

Article

Diagnostic Delays Drive Transmission in Dense Cities: An Operational Feasibility Framework for Mitigating the Waiting-Window Effect

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Abstract

In dense urban settings, diagnostic systems reduce transmission only when sampling, result return, and isolation are operationally feasible during the period of peak infectiousness. We define a waiting-window transmission externality that arises when infectious individuals remain mobile between diagnostic sampling and actionable isolation. The term is formalized as $E = N \times P \times TR \times D$, where N is daily testing volume, P is test positivity, TR is residual transmission during the waiting period, and D is sample-to-action turnaround time. The equation is used as a first-order operational risk-accounting framework rather than as a complete epidemic model. Using Monte Carlo uncertainty propagation, we compare centralized 48 h testing, surge conditions with coupled delay and crowding, near-patient rapid testing, and home sampling with isolation at sampling. Centralized 48 h workflows produce approximately 80 excess waiting-window infections per 1000 tests/day at $p = 10\%$ and approximately 401 at $p = 50\%$, increasing to approximately 126 and 628 under surge coupling. Near-patient testing and home sampling reduce these values to approximately 5–26 across the same positivity range. We also distinguish two operationally different but epidemiologically related approaches: home sampling with immediate precautionary isolation reduces TR while laboratory turnaround may remain nonzero, whereas home-based molecular testing reduces D by returning results at the point of collection. Sensitivity checks for surge coupling and household transmission floors show that the qualitative ordering of workflows is preserved, although the magnitude of benefit depends on adherence and local operating conditions. These findings support redesigning diagnostic workflows around sample-to-action time, isolation feasibility, decentralized logistics, and equity rather than assay performance alone.



Academic Editor: Giancarlo Ripabelli

Received: 5 May 2026

Revised: 9 June 2026

Accepted: 16 June 2026

Published: 26 June 2026

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Keywords: home sampling; home-based PCR; diagnostic delay; operational feasibility; turnaround time; quarantine; sensitivity analysis

1. Introduction

Epidemic control in dense urban environments depends not only on pathogen biology and assay sensitivity, but also on the operational time required to move from sampling to action. For respiratory pathogens such as SARS-CoV-2, peak transmissibility occurs

near or before symptom onset, so even short diagnostic delays can preserve a meaningful fraction of infectious contacts [1]. Prior work has shown that delay can undermine testing, tracing, and isolation strategies, and that testing frequency and turnaround time can be as important as analytical sensitivity for population-level control [2–4].

The operational problem is most acute in dense cities. Centralized testing workflows can require travel, public transit, indoor queues, appointment delays, and laboratory backlogs. These steps create contacts before and after sampling, and they can become socially patterned because access to testing, paid leave, home isolation space, and rapid result return are unequally distributed [5–8]. During surges, the same forces that increase positivity can also increase waiting time and crowding, creating a failure mode in which the diagnostic system becomes least controllable when demand is highest.

This study treats diagnostic delay primarily as an operational feasibility problem. The aim is not to reproduce all epidemic dynamics, contact-network structure, susceptible depletion, or secondary transmission. Instead, it isolates the preventable waiting-window term generated when an infectious person remains mobile while awaiting an actionable result. The workflow comparison focuses on mechanisms that reduce either turnaround time D or residual waiting-period transmission TR , with particular attention to home sampling, isolation support, sample adequacy control, decentralized molecular testing, and the distinction between home sampling plus isolation-at-sampling and home-based PCR returning results at the point of collection.

2. Materials and Methods

2.1. Waiting-Window Transmission Externality

Let N denote the number of tests performed per day, P the test positivity among those tested, TR the expected residual transmissions per infectious person per day during the waiting period, and D the sample-to-action turnaround time in days. The waiting-window contribution is:

$$E = N \times P \times TR \times D \quad (1)$$

$$E_{1000} = 1000 \times P \times TR \times D \quad (2)$$

Equations (1) and (2) are interpreted as short-horizon operational accounting terms, not as estimates of total epidemic growth. The linear form is appropriate for isolating the direct transmission opportunity created by a waiting interval, but it does not include susceptible depletion, contact-network clustering, repeated testing, heterogeneity in infectiousness, or secondary infections. Epidemics also include background transmission not prevented by the testing workflow; we represent that component with an additive baseline term X . Figure 1 displays the y-axis as $X + E_{1000}$ to avoid implying that the testing workflow explains all incidence.

2.2. Parameter Evidence and Operational Measurement

P can be operationalized using test positivity, a standard surveillance indicator routinely reported by public health systems [9]. D should be measured as sample-to-action time rather than laboratory analytical time alone: the relevant interval begins at sampling and ends when the individual receives a result or instruction that can change behavior. TR is distinct from pathogen-intrinsic infectivity. It reflects residual contact while awaiting action, including travel to testing, queue exposure, workplace or household contacts, and adherence to precautionary isolation. The scenario TR values are not fitted city-specific estimates; they are intended to span operational states that are plausible for low-contact home isolation and higher-contact centralized workflows. Low-contact household or isolation settings support a residual TR floor, whereas travel, indoor queues, public transit,

workplace exposure, and delayed isolation support higher centralized-workflow TR values. TR can be estimated locally from mobility data, queue observations, adherence surveys, contact-tracing data, household structure, and the fraction of people able to isolate immediately. It can also be reduced operationally through home sampling, paid sick leave, delivery or pickup logistics, and result-reporting systems that trigger isolation at the time of sampling rather than after laboratory confirmation.

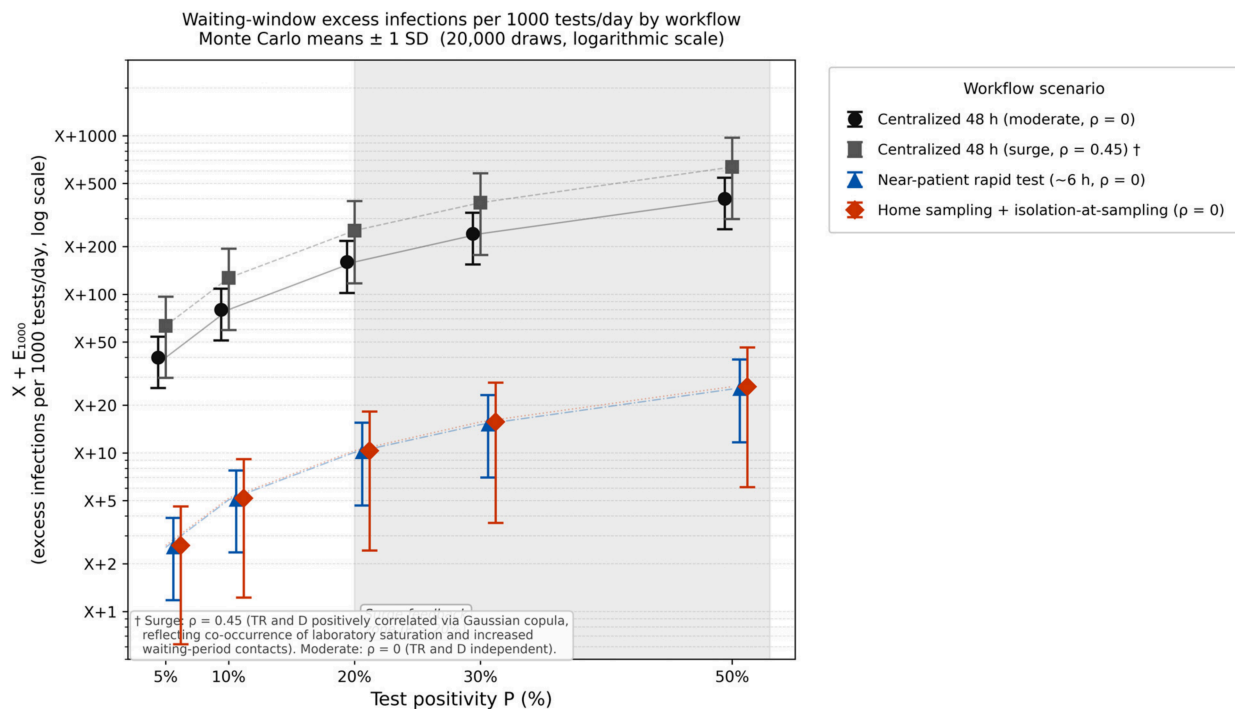


Figure 1. Waiting-window excess infections per 1000 tests/day by workflow (logarithmic scale). Discrete data points represent Monte Carlo means (20,000 iterations); error bars = ± 1 SD. The comparison is operational rather than a full epidemic forecast. Circles: centralized 48 h moderate ($\rho = 0$); squares: centralized 48 h surge ($\rho = 0.45$, Gaussian copula, wider bars reflect co-occurrence of laboratory saturation and increased waiting-period contacts); triangles: near-patient rapid test (~6 h, $\rho = 0$); diamonds: home sampling + isolation-at-sampling ($\rho = 0$). Shaded region ($p > 20\%$): surge feedback zone. Y-axis displayed as $X + E1000$ to avoid implying zero background incidence. † Surge scenario: $\rho = 0.45$ (TR and D positively correlated via Gaussian copula, reflecting co-occurrence of laboratory saturation and increased waiting-period contacts). Moderate scenario: $\rho = 0$ (TR and D independent under normal operations).

2.3. Scenario Definitions and Operational Uncertainty

We represent TR and D using truncated normal distributions with a lower bound of 0 and propagate uncertainty by Monte Carlo sampling (20,000 draws). The parameter values are illustrative workflow states, not empirical estimates from a single city. To reflect surge operations, the surge scenario uses a positive correlation between TR and D because laboratory saturation, longer queues, delayed isolation, and higher contact intensity can co-occur during system stress. The base surge value is $\rho = 0.45$; sensitivity analyses evaluate $\rho = 0.20$ – 0.60 . The moderate scenario uses $\rho = 0$ because under normal operating conditions, laboratory throughput and individual contact behavior are less tightly coupled.

Centralized 48 h, moderate operations ($\rho = 0$): TR = 0.40 ± 0.10 /day; D = 2.0 ± 0.5 days.

Centralized 48 h, surge operations ($\rho = 0.45$): TR = 0.60 ± 0.15 /day; D = 2.0 ± 0.8 days; ρ implemented by Gaussian copula.

Near-patient rapid test (~6 h, $\rho = 0$): TR = 0.20 ± 0.07 /day; D = 0.25 ± 0.10 days.

Home sampling + isolation-at-sampling ($\rho = 0$): $TR = 0.02 \pm 0.02/\text{day}$; $D = 2.0 \pm 0.8$ days. This scenario assumes that the person begins precautionary isolation at sampling, so risk reduction occurs through lower TR even if laboratory turnaround remains nonzero. Household-transmission floor checks with $TR = 0.05\text{--}0.10/\text{day}$ are evaluated separately in the sensitivity analysis. This is operationally distinct from home-based PCR or other self-contained molecular platforms that return results at the point of collection and reduce D toward zero.

2.4. Illustrative SIR Component

The SIR component (Figure 2) was used as an illustrative consistency check rather than as a primary source of inference. It was not used to estimate absolute numbers of infections or to validate the waiting-window equation. The base case used $\beta_{\text{eff}}(t) = \beta_{\text{base}} \times (1 + TR \times D) \times \max(0, 1 - m \times C(t))$, $\gamma = 0.1/\text{day}$, $R_0 = 2.5$, $m = 5$, $S(0) = 0.995$, $I(0) = 0.005$, $R(0) = 0$, and an 84-day horizon. Sensitivity checks varying γ from 0.07 to 0.14/day, R_0 from 1.8 to 3.5, and m from 3 to 8 changed the height and timing of illustrative curves but did not change the operational ordering of workflows, which follows directly from the E1000 term.

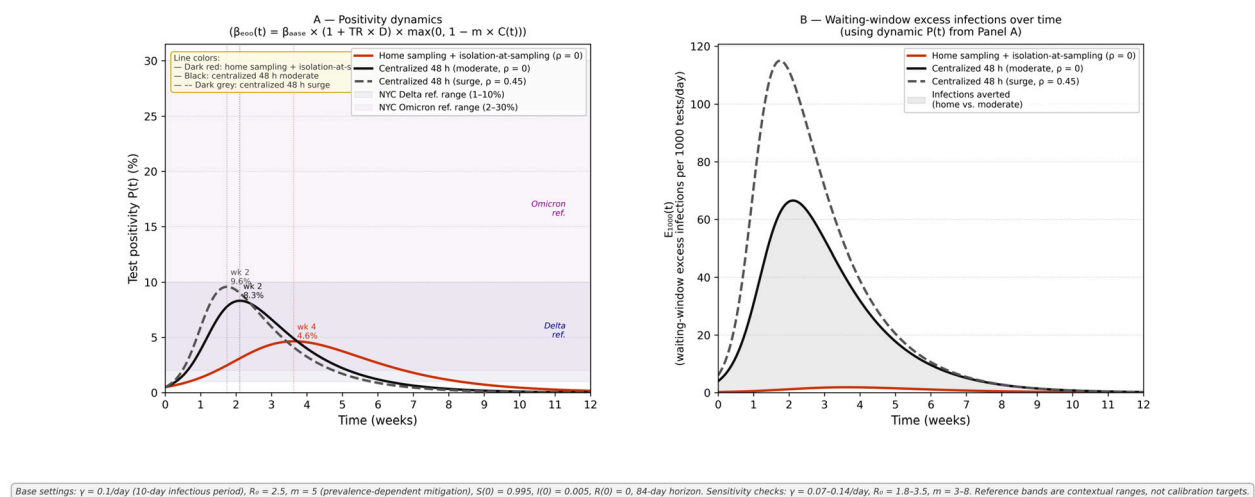


Figure 2. Illustrative epidemic-dynamics check with and without waiting-window feedback. Model form: $\beta_{\text{eff}}(t) = \beta_{\text{base}} \times (1 + TR \times D) \times \max(0, 1 - m \times C(t))$. Base settings: $\gamma = 0.1/\text{day}$, $R_0 = 2.5$, $m = 5$ (prevalence-dependent mitigation), $S(0) = 0.995$, $I(0) = 0.005$, $R(0) = 0$, 84-day horizon. Delta and Omicron reference bands are shown as contextual ranges rather than calibration targets. Sensitivity checks across $\gamma = 0.07\text{--}0.14/\text{day}$, $R_0 = 1.8\text{--}3.5$, and $m = 3\text{--}8$ altered peak height and timing but did not change workflow ordering. Line colors: dark red—home sampling + isolation-at-sampling ($\rho = 0$); black—centralized 48 h moderate ($\rho = 0$); dark grey dashed—centralized 48 h surge ($\rho = 0.45$).

2.5. Operational Break-Even Cost per Infection Averted

The break-even cost per infection averted (C_{case^*}) is calculated as:

$$C_{\text{case}^*} = (1000 \times C_{\text{test}}) / E1000(P)$$

where

$C_{\text{test}} = \$40$ is the cost per test

$E1000(P)$ is the expected number of excess infections per 1000 tests at prevalence P

Interpretation:

When the societal cost per infection exceeds C_{case^*} , an intervention that removes the waiting-window term is economically favorable relative to the comparator workflow.

The metric is designed for operational planning and should be recalculated using local test costs, isolation-support costs, hospitalization rates, and implementation constraints.

C_{case^*} is a threshold, not a direct estimate of cost-effectiveness.

Examples:

At $p = 10\%$ in the moderate centralized 48 h scenario, $C_{\text{case}^*} =$ approximately \$500 per infection averted.

At $p = 50\%$ under surge conditions, C_{case^*} falls to approximately \$64 per infection averted. Applying severity weights such as hospitalization and fatality rates can translate this threshold into outcome-based terms, but those estimates are illustrative and should be adapted to local severity, age structure, vaccination, and treatment conditions.

2.6. Use of Generative Artificial Intelligence Tools

Generative AI tools were used in two distinct and limited capacities during the preparation of this manuscript. First, ChatGPT (GPT-4o, OpenAI, 2024) and Claude (claude-sonnet-4-6, Anthropic, 2025) were used for language editing, notation consistency checks, and iterative revision of technical writing. Second, these tools assisted in developing and debugging the Python simulation code (Monte Carlo uncertainty propagation, Gaussian copula implementation, and SIR model integration). In both cases, all outputs were critically reviewed, verified, and edited by the authors. The analytical framework, parameter choices, interpretation of results, and scientific conclusions are the sole responsibility of the authors. No AI tool was used to generate, fabricate, or substitute for original data or scientific judgment.

3. Results

3.1. Positivity–Delay Scaling and Scenario Comparison

Figure 1 shows $X + E1000$ as a function of test positivity P on a logarithmic scale. The main operational finding is that centralized workflows accumulate preventable waiting-window transmission as positivity rises, whereas reducing either D (near-patient testing) or TR (home sampling with isolation-at-sampling) collapses the waiting-window term. The surge scenario shows wider uncertainty because delay and waiting-period contacts are coupled under system stress.

3.2. Monte Carlo Estimates for Representative Workflows

Table 1 summarizes daily $E1000$ across representative positivity values for the four main diagnostic workflows. Under the moderate 48 h workflow ($\rho = 0$), $E1000$ is approximately 80 ± 29 at $p = 10\%$ and 401 ± 144 at $p = 50\%$. Under surge mixing with TR - D correlation ($\rho = 0.45$), $E1000$ rises to approximately 126 ± 67 at $p = 10\%$ and 628 ± 334 at $p = 50\%$. Near-patient rapid testing and home sampling with isolation-at-sampling reduce $E1000$ to approximately 5 at $p = 10\%$ and approximately 25–26 at $p = 50\%$. These values should be interpreted as waiting-window infections prevented by workflow redesign, not as total epidemic infections.

3.3. Operational Sensitivity Checks

Operational sensitivity analyses addressed two feasibility checks (Table 2). First, varying the surge correlation coefficient from $\rho = 0.20$ to 0.60 had a limited effect on the mean $E1000$ because the mean product $TR \times D$ is dominated by high surge TR and two-day turnaround; however, stronger coupling increased uncertainty and right-tail risk. Second, imposing a household-transmission floor of $TR = 0.05$ – 0.10 /day raised the home-sampling estimates, but they remained below centralized surge estimates because household exposure is bounded and does not create additional queue, transit, or workplace contacts.

Table 1. Waiting-window excess infections and C_case* per 1000 tests/day under representative positivity (P).

Scenario	D (Mean +/- SD, Days)	TR (Mean +/- SD, /Day)	E1000 <i>p</i> = 5%	E1000 <i>p</i> = 10%	E1000 <i>p</i> = 20%	E1000 <i>p</i> = 50%	C_Case* <i>p</i> = 10% (\$)	C_Case* <i>p</i> = 50% (\$)
Centralized 48 h (moderate, rho = 0)	2.0 +/- 0.5	0.40 +/- 0.10	40 +/- 14	80 +/- 29	160 +/- 58	401 +/- 144	500	100
Centralized 48 h (surge, rho = 0.45)	2.0 +/- 0.8	0.60 +/- 0.15	63 +/- 34	126 +/- 67	252 +/- 134	628 +/- 334	316	64
Near-patient rapid test (~6 h, rho = 0)	0.25 +/- 0.10	0.20 +/- 0.07	3 +/- 1	5 +/- 3	10 +/- 5	25 +/- 14	7931	1573
Home sampling + isolation-at-sampling (rho = 0)	2.0 +/- 0.8	0.02 +/- 0.02	3 +/- 2	5 +/- 4	10 +/- 8	26 +/- 20	7711	1549

Notes: E1000 = mean +/- 1 SD (20,000 Monte Carlo draws, truncated normals, lower bound 0). Surge: rho = 0.45 via Gaussian copula. C_case* = (\$40 × 1000)/E1000(P). rho = 0 for moderate scenarios because D and TR are treated as independent under normal operations.

Table 2. Operational sensitivity checks for surge coupling and household-transmission floors.

Sensitivity Check	Scenario	Assumption Varied	E1000 <i>p</i> = 10%	E1000 <i>p</i> = 50%
Surge coupling	Centralized 48 h surge	rho = 0.20	123 +/- 62	615 +/- 308
Surge coupling	Centralized 48 h surge	rho = 0.45 (base)	126 +/- 67	628 +/- 334
Surge coupling	Centralized 48 h surge	rho = 0.60	128 +/- 71	638 +/- 354
Household floor	Home sampling + isolation-at-sampling	TR floor = 0.05/day	10 +/- 4	50 +/- 20
Household floor	Home sampling + isolation-at-sampling	TR floor = 0.10/day	20 +/- 8	101 +/- 39

Notes: Values are Monte Carlo means +/- 1 SD per 1000 tests/day. Surge-coupling rows use the centralized 48 h surge TR and D distributions while varying rho. Household-floor rows use the home-sampling D distribution with TR set to the stated residual floor. These checks evaluate sensitivity rather than define additional primary workflows.

4. Discussion

4.1. Epidemiological and Operational Implications

This study identifies diagnostic delay as an operational failure mode of epidemic control in dense cities. The waiting-window externality does not arise from pathogen biology alone; it arises when the testing workflow leaves infectious individuals mobile before a result or isolation instruction becomes actionable. The practical implication is that diagnostic performance should be judged by sample-to-action time, feasibility of immediate isolation, and equity of access, not by analytical sensitivity alone. Under surge conditions, laboratory delay and waiting-period contacts may become coupled: high demand creates longer queues, longer turnaround, delayed isolation, and greater uncertainty. Home sampling with isolation-at-sampling addresses the same mechanism by reducing TR during the waiting interval, while near-patient or home-based molecular testing addresses it by reducing D. A theoretical boundary comparator is mass simultaneous quarantine, which illustrates the upper limit of TR suppression but is not presented as a routine or scalable diagnostic workflow because it depends on administrative mandate, enforcement, essential-worker exemptions, and substantial socioeconomic disruption.

4.2. Economic Thresholds and Outcome-Based Analysis

C_case* is a break-even threshold, not a direct cost-effectiveness estimate. Its purpose is to help planners decide when the incremental cost of a lower-delay workflow is justified by waiting-window infections averted. The threshold falls as positivity and delay rise, which means that low-delay workflows become easier to justify during surges. Conversely, at very low positivity, centralized testing may remain operationally adequate. Local implementation should include the full cost of home sampling kits, logistics, reporting, isolation support, invalid-sample management, and equity measures. Outcome-based

translations using hospitalization or mortality weights are useful for context, but they should be treated as scenario-specific and updated as severity, vaccination, and treatment conditions change.

4.3. Socioeconomic Dynamics of Quarantine Breakdown

Operational feasibility is inseparable from adherence. In high-density settings with precarious work, limited paid sick leave, crowded housing, and unequal access to transportation, prolonged waiting windows can make quarantine practically non-viable. Non-adherence in this setting is not only a behavioral choice; it can be a predictable consequence of an infeasible workflow. Home sampling paired with clear result reporting, paid sick leave, food or medication delivery, and isolation support can reduce the need for coercive enforcement. Diagnostic delay should therefore be treated as an equity-sensitive amplification factor during surges.

4.4. Feasibility and Implementation Pathway

A feasible home-sampling pathway can be implemented as a hub-and-spoke workflow rather than as a single centralized bottleneck. Core elements include: pre-distributed self-collection kits; sample adequacy control to make negative results interpretable [10,11]; point-of-collection stabilizing or inactivating transport buffers compatible with extraction-free RT-qPCR and rapid workflows [12,13]; barcode or QR-based registration; once- or twice-daily front-door pickup or neighborhood drop boxes [14]; decentralized molecular testing with multiple daily runs; pooling when prevalence permits [15]; and rapid electronic reporting linked to isolation guidance. Home sampling + isolation-at-sampling and home-based PCR should not be treated as operationally identical. The former keeps D nonzero but lowers TR by asking the person to isolate immediately after sampling. The latter lowers D toward zero by returning a result at the point of collection. Both can collapse the E term, but they differ in cost, scalability, adherence needs, technical support, invalid-rate management, and equity implications.

5. Limitations

This analysis uses a deliberately simple multiplicative framework to isolate the operational effect of diagnostic delay. It does not explicitly model susceptible depletion, network structure, household clustering, heterogeneity in infectiousness, repeated testing behavior, behavioral feedback, or secondary transmission. Test positivity P is used as a proxy for the infectious fraction among those tested and will vary with testing strategy and ascertainment. TR values are scenario parameters rather than empirically estimated local measurements; future work should estimate them using mobility, adherence, queuing, contact-tracing, and household data. The surge correlation $\rho = 0.45$ is illustrative, and sensitivity analyses evaluated $\rho = 0.20$ – 0.60 . The home-sampling TR assumption is also sensitive to household transmission and adherence; household-floor checks used $TR = 0.05$ – 0.10 /day. C_{case} assumes a fixed comparator cost and excludes broader implementation costs and benefits unless locally added. The SIR component is illustrative and should not be interpreted as a calibrated epidemic forecast; sensitivity checks across γ , R_0 , and m change curve height and timing but do not drive the main inference. Finally, mass simultaneous quarantine is included only as a theoretical boundary case for TR suppression; it is not modeled as a routine diagnostic workflow because enforcement heterogeneity, backlogs, essential-worker exemptions, and socioeconomic disruption would dominate operational feasibility.

6. Conclusions

In dense cities, the epidemiologic value of testing depends on whether the workflow allows action during the waiting window. Centralized testing with multi-day turnaround can create a preventable transmission term that scales with positivity, residual waiting-period contacts, and delay. Near-patient rapid testing reduces this term by shortening D; home sampling with isolation-at-sampling reduces it by lowering TR; home-based PCR reduces it by collapsing D at the point of collection. This analysis therefore reframes the main contribution as operational: epidemic controllability requires diagnostic systems that are fast, feasible to comply with, decentralized enough to avoid surge bottlenecks, and equitable enough to work for populations most exposed to delay.

Author Contributions: Conceptualization: I.B. and M.O. Methodology: I.B. and S.B. Formal analysis: I.B. and S.B. Visualization: I.B. and S.B. Writing—original draft: S.B. and I.B. Writing—review and editing: S.B., I.B., M.O. and J.V. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All simulation parameters and scenario definitions are provided in the manuscript. Python simulation code was written in Python 3.11 using NumPy 1.26, SciPy 1.12, and Matplotlib 3.8. The simulation code is available from the corresponding author on reasonable request.

Acknowledgments: We thank Benoit Houle, Montreal, for advice and encouragement to visualize different pandemic scenarios. Microbiology Department members at JGH, Montreal, shaped pandemic discussions in the past, affecting this work. During the preparation of this work the authors used ChatGPT (GPT-4o, OpenAI, 2024) and Claude (claude-sonnet-4-6, Anthropic, 2025) to assist with language editing, notation consistency, and simulation code development. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Conflicts of Interest: The authors declare no competing interests.

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