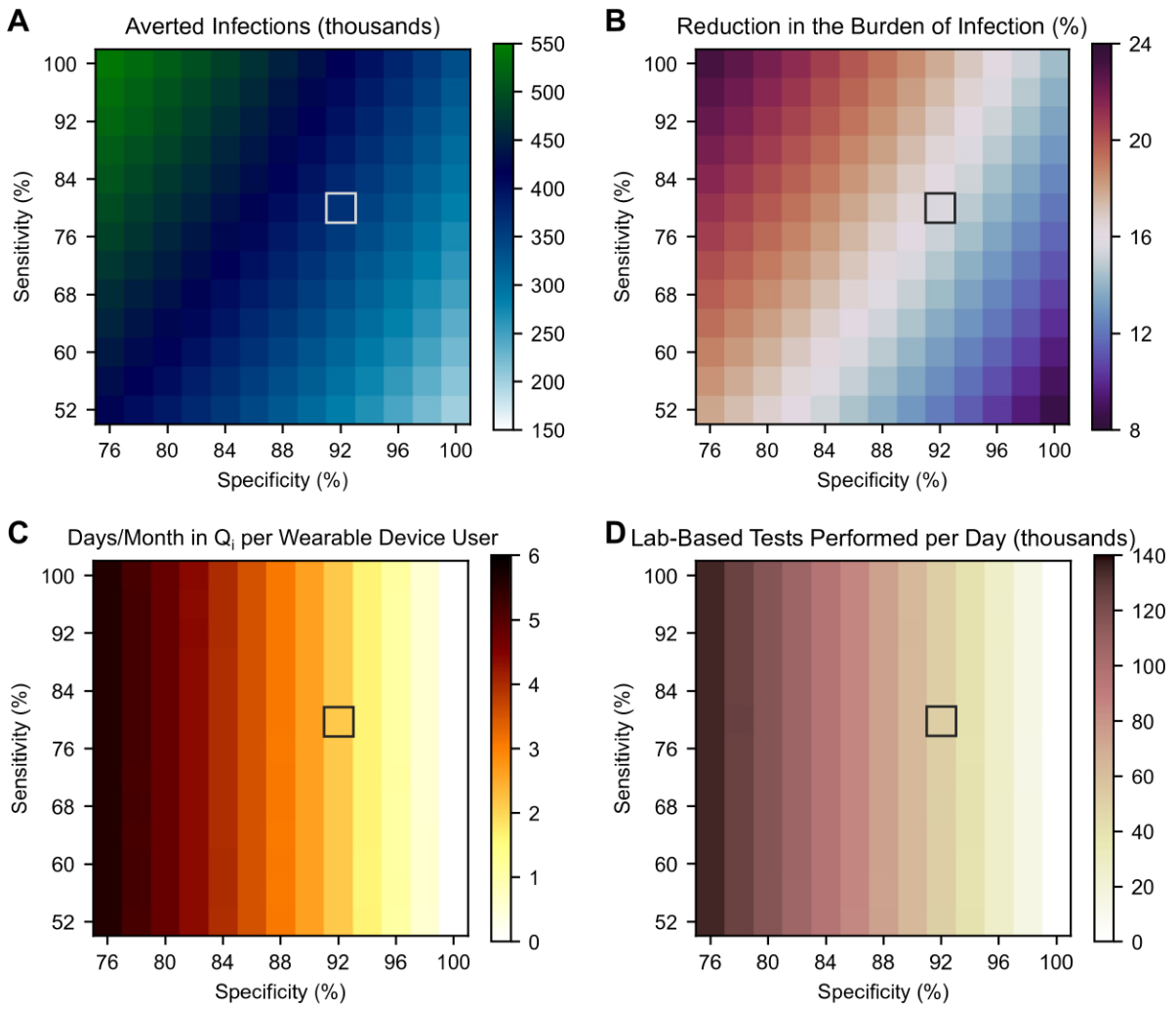


Figure 6: Trade-off between detection sensitivity and specificity. (A) Averted infections, (B) reduction in the burden of infection, (C) days incorrectly spent in quarantine per month per user, and (D) average daily demand for lab-based tests, all over the simulation period, as a function of detection sensitivity and specificity. Grey boxes denote nominal sensitivity (80%) and specificity (92%).

Increasing detection sensitivity increased the number of averted infections by prompting more *Infectious* users to quarantine (Figures 6A and 6B). On the other hand, increasing specificity had a two-part effect. First, as specificity approached 100%, the number of days incorrectly spent in quarantine approached zero (Figure 6C); sensitivity had negligible impact on incorrect quarantines. Second, by virtue of decreasing the number of incorrect quarantines, increasing specificity resulted in a larger pool of *Susceptible* individuals; in turn, fewer infections were averted. Despite this second effect, incorrect quarantines were not

central to the strategy's public health impact. We compared the number of averted infections achieved with nominal (92%) and perfect (100%) detection specificity as detection sensitivity increase; we held uptake and adherence constant at their nominal values of 4% and 50%, respectively (Figure 7). We found that 22.7% (95% CI: 13.1–32.5%) of averted infections were driven by incorrect quarantines in the baseline scenario presented above in Section 3.3. This proportion decreased with increasing detection sensitivity.

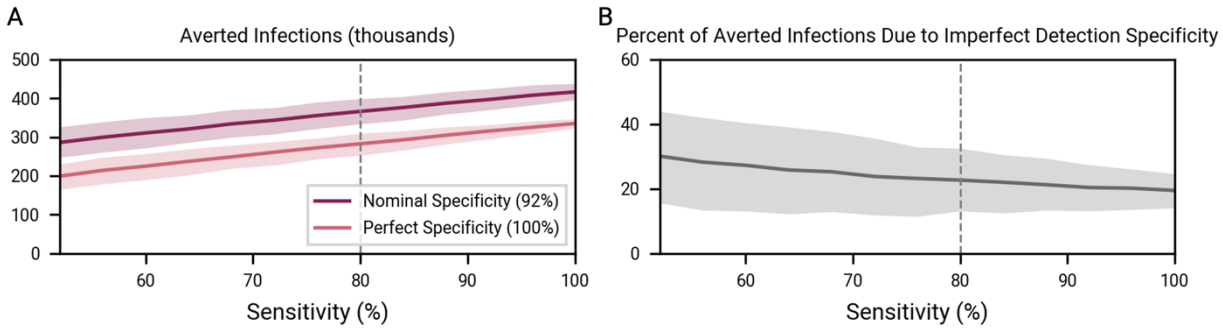


Figure 7: Impact of incorrect quarantines on averted infections. The percentages in the plot on the right are calculated by dividing the difference in the number of averted infections achieved with nominal (92%) and perfect (100%) detection specificity by the number of averted infections achieved with nominal detection specificity. We kept uptake and adherence constant at 4% and 50%, respectively. The vertical dashed grey line depicts nominal detection algorithm sensitivity (80%).

In theory, increasing detection sensitivity would increase demand for lab-based tests. We found that this effect paled in comparison to the number of lab-based tests prompted by false positive notifications (Figure 6D). Lab-based test demand expectedly decreased as detection specificity increased.

3.5 Influence of uptake and adherence

Ensuring that public health measures reach sufficient levels of uptake has been a continued challenge through the COVID-19 pandemic. Digital contact tracing and vaccination efforts around the world have shown that well-constructed policies—for example, incentivizing participation—can improve uptake of measures [104, 113]. Here, we explored the role of uptake to provide relevant context for the design of wearable sensor deployment policies (Figure 8). We estimated that uptake would fall between 0.5% and 7.5% (Tables 5 and 6) at baseline but chose to present outcomes at all levels of uptake (i.e., from 0% to 100%) to

illustrate emergent phenomena. We also explored multiple technology scenarios, setting "high" detection sensitivity and specificity at 96.0% and 98.4%, respectively; we based these increases on the respective goals of capturing 20% more infections and reducing the false positive rate by 80% relative to nominal values. We kept adherence constant at 50%.

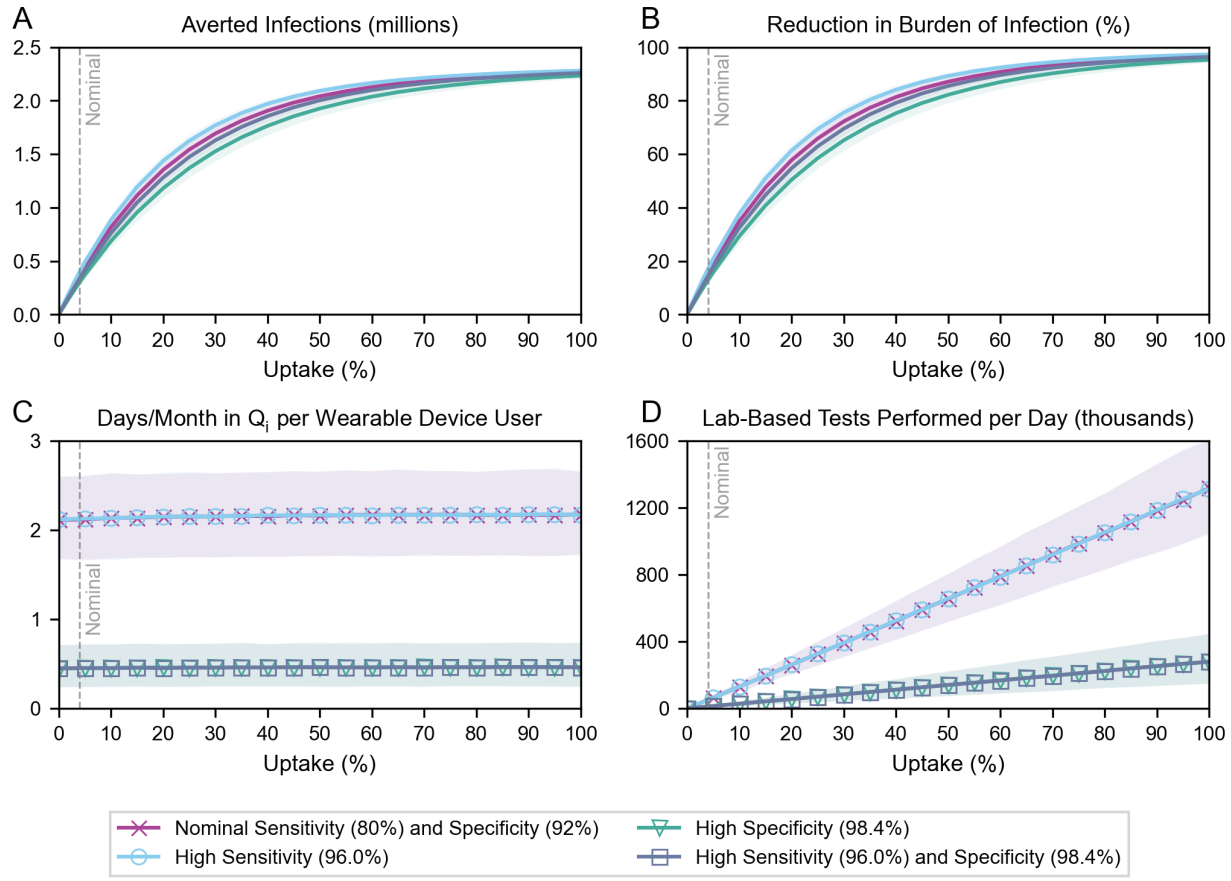


Figure 8: Impact of increasing uptake. (A) Averted infections, (B) reduction in the burden of infection, (C) days incorrectly spent in quarantine per month per user, and (D) average daily demand for lab-based tests, all over the simulation period, as a function of increasing uptake. Grey dashed lines denote nominal uptake (4%). In the "High Sensitivity" and "High Specificity" scenarios, detection specificity and sensitivity are kept at their nominal values, respectively. Symbol markers are added in (C) and (D) to distinguish overlapping curves: in these charts, the "Nominal Sensitivity and Specificity" and "High Sensitivity" curves overlap, and the "High Specificity" and "High Sensitivity and Specificity" curves overlap.

In all technology scenarios, increasing uptake averted more infections, though with eventual diminishing returns (Figures 8A and 8B). Within our estimated range of uptake (0.5% to 7.5%), and with nominal detection sensitivity and specificity, each percent increase in

uptake resulted in an additional 3.4% (95% CI: 2.8–4.0%) reduction in the burden of infection (Figure 8B). As expected, improving detection specificity resulted in fewer averted infections when uptake was held constant; this effect was most pronounced between ~30% and ~60% uptake. The number of days incorrectly spent in quarantine per month per device user remained constant as a function of uptake but decreased from ~2.15 to ~0.45 when detection specificity increased (Figure 8C). This ~80% decrease was consistent with how we defined "high specificity" underscoring that detection specificity directly influences the burden of incorrect quarantines on users. The average daily demand for lab-based tests scaled linearly with uptake, but at a slower rate with higher detection specificity (Figure 8D).

Adherence to public health guidelines also impacts the success of pandemic control measures. Targeted policies—for example, compensating individuals in self-isolation—could help improve compliance with public health recommendations [114]. Here, we explored the role of adherence in wearable sensor deployment strategies (Figure 9). We captured adherence in one parameter to preserve model parsimony but recognize that there is likely to be great variation in the extent to which notified users adhere to recommended next steps in practice, as outlined in Table 4. For this reason, we chose to explore outcomes at all values of adherence—from 0% adherence, where no users comply with any recommended next steps, to 100% adherence, where all users comply with all recommended next steps. We kept uptake constant at 4% and assessed multiple technology scenarios using the same definitions of "high" detection sensitivity and specificity as before.

Adherence meaningfully impacted the achievable reduction in the burden of infection (Figure 9B). With nominal detection sensitivity and specificity, increasing adherence among participating wearable device users from 20% to 80% tripled the achieved reduction in the burden of infection, raising it from 7.2% (95% CI: 6.3–8.1%) to 22.1% (95% CI: 20.4–23.6%). However, increasing the proportion of users who comply with notifications also magnified the consequences of false positive notifications: the number of days incorrectly spent in quarantine per month per user (Figure 9C) and the demand for lab-based tests (Figure 9D) grew proportionally with adherence. These social and resource costs grew at a slower rate with improved detection specificity.

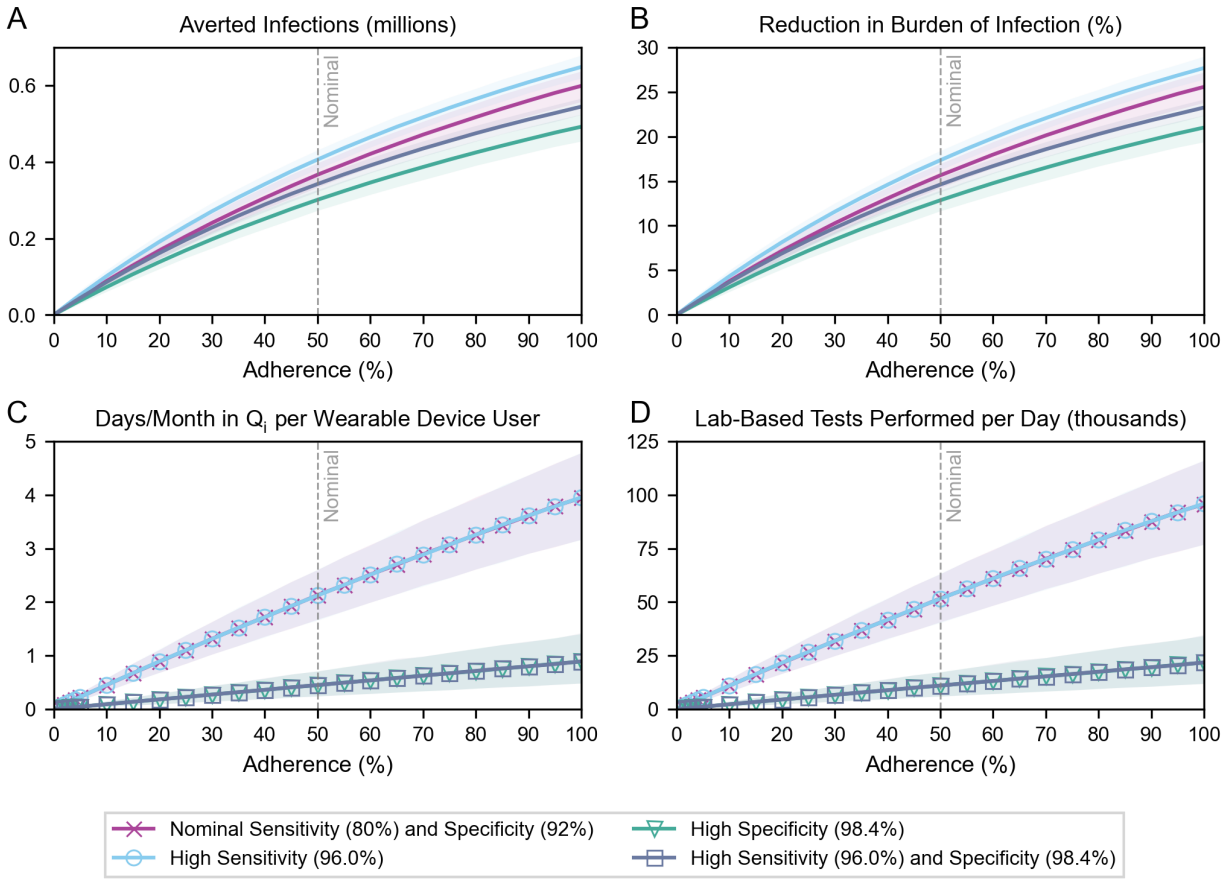


Figure 9: Impact of increasing adherence. (A) Averted infections, (B) reduction in the burden of infection, (C) days incorrectly spent in quarantine per month per user, and (D) average daily demand for lab-based tests, all over the simulation period, as a function of increasing adherence. Grey dashed lines denote nominal adherence (50%). In the "High Sensitivity" and "High Specificity" scenarios, detection specificity and sensitivity are kept at their nominal values, respectively. Symbol markers are added in (C) and (D) to distinguish overlapping curves: in these charts, the "Nominal Sensitivity and Specificity" and "High Sensitivity" curves overlap, and the "High Specificity" and "High Sensitivity and Specificity" curves overlap.

We also explored the impact of behaviour-driven changes to users' contribution to transmission as part of our analysis of adherence (Figure 10). In particular, we considered scenarios in which (1) the relative contribution to transmission of users who do not receive a positive notification increases due to a sense of false confidence, and (2) that of users who ignore a positive notification decreases due to a sense of caution (i.e., partial adherence) [65]. Wearable device users stay in *Susceptible*, *Presymptomatic Infectious*, and *Asymptomatic Infectious* compartments either because they do not receive a positive notification or because

they ignore a positive notification. By modulating *a* in Equation 17, we captured the weighted average change in the relative contribution to transmission driven by these two groups. Increases in transmission by users relative to historical levels resulted in smaller reductions in the burden of infection while decreases had the opposite effect. The number of incorrect quarantines was not impacted.

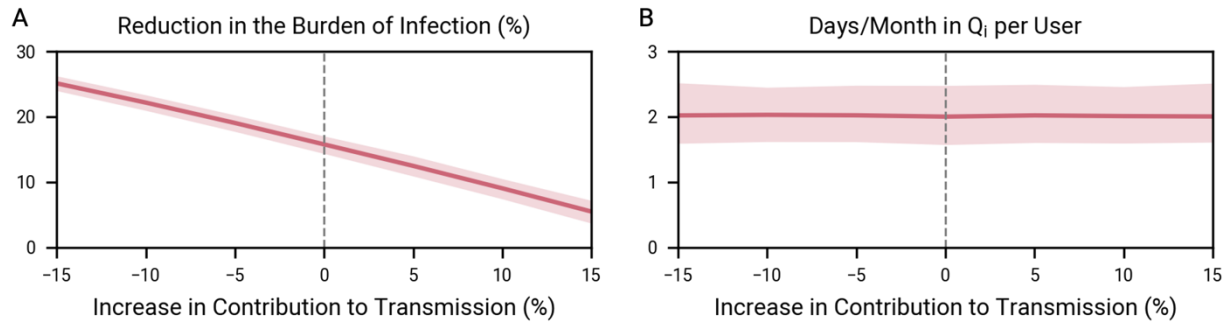


Figure 10: Impact of behaviour-driven changes to users' contribution to transmission. When *a* in Equation 17 is below 1, the average wearable device user in the *Susceptible*, *Presymptomatic Infectious*, and *Asymptomatic Infectious* compartments acts more cautiously relative to historical behavior. When *a* is above 1, the average user in these groups acts in a riskier fashion. We set uptake, adherence, detection sensitivity, and detection specificity at their nominal values of 4%, 50%, 80%, and 92%, respectively. We assumed that transmission among non-users was unchanged. The vertical dashed grey line at 0% reflects the change in contribution when *a* is nominally set to 1.

3.6 Impact of offering confirmatory rapid antigen tests

Our earlier findings suggested that false positive notifications of potential infection were the primary cause of unnecessary quarantines and lab-based tests. Improving detection specificity was one way to decrease false positive notifications. Here, we investigated whether offering confirmatory RATs to users with a positive notification could also contribute to reducing unnecessary quarantines and lab-based tests (Figure 11; Tables 7 and 8). We considered multiple scenarios, each with either low levels of uptake (0.5%) or adherence (14%), nominal levels of uptake (4%) or adherence (50%), or high levels of uptake (12.5%) or adherence (86%). We examined these scenarios in the cases of nominal detection sensitivity and specificity, and of "high" detection sensitivity and specificity (using the same definitions of "high" as above).

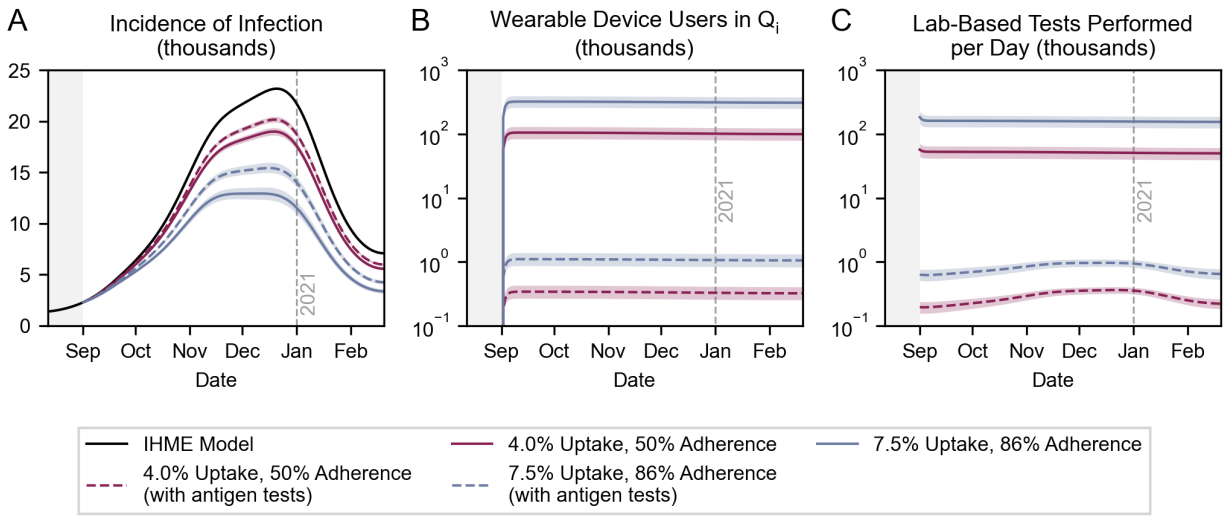


Figure 11: Wearable sensor deployment with confirmatory rapid antigen tests. Time series depiction of (A) the incidence of infection, (B) the number of wearable device users incorrectly in quarantine, and (C) the daily demand for lab-based tests. Detection sensitivity and specificity are set to their nominal values of 80% and 92%, respectively.

Table 7: Impact of offering confirmatory rapid antigen tests. 95% confidence intervals are listed in parentheses. Table 8 below depicts outcomes in analogous scenarios without rapid antigen tests.

Uptake (%)	Adherence (%)	Averted Infections (thousands)	Reduction in Burden of Infection (%)	Days/Month in Q_i per User (thousands)	Additional Lab-Based Tests Performed per Day	Additional Rapid Tests Performed per Day (thousands)
Nominal Detection Sensitivity (80%) and Specificity (92%) Scenario						
0.5	14	11.0 (9.4–12.6)	0.5 (0.4–0.5)	1.92 (1.47–2.46)	11 (9 – 13)	1.9 (1.5–2.5)
0.5	50	34.4 (30.9–37.6)	1.5 (1.3–1.6)	6.85 (5.29–8.55)	37 (32 – 43)	6.9 (5.4–8.7)
0.5	86	52.6 (47.9–56.5)	2.2 (2.0–2.4)	11.81 (9.23–14.68)	60 (52 – 69)	11.9 (9.3–14.8)
4.0	14	86.5 (73.5–99.5)	3.7 (3.1–4.2)	1.92 (1.46–2.45)	88 (73 – 103)	15.5 (11.8–19.8)
4.0	50	263.4 (237.1–286.6)	11.2 (10.1–12.2)	6.87 (5.34–8.53)	284 (244 – 326)	55.6 (43.2–69.0)
4.0	86	393.5 (362.2–420.3)	16.8 (15.5–17.9)	11.84 (9.29–14.79)	454 (391 – 527)	95.8 (75.2–119.6)
7.5	14	160.0 (136.9–183.9)	6.8 (5.8–7.8)	1.92 (1.46–2.46)	162 (135 – 191)	29.2 (22.2–37.3)
7.5	50	472.4 (427.8–511.5)	20.2 (18.3–21.8)	6.87 (5.32–8.60)	510 (438 – 592)	104.1 (80.7–130.3)
7.5	86	687.0 (636.8–728.4)	29.3 (27.2–31.1)	11.88 (9.24–14.79)	805 (686 – 936)	180.1 (140.2–224.2)
High Detection Sensitivity (96.0%) and Specificity (98.4%) Scenario						
0.5	14	13.0 (11.5–14.6)	0.6 (0.5–0.6)	0.38 (0.21–0.63)	7 (6 – 9)	0.4 (0.2–0.6)
0.5	50	39.9 (37.6–41.9)	1.7 (1.6–1.8)	1.37 (0.73–2.18)	23 (21 – 26)	1.4 (0.8–2.2)
0.5	86	59.9 (57.6–61.7)	2.6 (2.5–2.6)	2.35 (1.26–3.74)	35 (31 – 39)	2.4 (1.3–3.8)
4.0	14	102.6 (91.1–114.6)	4.4 (3.9–4.9)	0.39 (0.21–0.63)	58 (50 – 67)	3.2 (1.7–5.2)
4.0	50	303.0 (286.6–317.5)	12.9 (12.2–13.5)	1.37 (0.72–2.20)	167 (149 – 188)	11.2 (5.9–17.9)
4.0	86	443.2 (426.2–455.3)	18.9 (18.2–19.4)	2.35 (1.26–3.73)	241 (215 – 276)	19.2 (10.4–30.4)
7.5	14	188.8 (167.3–210.9)	8.1 (7.1–9.0)	0.38 (0.20–0.62)	105 (91 – 121)	5.9 (3.2–9.5)
7.5	50	539.4 (511.4–562.9)	23.0 (21.8–24.0)	1.38 (0.74–2.23)	284 (253 – 324)	21.1 (11.5–34.0)
7.5	86	767.3 (741.7–785.9)	32.7 (31.6–33.5)	2.37 (1.24–3.82)	395 (343 – 461)	36.2 (19.1–58.1)

Table 8: Various wearable sensor deployment scenarios. 95% confidence intervals are listed in parentheses. This table is a counterpart to Table 7 such that analogous scenarios with and without confirmatory antigen tests can be compared.

Uptake (%)	Adherence (%)	Averted Infections (thousands)	Reduction in Burden of Infection (%)	Days/Month in Q_I per User (thousands)	Additional Lab-Based Tests Performed per Day
Nominal Detection Sensitivity (80%) and Specificity (92%) Scenario					
0.5	14	15.5 (13.3–17.8)	0.7 (0.6–0.8)	0.63 (0.48–0.79)	1.9 (1.5 – 2.4)
0.5	50	48.8 (44.1–53.3)	2.1 (1.9–2.3)	2.11 (1.66–2.60)	6.4 (5.1 – 7.9)
0.5	86	75.3 (69.2–81.1)	3.2 (3.0–3.5)	3.45 (2.77–4.19)	10.5 (8.4 – 12.7)
4.0	14	121.7 (104.4–139.5)	5.2 (4.5–6.0)	0.63 (0.48–0.80)	15.3 (11.6 – 19.3)
4.0	50	366.4 (333.9–398.7)	15.6 (14.2–17.0)	2.13 (1.68–2.61)	51.6 (40.7 – 63.2)
4.0	86	543.4 (503.7–579.4)	23.2 (21.5–24.7)	3.47 (2.78–4.22)	84.2 (67.5 – 102.4)
7.5	14	222.9 (193.3–253.4)	9.5 (8.2–10.8)	0.63 (0.48–0.79)	28.5 (21.7 – 36.1)
7.5	50	642.6 (589.3–694.7)	27.4 (25.1–29.6)	2.13 (1.68–2.62)	96.9 (76.6 – 119.0)
7.5	86	919.4 (859.9–974.4)	39.2 (36.7–41.6)	3.49 (2.79–4.22)	158.8 (126.8 – 192.1)
High Detection Sensitivity (96.0%) and Specificity (98.4%) Scenario					
0.5	14	14.9 (13.1–16.7)	0.6 (0.6–0.7)	0.13 (0.07–0.21)	0.4 (0.2 – 0.6)
0.5	50	45.5 (42.7–48.1)	1.9 (1.8–2.1)	0.45 (0.24–0.72)	1.4 (0.8 – 2.2)
0.5	86	68.0 (65.0–71.0)	2.9 (2.8–3.0)	0.76 (0.42–1.19)	2.3 (1.3 – 3.6)
4.0	14	117.1 (103.9–131.1)	5.0 (4.4–5.6)	0.13 (0.07–0.21)	3.1 (1.7 – 5.1)
4.0	50	342.7 (323.7–361.6)	14.6 (13.8–15.4)	0.45 (0.25–0.72)	11.1 (6.1 – 17.5)
4.0	86	497.1 (476.6–517.3)	21.2 (20.3–22.1)	0.77 (0.42–1.21)	18.8 (10.4 – 29.6)
7.5	14	215.6 (191.5–240.7)	9.2 (8.2–10.3)	0.13 (0.07–0.21)	5.9 (3.2 – 9.5)
7.5	50	604.7 (572.4–635.0)	25.8 (24.4–27.1)	0.45 (0.24–0.72)	20.8 (11.3 – 33.0)
7.5	86	850.7 (818.7–881.8)	36.3 (34.9–37.6)	0.77 (0.43–1.21)	35.3 (19.6 – 55.4)

The use of RATs reduced the number of days incorrectly spent in quarantine by ~300-fold by increasing the "effective specificity" of the strategy (Figure 11B). That is, with RATs, the likelihood of a *Susceptible* user being incorrectly prompted to quarantine on a given day fell from $(1 - \nu_w)$ to the product of $(1 - \nu_w)$ and $(1 - \nu_a)$, where ν_w and ν_a are detection algorithm specificity and RAT specificity, respectively. In earlier scenarios (Figures 8A and 9A), the number of averted infections was decreased by improving detection specificity more than it was increased by improving detection sensitivity; fewer infections were averted in scenarios with "high" as opposed to nominal detection sensitivity and specificity. Here, the specificity contributed by the RATs diminished the relative impact of improving detection specificity on the number of averted infections: the "effective specificity" of the broader intervention was 99.976% with nominal detection specificity and 99.995% with high detection specificity (Table 8) [99]. Instead, improving detection sensitivity was what increased the number of averted infections. Importantly, offering confirmatory RATs had the secondary effect of decreasing the broader intervention's "effective sensitivity"—the product of RAT sensitivity (91.1%) and detection algorithm sensitivity [99].

Offering confirmatory RATs also decreased the demand for lab-based tests by ~200-fold, alleviating the burden on testing infrastructure (Figure 11C). We earlier found that in a baseline scenario (4% uptake, 50% adherence, 80% detection sensitivity, 92% detection specificity), between ~40,000 and ~65,000 additional lab-based tests would be required each day (Figure 4C; Table 8). Here, in an analogous scenario, only 284 (95% CI: 244–326) additional lab-based tests would be required each day, on average, and 55,600 (95% CI: 43,200–69,000) RATs would be performed instead (Table 7).

We investigated the impact of lower RAT sensitivity (Figure 12). Fewer infections were averted when RATs were used at all because using RATs to minimize incorrect quarantines increased the pool of *Susceptible* individuals. As well, the reduction in the burden of infection grew linearly with RAT sensitivity: each ~10% increase in RAT sensitivity resulted in a ~1% reduction in the burden of infection. These two effects result in a trade-off between missing more *Infectious* individuals (due to imperfect RAT sensitivity) and decreasing false positive prompts to seek a lab-based test and quarantine while waiting for the results (due to near perfect RAT specificity).

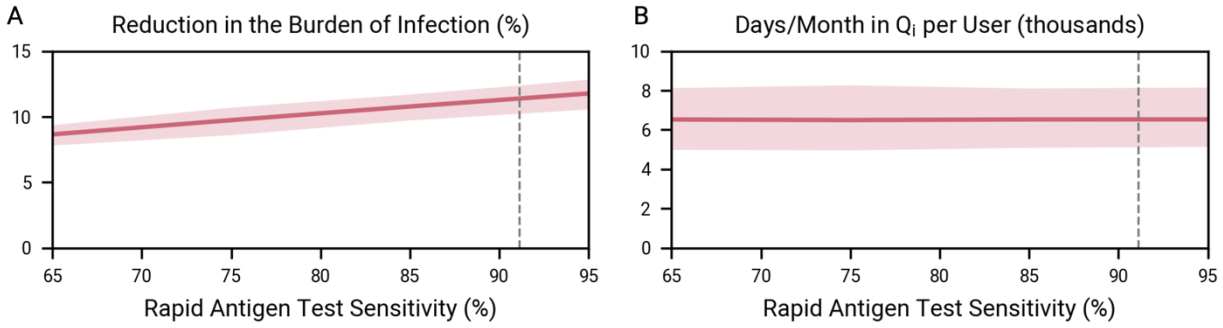


Figure 12: Impact of rapid antigen test sensitivity. We set uptake, adherence, detection sensitivity, and detection specificity at their nominal values of 4%, 50%, 80%, and 92%, respectively. The vertical dashed grey line represents nominal antigen test sensitivity (91.7%).

3.7 Additional sensitivity analyses

We explored the impact of lab-based test turnaround time to determine whether minimizing this variable should be a policy priority (Figure 13). With longer turnaround times,

individuals incorrectly in quarantine remained there longer, further decreasing the pool of *Susceptible* individuals. As expected, greater reductions in the burden of infection resulted, but with substantial growth in the social costs of the intervention.

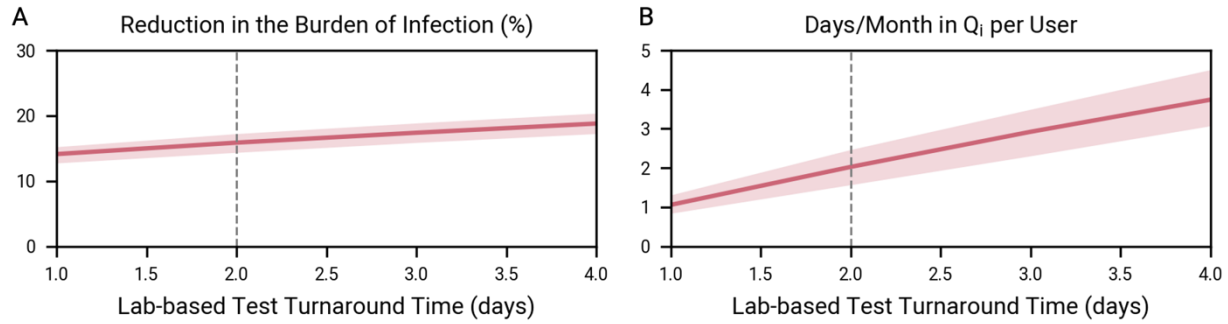


Figure 13: Impact of lab-based test turnaround time. We set uptake, adherence, detection sensitivity, and detection specificity at their nominal values of 4%, 50%, 80%, and 92%, respectively. The vertical dashed grey line represents nominal lab-based test turnaround time (2 days).

We also performed a sensitivity analysis on the asymptomatic prevalence (Figure 14). In our model, notifications are sent to presymptomatic and asymptomatic individuals, but there is a lack of consensus on a specific value for the asymptomatic prevalence [52]. As expected, with greater asymptomatic prevalence, more individuals could benefit from wearable device use and more infections were averted. The number of incorrect quarantines was unchanged.

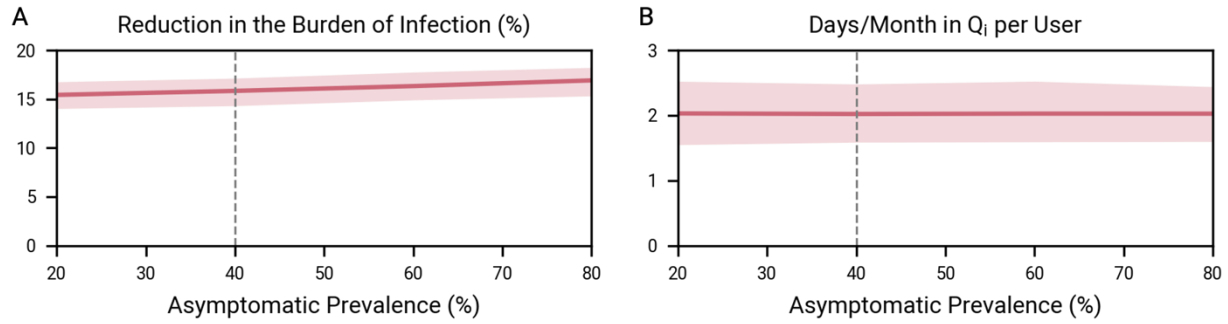


Figure 14: Impact of asymptomatic prevalence. We set uptake, adherence, detection sensitivity, and detection specificity at their nominal values of 4%, 50%, 80%, and 92%, respectively. We continued to model asymptomatic prevalence as a beta-distributed random variable. The vertical dashed grey line represents nominal asymptomatic prevalence (40%).

4

Interpretation of Findings and Future Work

4.1 Interpretation of Findings

In this thesis, we used a counterfactual model of Canada's second COVID-19 wave to show that wearable sensors capable of detecting infections before or absent symptoms have meaningful potential to help mitigate the acute phase of a pandemic. Through continuous and non-invasive monitoring of physiological parameters, these devices can help Find-Test-Trace-Isolate (FTTI) systems identify hidden infection chains with minimal delay and without active user engagement or broad sharing of user data. We demonstrated that (1) deploying currently available detection algorithms could have helped reduce the acute phase burden of infection, but with substantial social and resource costs; (2) improving detection algorithm specificity and offering confirmatory rapid antigen tests can help minimize unnecessary quarantines and lab-based tests; and (3) once false positive notifications are minimized, increasing uptake and adherence become effective strategies to scale the number of averted infections.

In theory, wearable sensor deployment reduces the burden of infection by decreasing the pool of *Infectious* individuals (a function of detection algorithm sensitivity). Here we found that detection specificity played an unexpectedly large role as well, with false positive notifications of potential infection prompting unnecessary quarantines and thereby decreasing the pool of *Susceptible* individuals. Thus, although prioritizing uptake and adherence as part of a wearable sensor deployment strategy could mitigate a substantial number of infections, the unsustainable growth of associated costs should also be considered. In a baseline scenario, without improvements to detection specificity, every user would spend over two days a month on average incorrectly quarantining, and ~40,000 to

~65,000 additional confirmatory lab-based tests would be required each day. The social and economic harm caused by solely promoting uptake or adherence without improvements to detection specificity would likely undermine public confidence in and compliance with a wearable-based pandemic mitigation strategy [115]. Alavi et al. found that many false positives were due to the detection algorithm identifying lifestyle-driven changes in resting heart rate (e.g., after intense exercise or alcohol consumption); accounting for these factors using more advanced algorithms may be one way to improve detection specificity [27].

We found that the inclusion of confirmatory antigen testing was a valuable mechanism, beyond improving detection specificity, to increase the "effective specificity" of the strategy and decrease the overall false positive rate. The inclusion of antigen testing decreased days incorrectly spent in quarantine by ~300-fold and brought the additional demand on lab-based testing infrastructure to justifiable levels. However, even with the inclusion of antigen tests, improvements to detection specificity still had value. In scenarios with "high" nominal detection specificity, we observed a ~4-fold reduction in days incorrectly spent in quarantine per month per user, a ~2-fold reduction in lab-based tests performed each day, and a ~5-fold reduction in antigen tests used each day. Importantly, a strategy in which antigen tests support the deployment of wearable sensors is notably different from one involving frequent use of rapid antigen tests for surveillance testing [116]. On their own, broad antigen test-based screening approaches require tremendous manufacturing volumes, infrastructure, and funding [117]. Conversely, wearable sensors can non-invasively detect infections without active user engagement, reducing the effort required to participate. Further, wearable sensors may even help improve test allocation by directing tests toward individuals with a higher pre-test probability of infection [118].

The COVID-19 pandemic's evolution has been shaped by the uptake of vaccines, the emergence of more transmissible and immune-evasive variants of concern (VOCs), and the potential for breakthrough and repeat infections [119]. Although we did not consider these factors when modelling Canada's second wave, we speculate that their effects on wearable sensor-based mitigation strategies would be driven by changes in users' physiological responses and in SARS-CoV-2 epidemiology. In particular, we hypothesize that wearable

sensor-based mitigation would be impacted in four major ways. First, vaccination has been found to elicit similar physiological responses to infection (e.g., elevated resting heart rate) and these physiological responses might be captured by wearable sensor-based detection algorithms [27, 120]. We expect this to manifest as an increase in the incidence of false positive notifications, which we have considered in depth in our analyses related to detection specificity. However, we also speculate that vaccination-driven false positive notifications would likely be flagged as such by the user and ignored. Second, prior immunity from vaccination may attenuate physiological responses elicited by breakthrough infections, altering detection sensitivity [121]. Although it might generally be expected that the degree of attenuation would depend on the VOC causing infection, as well as the specific infection and vaccination history of the individual, evidence of minimal differences between physiological responses to breakthrough infections during Germany's Delta and Omicron waves has been reported [121]. From a modeling perspective, incorporating temporal changes in detection sensitivity may be an appropriate starting point for exploring this effect. Third, the onset of symptoms may occur earlier in the infectious period in individuals with pre-existing immunity than in immunologically naïve individuals [51, 122]. In these scenarios, the early onset of symptoms would already contribute to the detection of infections earlier in the infectious period. However, we speculate that if detection algorithms retained their ability to identify presymptomatic infections, wearable sensors could even further reduce the fraction of the infectious period in which users unknowingly transmit the virus—and in turn, even further decrease the burden of infection. Finally, increases in transmissibility—whether due to higher viral loads or immune evasion in VOCs—would also influence the impact of wearable sensor-based mitigation strategies, likely by attenuating the achievable reduction in the burden of infection [17, 123–125]. Moving forward, more empirical data will be needed in order to develop models of wearable sensor deployment in the SARS-CoV-2 vaccine and variant era, and in turn explore these hypotheses.

4.2 Future Work

Our work has important limitations. First, we do not account for heterogeneities in wearable device use that, in reality, is influenced by age, race, level of education, and income [126,

127]. Future analyses could more precisely address how a device user being removed from the pool of *Susceptible* or *Infectious* individuals will impact the epidemic trajectory based on that user's demographic and socioeconomic profile. Indeed, the COVID-19 pandemic has disproportionately impacted low-income and minority groups, while younger individuals are more likely to be super-spreaders [128–130]. It would be important for future studies to characterise how the benefits of wearable sensor-based detection are likely to be distributed across the population, and whether or not this intervention could exacerbate existing health inequities. Future studies could also consider policies that subsidize wearable devices, reducing the participation barrier for groups underrepresented among current device owners. Second, we made the simplifying assumption that all users without symptoms (and that no users with symptoms) could benefit from wearable-informed prompts to seek a confirmatory test and tentatively quarantine. Because wearable sensors show promise in detecting symptomatic SARS-CoV-2 infection and many symptomatic individuals did not historically self-isolate, considering this group in future analyses could modify the magnitude of our estimates [61, 96, 97]. Third, we did not consider how uptake or adherence may vary with time, detection accuracy, or other factors [96, 104, 115, 131]. Finally, we did not consider how detection algorithm performance varies over the course of infection.

Some of these limitations can be overcome with an agent-based modelling (ABM) approach. First, with an ABM, it would be possible to account for heterogeneity in SARS-CoV-2 epidemiology *and* in wearable device ownership (e.g., on the basis of age or income) to more precisely capture the effect of removing someone from the pool of *Susceptible* individuals. Second, an ABM that simulates transmission in different contact settings could be used to study more specific wearable sensor-based interventions (e.g., distributing devices at workplaces to detect infectious workers and better prevent outbreaks). Third, the ability to specify interventions at the individual level would allow detection algorithm sensitivity to be parameterised as a function of time, peaking immediately prior to onset instead of being applied uniformly across the applicable time window [27]. Finally, an ABM would enable the study of other public health applications of wearable sensor-based detection, for example, to support infectious disease surveillance [106, 132].

Before wearable sensor-based mitigation can be implemented through policy, several dimensions must be considered: effectiveness, unintended effects, equity, acceptability, cost, and feasibility [133]. Our study provides insight into the effectiveness and some potential unintended effects (e.g., incorrect quarantines) of this intervention, and we have also highlighted important concerns relating to equity. There are multiple aspects of achieving sufficient acceptability. First, messaging to the public will be important; public health leaders, for example, will need to communicate the limitations of wearable sensors with respect to detecting infections and emphasize that a lack of a notification does not rule out potential infection. Second, users should be engaged on an ongoing basis to ensure that the intervention's implementation adheres to their expectations (e.g., around privacy, usability, etc.). Finally, it will be crucial to provide appropriate supports for users prompted to quarantine [114]. In assessing the costs of wearable sensor-based mitigation, health economists should be engaged to develop financial estimates for a range of deployment scenarios. Technical feasibility and related opportunities should also be explored, including issues related to data format and secure storage, as well as the potential to link wearable sensor data with other health data (e.g., laboratory tests) to yield more impactful diagnoses [134]. Working closely with communities, particularly in resource-constrained settings, will be vital to tailor this strategy and ensure its long-term feasibility [135]. Ultimately, wearable sensor-based mitigation will need to be systematically compared to conventional mitigation strategies along each of these dimensions to demonstrate its suitability for implementation.

4.3 Conclusion

Using the example of COVID-19, we demonstrated the potential of wearable sensors to support FTTI systems with real-time detection of presymptomatic and asymptomatic infections and thereby reduce the burden of infection during a pandemic. Ultimately, as sensor technology and detection algorithms evolve—for example, to potentially distinguish infections with SARS-CoV-2 from those with seasonal influenza [136]—there is clear merit to continuing to explore how wearable sensors can be incorporated into FTTI systems to improve pandemic mitigation.

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