Within-laboratory SARS-CoV-2 real time PCR testing operations in Nepal: a simulation-based analysis

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Summary

Background COVID-19 has challenged entire health systems, including laboratories. To address the increasing demand for tests to inform the epidemiology of the disease and for case management purposes, many countries made significant investments to rapidly expand laboratory capacity for detecting SARS-CoV-2. In this study, we used a simulated laboratory environment, based on a model of operating laboratories in Nepal, to identify opportunities for improvement.

Methods We developed a discrete event simulation (DES) model, based on data from and in collaboration with Nepali health authorities, to analyse laboratory operations in Nepal. We used a series of "what-if" scenarios under different levels of testing demand and staffing to investigate bottlenecks in the processing of COVID-19 samples in a simulated laboratory environment, assess the impact of potential reagent shortages and increased automation, and more generally, explore the key factors that drive the performance and resilience of the testing system.

Findings Suboptimal staff allocation and scheduling can limit the timely return of laboratory results; however, better staff allocation can mitigate bottlenecks and reduce the impact of reagent shortages. For example, when the demand is 720 samples per day and seven staff members are on duty, adding one additional staff member improves reporting time (reduction from 48 h to approximately 32 h). However, changes in scheduling can increase the average time to return the results to over 200 h. A one-day reagent shortage appears to have minimal impact, but a delay of five days significantly increases the reporting time, reaching nearly 150 h. Increasing automation or better process coordination for sample registration can also lead to better performance, reducing the average reporting time from over 60 h to just under 24 h.

Interpretation Our findings identify important bottlenecks and challenges, along with ways to address them, and thus provide important lessons for improving disease testing operations for this and future pandemics.

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Keywords: COVID-19; SARS-CoV-2; PCR; Laboratory capacity assessment; Discrete event simulation (DES); Sensitivity analysis

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Research in context

Evidence before this study

To identify related studies, we searched Scopus, Google Scholar, and Web of Science, using the keywords "COVID-19 testing" and "discrete event simulation". By the completion of this project (Dec 15, 2023), a small number of related studies were identified that use simulation methods to examine the operation of COVID-19 testing laboratories; studies focused on the sample collection process only were excluded. The three relevant studies examined operations at laboratories in two different universities in the USA and a hospital in China; each study identified different bottlenecks and resource requirements specific to their setting.

Added value of this study

The present study examines COVID-19 testing in public health facilities in Nepal, a setting that has not been previously studied. In addition to identifying bottlenecks specific to this novel case, the present study also shows that laboratories in resource-limited settings, which rely heavily on manual rather than automated testing processes, have different paths to efficiency and performance improvement than those described in the previous studies. The present study also provides the first benchmark comparison between results for different settings.

Implications of all the available evidence

Taken together, the evidence suggests that improving the operations of COVID-19 testing laboratories is possible, even with limited financial investment. However, the specific characteristics of each laboratory and the resource limitations in each context must be considered in designing these improvements.

Introduction

The COVID-19 pandemic has challenged entire health systems, including laboratory operations which have been a cornerstone of the pandemic response. To address this challenge, most countries rapidly expanded and enhanced laboratory capacity for detecting SARS CoV-2 using existing and novel laboratory and surveillance networks.[1] In the WHO South-East Asia Region (SEAR), rapid expansion of testing capacity reached to the sub-national level, with over 3500 laboratories (68% from India) performing real time reverse transcriptase polymerase chain reaction (rRT-PCR) using different platforms at the peak of the pandemic. An example of such expansion at sub-national level occurred in Nepal. From a baseline of a single public health laboratory with rRT-PCR capability at the start of the epidemic in early 2020, a network of more than 100 laboratories (of private and public ownership) was established by fall 2023. These laboratories helped in the diagnosis and confirmation of COVID-19 through molecular testing and covered all seven provinces. Resourcing of these laboratories with trained personnel and equipment required a significant investment. Furthermore, when disruptions occurred or when cases surged, it was desirable to find ways to maintain or improve testing throughput to keep up with the urgent demand.

To prepare for future pandemics, it is essential to learn from experience. Nepal's COVID-19 testing system offers a useful context in which to investigate ways to improve testing operations and enhance system resilience in a resource-limited context. This is particularly important in Nepal as the country reflects on the results of its first Joint External Evaluation (JEE) exercise conducted in November 2022 that identified operational research as a critical area to inform the strengthening of the country laboratory system.[2] The approach presented here, together with studies by Bakker and colleagues[3] and Khrisnan and colleagues,[4] provide a starting point to evaluate laboratory investment strategies in silico in Nepal. To the best of our knowledge, it is the first time that such mapping of laboratory processes has been conducted in the country. Albeit COVID-19 specific, we note that core elements of our model are applicable to other conditions of interest to Nepal health authorities.

Nepal is one of south Asia's poorest nations, ranking 146th on the Human Development Index in 2024, with high levels of poverty and income inequality.[5] Inadequate infrastructure, especially in remote areas due to rugged terrain, hampers Nepal's development. Furthermore, the rugged geography challenges supply chains and the availability of skilled staff in remote locations. In this context, Nepal's laboratory testing systems faced a series of challenges, including limited resources for automated testing machinery, disruptions in reagent availability, and limited capacity for processing surging numbers of samples. During the peak of the epidemic waves of COVID-19, the laboratories were used to their capacity, with some private laboratories adding extra capacity as the demand for testing surged. Similar challenges were also experienced by many other resource-limited countries, and solutions identified for Nepal may be adaptable to similar settings.

We aim to identify opportunities for improvement, using a simulated laboratory environment built on a model of operating laboratories in Nepal. Discrete event simulation (DES) is well suited to this purpose. Discrete event simulation is one of the primary stochastic modelling approaches used to address dynamic and complex systems and to inform policy.[6,7] DES models have been extensively used in healthcare to inform questions related to operations and efficiency,[8,9,10,5,11] most commonly by exploring what-if scenarios before investing in process changes.[12] DES models can, for example, explore the relative impact of investments—such

as buying equipment, or training and re-scheduling staff—in terms of their cost and effectiveness. In a study by Rositch and colleagues,[13] DES models were used to guide the planning of resilient operations for a new human papillomavirus-based screening program in Iquitos, Peru. We refer the reader to the survey in healthcare settings by Forbus and Berleant,[14] and to additional applications of DES modelling supporting health decisions for breast and colon cancer screening[15,16,17]; to predict the impact of preventive interventions for sudden cardiac deaths[18]; and to improve operations in manufacturing and business.[19]

Similar approaches have been used to explore COVID-19 testing operations specifically. COVID-19 testing involves a series of activities beginning with sample collection and ending with the reporting of results. The literature typically separates this process into two sub-processes for analysis: the sample collection process, in which samples are collected and shipped to the laboratory for analysis, and the laboratory process, in which samples are tested and results reported. They are analysed separately because they are typically managed separately and conducted in different locations. Following this logic, our analysis focused only on the laboratory portions of the process. Three papers have studied COVID-19 laboratory testing operations with discrete event simulation. A study by El Hage and colleagues[20] used DES models to facilitate scale-up of testing capacity for COVID-19 in a large testing centre at the University of Maryland, USA, which was processing between 3000 and 8000 samples per day in late 2020. The model was used to identify bottlenecks in the process, and a series of what-if scenarios explored a range of potential changes to increase testing capacity. The most impactful change identified was to speed up the deswabbing step (removal of swabs from the sample containers), which could almost double the testing capacity. The analysis also suggested minimum resources needed to meet sample throughput targets. A study by Saidani and colleagues[21] used a DES model to design COVID-19 testing stations for the University of Illinois, USA, which was processing around 10,000 samples per day in late 2020. Using what-if scenarios, the study also identified the minimum number of resources (operators and machines) for each task to meet various sample throughput targets. A study by Guan and colleagues[22] analysed the operations of a testing facility at a hospital in Guangdong Province, China, which was processing about 2000–3500 samples per week (or 285–500 samples per day). The authors also used a DES model and what-if scenarios to test the potential impact of process improvements. The most impactful change identified in their work was to shift worker schedules to better match the arrival times of specimens for testing. Beyond these three papers, additional simulation studies examined the sample collection portion of the testing process, which is not examined in this paper. To briefly summarise, a study by Gowda and colleagues[23] used a DES model and what-if scenarios to increase throughput at a testing facility in a New Delhi hospital: the authors found a bottleneck in preparing sample kits and alleviated it by increasing the staff allocation. A study by Kuncova and colleagues[24] used a DES model and what-if scenarios to show that adding staff alleviated bottlenecks at a Czech hospital's drive-in sample collection point. Another study by Lazo and colleagues[25] used a DES model and what-if scenarios to optimally allocate resources between sample collection tasks and show that smaller appointment intervals decreased contact time among testees.

Collectively, this small set of studies shows that improving the operations of COVID-19 testing laboratories is possible even with limited financial investment, by manipulating features such as scheduling of staff, number and allocation of resources, and innovations that reduce the time required for specific process steps. However, the specific resource requirements and improvement strategies depend on the characteristics of each laboratory, since different resources and improvements were identified in each of the three different cases. Further, the resource limitations of each context must be considered in designing the improvements. All three of the existing studies of laboratory operations examined relatively high-resource settings, in which automated equipment was available for many steps in the testing process. In contrast, the Nepal laboratory system studied in the present paper relies heavily on manual processing of samples. Therefore, it is a useful case in which to explore opportunities for improvement in such resource-limited settings.

This research article therefore (i) maps out the steps of standard rRT-PCR testing for COVID-19 in a representative sub-national laboratory in Nepal and develops a simulation model based on data from the laboratory system. Next, the model is used to (ii) analyse the laboratory's capacity and performance under varying numbers of staff and sample delivery patterns, in order to identify resource requirements for different target demand levels; (iii) identify the bottlenecks in the processing of COVID-19 samples, and evaluate options (including staff scheduling) for alleviating these bottlenecks to improve sample throughput; (iv) quantify the impact of reagent shortages and evaluate options for mitigating these impacts; and (v) quantify the benefit of investments in automation. In doing so, we identify the key factors that drive the performance and resilience of the system.

Methods

Data sources

Four main data sources were employed, all of which were obtained through collaboration with laboratory experts in Nepal.

Data source 1

Laboratory experts in Nepal, at the National Public Health Laboratory, the Ministry of Health and Population, the WHO country office, and the WHO South-East Asia Region (see list of authors). Information was gathered from these experts during a series of online facilitated discussions: sessions with a small group of experts were conducted 2–4 times per month between June 2021 and April 2022; three sessions were also conducted with a larger group of stakeholders. The sessions included not only information gathering but also validation of the model and its results.

Data source 2

An exhaustive description of the equipment, staff, and operations at all the laboratories (both government and privately run) across Nepal.[26] This information was gathered through a one-off survey jointly coordinated by the WHO country office and MOHP sent in mid-November 2020 to all the operating laboratories. The document provides details, for each of the 77 laboratories operating at the time of the survey, of the installed equipment, consumables used, staffing with details of the different roles, staff training, laboratory biosafety and bio-security measures, quality assurance and data management.

Data source 3

Daily COVID-19 situation reports by the Ministry of Health and Population that provide, for each laboratory, the number of processed samples per day and the number of positive test results.[26] There were very few missing values, supporting the completeness of the dataset.

Data source 4

A survey sent in late 2021 to three laboratories operating at the time to collect processing times and validate process flow. The survey was designed by our team. The laboratories were selected by the laboratory experts for their diversity: the large national public health laboratory, a smaller provincial public health laboratory, and a private laboratory. Most of the data were identical across the three respondents, which supports the validity of this dataset.

In parallel, we drew on our previous work on COVID-19 laboratory testing in a large university laboratory in the US, which will be used as an international benchmark to compare aspects of Nepali laboratory operations.[20] The data from sources two through four was available to the research team in late-2021, following approvals from WHO and MOHP. The data provided a good representation of Nepal laboratory operations during the period from late 2020 to late 2021, according to the Nepal laboratory experts. A further validation process was performed when developing the model, as described below.

Discrete event simulation model

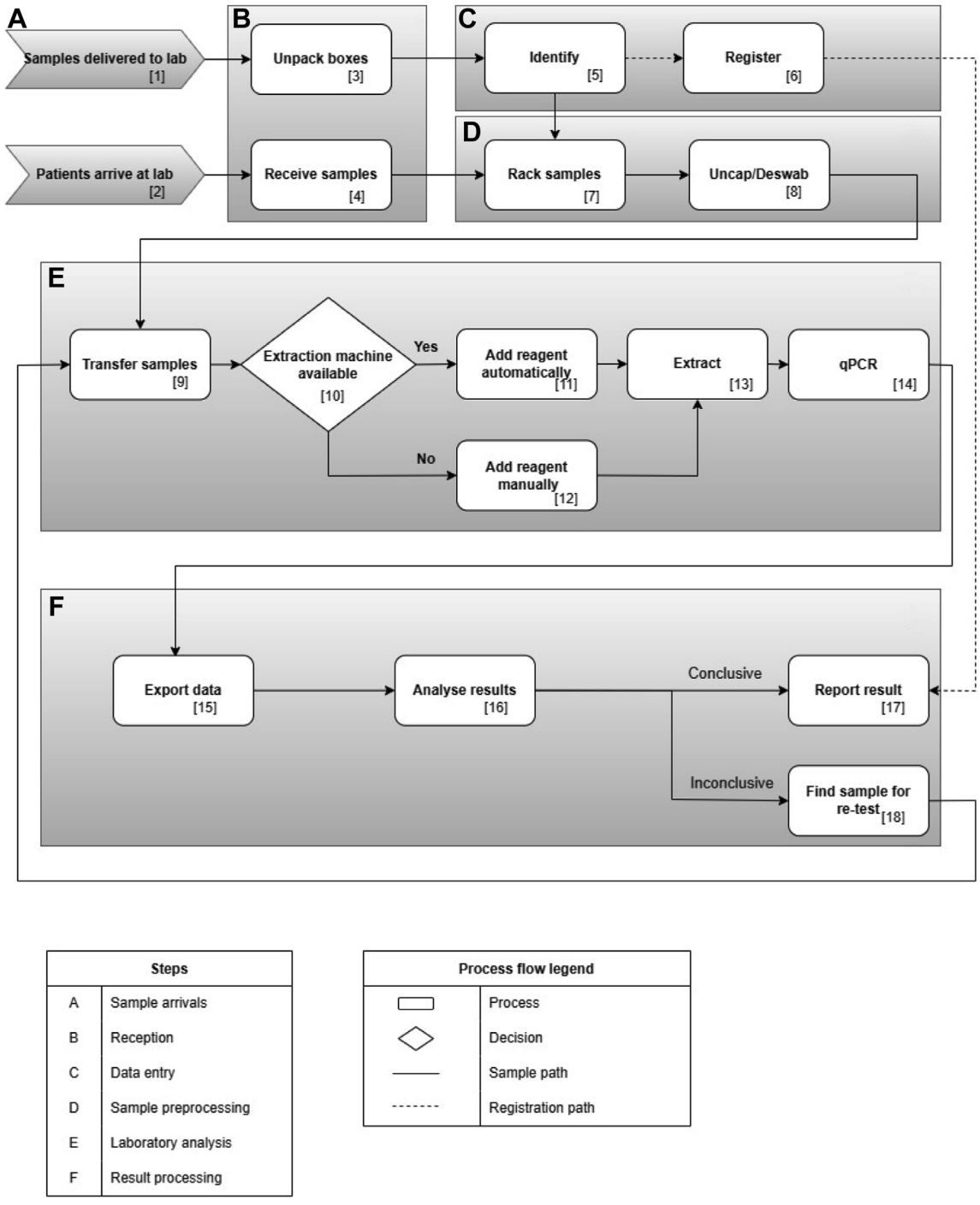
Discrete event simulation (DES) models represent entities, such as patients or samples, as they proceed through a process. The models are designed to represent a service system based on all the data available to characterise it, such as the process flow, processing times, and resource availability. Then, the models allow decision-makers to explore a variety of what-if scenarios. These scenarios allow testing different combinations of operational decisions and predicting how they might impact the system's performance and its ability to meet its goals. The what-if scenarios are built based on expert input and typically modify one aspect of laboratory operations at a time, such as introducing a disruption in the availability of reagent or modifying the staff schedule.

We followed Law's six steps[27] in building our model, namely: (1) setting goals and objectives and defining the scope of the problem; (2) mapping the process: designing the model at a conceptual level by describing the process to be modelled in sufficient detail to capture interactions among entities (such as patients or samples) as they move through the steps in the process and encounter resource constraints; (3) implementation: building the simulation model; (4) verification and validation: ensuring that the model represents the process and meets stakeholder needs; (5) experimental design: specifying the key performance indicators (KPIs) to evaluate performance and the 'what-if' scenarios to be tested; and (6) analysis: computing the KPIs for the 'what-if' scenarios and interpreting the results. Step 1 was already discussed when defining the scope of the problem. We discuss steps 2–5 in this section and step 6 later. In accomplishing all six steps, we have made a set of simplifications that were agreed upon by the stakeholders. As in the study by Robinson,[28] we believe that these simplifications are reasonable and that the model represents the overall process, as we regularly coordinated with the stakeholders (see Section Data sources) to ensure that the work was accurate and met the objectives.

Mapping the process

Fig. 1 represents the processes executed in a standard laboratory performing real time PCR testing for SARS-CoV-2 in Nepal. There are six major steps: sample arrival (step A), reception of samples (step B), data entry (step C), preprocessing of the samples (step D), analysis of samples (step E), and processing or reporting of results (step F).

At Step A the samples may arrive in two distinct ways, either from within the facility where the laboratory is installed (Step A2; e.g., a patient referred for testing from doctors within the same hospital where the testing facility is located), or from outside by courier or other means (Step A1; e.g., samples taken at a testing centre elsewhere). The arrival distributions of these two



Steps	
A	Sample arrivals
B	Reception
C	Data entry
D	Sample preprocessing
E	Laboratory analysis
F	Result processing

Process flow legend	
▭	Process
◇	Decision
———	Sample path
- - - - - - -	Registration path

Fig. 1: **Flow of samples in a standard COVID-19 laboratory in Nepal**.

modalities are different. Outside samples are received in boxes of about 30 samples for example (Step B3), whereas samples from within the same facility are received in batches already unpacked (Step B4). Outside samples are then manually identified (the sample number is handwritten in different places; Step C5). At this point, two different trajectories are followed in parallel for these outside samples: the 'sample' is sent for processing (solid line in Fig. 1), but it must also be 'registered' (dashed line in Fig. 1). Registration involves

entering patient information in an information system (Step C6). After identification, samples are racked and either registered directly or sent for processing if the wait time for registration is high. Registration must be completed before results can be reported. Samples arriving from within the same facility are already registered and therefore go directly from receipt (B4) to rack samples (D7). All samples are then racked, uncapped, and deswabbed (Step D). Next, samples are transferred into 96-well plates (Step E9). When the plate is filled, RNA extraction commences either automatically (if the RNA extraction machine and reagent are available) or manually (in any other situation, such as absence of automatic RNA extraction equipment or lack of the appropriate reagent). RNA extraction will take different amounts of time depending on the type of extraction kit used. Once completed, samples are transferred to real time PCR for the amplification reaction (Step E14). Step F (processing of results) comprises export of the results to the system. Results are then analysed by senior microbiologists or technologists. If results are conclusive, they are reported; otherwise, samples are retrieved and sent back to be re-processed (to Step E).

The steps above are generic and reflect the process carried out in a standard laboratory. The process map was validated by laboratory experts. Discussions with laboratory experts show that the major differences across laboratories are not in the process flow but in staff organisation (e.g., scheduling), capacities (e.g., number of staff and number and type of equipment), level of automation (e.g., barcoding), and demand (e.g., sample arrivals). Note also that the model represents the most important steps in the testing process but does not represent minor variations between laboratories, such as whether samples are aliquoted into multiple tubes after deswabbing.

Model input data

Parallel to process mapping, we also analysed the collected data (see Section Data sources) to develop inputs for the model. The model's inputs include staffing levels, equipment availability, processing times, and other operational characteristics. These inputs were computed for operations under normal circumstances in a standard laboratory.

Table 1 shows the inputs for the model along with the data sources from which they were computed. For the processing time distributions, the survey (Data Source 4) requested laboratories to provide the typical range of processing times for each step (such as 1–2 min); these are ranges because processing times vary slightly based on differences in operators or other factors. The reported ranges were nearly identical across all three laboratories. We use a triangular distribution, where the low and high end of the reported ranges are the minimum and maximum of the distribution and the centre is the most common processing time. This reflects the limited availability of data and captures possible lack of knowledge and inaccuracies. The inconclusive test rate was not available from the Nepal data, so we extrapolated the value from a laboratory with a similar setup and validated it with stakeholders.[20]

To compute the number of staff and amount of equipment, we analysed the data provided in the description of laboratory equipment and staffing (Data Source 2), to identify the average parameters across all laboratories. Then, based on consultations with experts, we instead selected a subset of the data that represented a standard laboratory and a representative period of

Parameters	Baseline scenario	Data source(s)
Processing times	Triangular distributions governed by three parameters (a, c, b), where a = lower limit, b = upper limit, and c = mode. Specifically: Identify (in s/sample): Triangular (25, 27.5, 30) Register (in s/sample): Triangular (30, 60, 90) Export data (in min/plate): Triangular (20, 25, 30) Analyse result (in min/plate): Triangular (18, 20, 22)	Source 4: Process and times survey; Source 1: Expert input.
Inconclusive test rate	5%	Extrapolated from study by El Hage and colleagues.[20]
Equipment	2 RNA extraction, 2 real time PCR (96 samples)	Source 2: Equipment and staffing survey; Source 1: Expert input.
Number of staff	8 staff working 8 h under different schedules (2 data entry, 4 technical staff, 2 scientific staff)	Source 2: Equipment and staffing survey; Source 1: Expert input.
Number of samples arriving per day	Historical sample arrival data (see Supplementary Figure S1), approximately 630 samples per day	Source 3: Situation reports.
Sample arrival pattern	80% of samples arrive from external sources in four batches arriving every 2 h starting at 8:00 h. 20% of samples arrive in small batches evenly distributed every hour between 8:00 h and 16:00 h.	Source 1: Expert input.
Staff schedule	Shown in Supplementary Figure S2: a staggered schedule, where data entry (identification and registration) begins early, and scientific staff arrive later in the day.	Source 1: Expert input.

Data sources are described in detail in the Data sources section.

Table 1: **Model inputs for the baseline scenario.**

operations: that is, when the laboratory was neither exceptionally busy nor exceptionally idle. The experts (part of this study) confirmed that the final parameters were a good representation of standard laboratory operations.

To compute the number of samples arriving per day, experts suggested using sample arrival data from a typical laboratory on a typical week. The sample arrivals were found by averaging the total sample arrivals each day of the week over three weeks of November 2020, based on the daily situation reports (Data Source 3) for a provincial public health laboratory; see Supplementary Figure S1. The number of samples varies between 155 and 958, with a clear trend of a higher sample count at the beginning of the week. Experts confirmed that these data were typical of other laboratories.

Another important characteristic is the sample arrival pattern, which describes how frequently samples arrive at the laboratory for testing. The data and discussions with the experts made clear that sample arrival patterns differed across laboratories in terms of how frequently they arrive, and whether they need to be identified and registered. Some laboratories mainly serve internal patients whose samples arrive occasionally throughout the day and do not need to be registered (skipping Step C in Fig. 1), while others receive larger batches containing many samples which all need to be registered, and some receive a mix. Table 1 shows our baseline scenario with some samples (20%) arriving from internal sources throughout the day and others (80%) from external sources in four different batches. Note that other arrival patterns tested as what-if scenarios are described later. These patterns were developed in consultation with experts, with the goal of representing several different types of arrival patterns seen in laboratories across Nepal.

Regarding manpower, experts confirmed basic features of a typical schedule. Laboratories often employ a staggered schedule, in which data entry staff arrive early and scientific staff arrive later in the day. Staff members may switch back and forth between different tasks frequently throughout the day. At the same time, staff with different skills performed different sets of tasks. (Typically, technical skills are required for Steps B, D, and E in Fig. 1; scientific skills are required for Step F; and Step C does not require any specific domain skills). To represent this situation, the model takes as an input a schedule showing which staff worked on each task for every hour of the day. Supplementary Figure S2 shows an example schedule. The schedule, of course, has an important influence on the processing time for sample testing (as we show later). To create the schedule, we followed a heuristic: an initial schedule is created for a given number of staff with different skillsets (based on discussions with the experts, we selected a baseline case with 8 staff members). Next, the DES model is run with this schedule, and we examine the utilisation rates (defined as the ratio between the total number of hours worked and total number of available hours) for all the process steps to see whether some are particularly high. If one step is more highly utilised than others, a qualified staff member (a staff member with sufficient skills) is moved to this task from a less-utilised task, for one or more hours of the day. With the updated schedule, the model is run again, and the process repeats until further movements do not improve performance. This process replicates the types of improvements a skilled manager would make as (s)he observes laboratory performance. Experts confirmed that the schedule and the schedule generation process were reasonable.

Model outputs

The model's primary outputs are two performance metrics: (i) total time to report results (or turnaround time) and (ii) utilisation rates of human resources. Total time to report results refers to the time in the system from sample arrival until the results are reported. Optimally, this time should be as short as possible. After discussion with the experts, a 48-h target was agreed upon. Utilisation rate (or % utilisation) refers to the ratio between the 'time used to process the samples' and the 'time available' for a given step in the process. For example, the utilisation rate for the uncap or deswab step is equal to the total time technicians worked on this task divided by the total time they were scheduled to work on the task. If they are busy for that entire period, the utilisation rate would be 100%. Where specialised equipment is required for a task, the equipment schedule is also relevant to determining the utilisation rate; in this case, the 'time available' is the time when the equipment and a technician, if required, are scheduled to work on a task. These two performance metrics were selected for different reasons. The time to report results is a key metric in determining the performance of testing systems, as reported by experts from Nepal and analysed in the literature.[20,22,21] It is also correlated with the overall capacity or throughput of the system, but more straightforward to compute and to compare across scenarios. The utilisation rate, on the other hand, serves an internal diagnostic purpose: it supports the identification of bottlenecks and therefore potential improvements within the system.

Implementation and validation

The model was developed in Simio, a commercial simulation software package designed for DES. All experiments were run for one complete month of laboratory operations, preceded by a one-week warm-up period (to account for samples already in the system at the start of the month). To capture the variability in the system (such as varying sample arrival times and processing times), the model was run 20 times for each scenario to produce a probability distribution of the resulting performance metrics (defined in Section Model outputs).

The model was then verified to test whether it represented the process map (in Fig. 1). We tested multiple input data (e.g., different values) to verify that the model behaved as planned (i.e., results are accurate and aligned with our expectations based on the process map). We used the performance metrics as a proxy of how the system reacts to changes and how it performs in general.

The next step was validation. Validation is extremely important as it allows us to determine whether the simulation model reflects the system it represents. The first step in the validation process was to identify input data that represents the typical operation of the system: we used the baseline sample arrivals (see Table 1 and Supplementary Figure S1). Next, we began an iterative validation process with three steps. (i) The simulation model was run to compute the time required to report results (the first KPI), broken down into the times for the registration path and sample path (paths illustrated in Fig. 1). The results are shown in Supplementary Figure S3. We also identified the bottlenecks in the process. (ii) These results were shared with the laboratory experts. We asked the experts to comment on whether the processing times and bottlenecks matched their experience in the laboratories, and where it did not, to identify the parts of the model which did not match the real process. (iii) The model was refined to fix the identified mismatches, and the process was repeated until no further discrepancies were identified. This process identified two key discrepancies (subsequently corrected): the initial number of staff was overestimated because staff were occasionally borrowed from other tasks and these were mis-counted; and registration was discovered to be completed in parallel with sample processing rather than beforehand. Additional minor sources of inconsistency were identified and corrected, such as the processing time for registration.

The model validated by the experts produces the processing time results shown in Supplementary Figure S3.

The validation process also helped to show some of the key behavioural dynamics of the testing system. Average processing times were 4.4 h for the "Registration" path and 28.6 h to report the results (the "Sample" path). The "Sample" path almost always takes longer than the "Registration" path. On the "Sample" path, we also observe that 50% of samples are processed in less than 30.4 h and that 95% are processed in less than 60 h. These insights were leveraged to design experimental scenarios.

Experimental design

The experimental design aims to address the objectives raised earlier in the introduction. To that end, we tested the following four scenarios:

- Scenario 1: Variation of the total number of staff, the number of sample arrivals, and the pattern of sample arrivals. This scenario helps to assess bottlenecks and understand the capacity of the system.
- Scenario 2: Variation of the staff schedule, to alleviate the identified bottlenecks in the process.
- Scenario 3: Disruption in availability of reagent, to identify the impact of reagent shortages and evaluate options for mitigation.
- Scenario 4: Automation of particular steps (registration and sample transfer), to quantify the benefit of investments in automation.

These scenarios were designed in collaboration with the laboratory managers in Nepal to represent variations witnessed across the laboratory system (Scenarios 1 and 2); disruptions they had experienced (Scenario 3); and investments that could alleviate bottlenecks (Scenario 4). Note that all scenarios are independent and investigate one dimension at a time. The model inputs for each scenario were found from the same data sources described in Section Data sources, using the same approaches described in Section Model input data, with the final input values confirmed by laboratory experts. The specific input values are described in the Results section, below.

The model's sensitivity to variations in input parameters was evaluated as part of Scenarios 1 and 2. In the data and expert input, the most variable features were the number of staff, the number and pattern of sample arrivals, and the staff schedules. Therefore, each of these parameters were varied across the observed range to evaluate the impact on performance.

Role of the funding source

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Results

Laboratory capacity and performance

We first examined the performance of the laboratory in providing results within the 48-h target, for various numbers of samples arriving per day. The number of arrivals per day was set based on the laboratory's maximum estimated capacity of 900, then reduced by 10% of that capacity, iteratively, to a low value of 90. Fig. 2 shows the distribution of average time to return results for the baseline scenario (8 staff), across all replications, with three different numbers of samples arriving per day (720, 810, and 900 samples). For the two lower numbers, 720 and 810 samples per day, nearly all the samples are processed in less than 48 h (below the red line in the figure). For 900 samples per

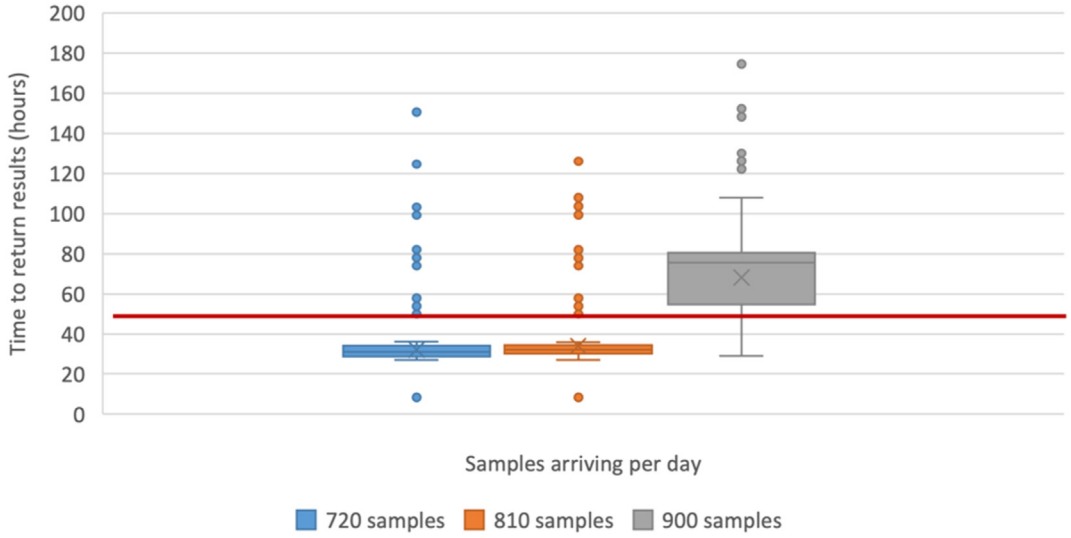

***Fig. 2:* Distribution of time to return results for each sample in the baseline scenario (8 staff), with different numbers of samples arriving per day**. The target is to return 95% of results within 48 h (shown as a red line on the plot).

day, very few are processed in 48 h because there is not enough capacity to process all the samples and therefore, they continually queue up to wait at different stages of the process. Thus, the approximate capacity of the baseline laboratory setup was 810. Using this approach, we tried to identify the approximate capacity of different laboratory setups by finding the maximum number of samples per day for which 95% of samples are processed within 48 h.

Next, we examined the capacity of the laboratory—the maximum number of samples per day—for varying numbers of staff (assuming, as discussed above, that 95% of the samples are to be processed within 48 h). The analysis assumed the baseline pattern of sample arrivals. The results are shown in Fig. 3. As expected, the capacity increases as the number of staff grows, but not in a strictly linear relationship. The capacity is quite low when only 4 or 5 staff are available and rises more quickly with 6 or 7 staff. Apparently, economies of scale can be achieved with a higher number of staff and samples. Specifically, this efficiency gain appears due to two factors occurring at lower capacities: (i) waiting to process samples until a real time PCR plate of 96 wells is completely filled, which takes time when sample arrivals per day are low, and (ii) keeping staff working on one task for a full hour, which may be too long when sample arrivals are low.

The remaining analyses report the mean time to return results rather than entire distributions since our analysis shows that the mean follows the same trend as

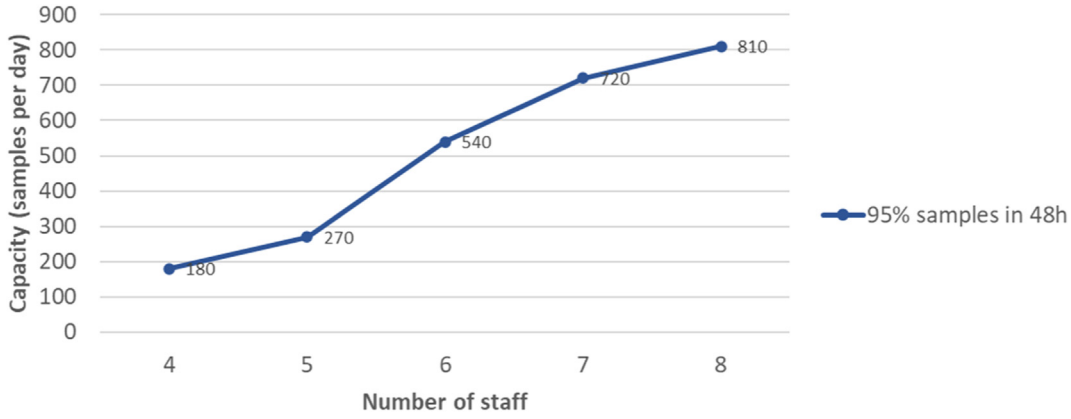

***Fig. 3:* Maximum laboratory capacity (number of sample arrivals per day) with various numbers of staff, for the baseline sample arrival pattern**. The capacity is determined by requiring 95% of results to be processed within 48 h.

the time to process 95% of the results, as evidenced by Fig. 2.

Next, we examined how laboratory performance changes when the pattern of sample arrivals changes. As discussed earlier, different arrival patterns represent the conditions at different laboratories. Recall that samples may arrive consistently throughout the day from internal sources within the same facility and need not be registered (A2 in Fig. 1); alternatively, samples may arrive in larger batches from external sources, in which case they do need to be registered (A1 in Fig. 1). We tested four scenarios, to investigate the sensitivity of the results to changes in arrival patterns:

- "80/20": 80% of samples arrive from external sources in four batches arriving every 2 h starting at 8:00 h; 20% of samples arrive from internal sources in small batches evenly distributed every hour between 8:00 h and 16:00 h (the baseline scenario).
- "50/50": Same as "80/20" except that samples are evenly divided between external and internal sources.
- "One batch": All samples arrive from external sources in one batch at 8:00 h.
- "Constant": All samples arrive from external sources in small batches evenly distributed every hour between 8:00 h and 16:00 h.

Fig. 4 shows that the mean time to return results does not vary if the number of samples arriving per day is lower than 630. However, it increases significantly when the number of samples arriving per day reaches 810, especially for the one batch and the constant arrival cases. These two sample arrival patterns behave very similarly, while the 80-20 and 50-50 patterns are also comparable. The latter have shorter processing times because some of the samples come from internal sources and therefore do not require registration. It is also worth noting that sample arrivals in one batch at the start of the day result in slightly worse performance than smaller batches throughout the day, likely because the single batch means a lot of waiting while the entire batch is processed.

This trend was also confirmed by the increase in variability in the time to return results. When the number of samples is relatively low (e.g., 540), the distribution of the time to return results is very stable around the mean (±4 h in general) and does not depend on the sample arrival pattern. On the other hand, when the number of samples is 900 for example, not only does the average increase, but also the variability of the observed times. The greatest variability (more than 30 h around the mean) is observed for the "One batch" and "Constant" patterns.

Bottlenecks and staff scheduling

Next, we considered variations in staff scheduling. Staff schedules varied significantly across laboratories and even across days within the same laboratory. Laboratory experts explained that schedules were adjusted based on the bottlenecks where extra help was needed, so we replicated this adjustment process with the heuristic described in Section Model input data. In this section, we analyse the sensitivity of the laboratory performance to variations in the schedule, using four example schedules to illustrate the impact.

An analysis of the utilisation rates of each process step identified bottlenecks that slow down the entire

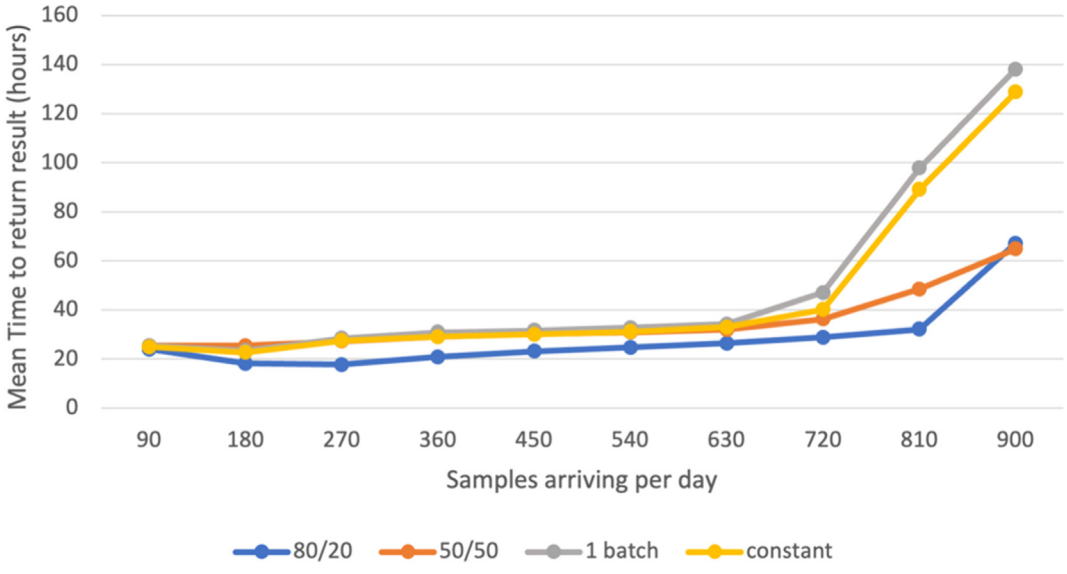

Fig. 4: **Mean time to return results, with various sample arrival patterns**. A baseline staffing level is assumed (8 staff).

process, to inform re-allocation of staff to appropriately expand capacity at the bottlenecks. A process step operating near 100% utilisation represents a bottleneck in the system, in that it restricts the overall flow through the process (even if capacity exactly equals demand, natural variability in the timing of sample movement through the system means that samples will often have to wait to be processed through any process step operating near 100% capacity). The capacity of the entire process is equal to the lowest capacity of any constituent step. Therefore, re-allocating staff to add more capacity to a bottleneck step can increase the overall rate of sample processing.

In this section, we analysed a scenario with 7 staff rather than 8 as in the baseline scenario, to clearly see the effects of bottlenecks and scheduling. (Teams of 8 staff can process nearly all the samples without any bottlenecks (see Fig. 2 assessing capacity); with 7 staff, bottlenecks appear at lower sample arrival rates (between 450 and 720 samples), so we can more clearly see the effects of schedule changes). Consider Table 2, which shows utilisation rates for all the process steps for four different schedules. In Schedule 1, the bottleneck steps (those at 100% utilisation rate) are "Identification" and "Registration".

We considered how to reallocate staff to add capacity to these bottleneck steps. As in reality, the model employs a staggered schedule, where data entry (identification and registration) begins early, and scientific staff arrive later in the day. The scientific staff have the lowest utilisation rates, so we transfer them (1 h at a time) to the bottleneck steps. We develop three alternative schedules in this manner: Schedule 2 sees scientific staff assigned 2 h to data entry (between 13:00 and 14:00 h and 16:00 and 17:00 h; schedule 3 assigns 3 h, between 13:00 and 15:00 h and 16:00 and 17:00 h and schedule 4 assigns 4 h between 13:00 and 17:00 h). All the schedules respect the existing policies governing which staff can be assigned to which tasks (for example, staff cannot be assigned to tasks for which they are not qualified). The utilisation rates for these three schedules are also given in Table 2. We clearly observed that the bottlenecks (steps at 100% utilisation rate) remain "Identify" and "Register" for schedules 1 to 3 but shift to "Export data" and "Analyse results" for schedule 4, because the scientific staff were now spending too little time on their original tasks.

The overall performance of the laboratory was sensitive to the capacity of the bottleneck steps and therefore was highly sensitive to the scheduling of staff: who works on what tasks, when, and for how long. Fig. 5 compares the overall laboratory performance of Schedules 1 through 4, in terms of mean time to report results, for different levels of demand (samples arriving per day). Schedule 2, which shifts scientific staff from their former duties to add 4 h of registration and identification, dramatically improved the performance compared to Schedule 1. Schedule 3, which adds another 2 h on these tasks, also improved performance, but the impact was smaller. With Schedule 4, however, the trend was reversed. By shifting the scientific staff to do 8 h of registration and identification, the system bottleneck shifted to their original (but now somewhat neglected) tasks: analysing results and exporting data (as shown in Table 2). This bottleneck now restricted the overall capacity of the system more severely than in the original Schedule 1, leading to even worse performance. We performed a more extensive sensitivity analysis to schedule changes, but the results reported here for these four schedules are representative of the patterns we saw.

Availability of RNA extraction reagent

A reagent is required to extract the RNA, in Step E of the process, but laboratory experts explained that the reagent was sometimes not available due to supply chain issues. Fig. 6 shows the average time to return results,

Steps	Total no. samples per day at bottleneck:	Schedule 1	Schedule 2	Schedule 3	Schedule 4
		450	720	720	450
B–D	Unpack boxes [3]	50%	40%	40%	25%
	Receive samples [4]	72%	57%	57%	36%
	Uncap or deswab [8]	63%	73%	73%	49%
C	Identify [5]	**100%**	**100%**	**100%**	47%
	Register [6]	**100%**	**100%**	**100%**	52%
E	Transfer samples [9]	79%	90%	90%	45%
	Add reagent [11]-[12]	37%	41%	41%	53%
	Real time PCR [14]	52%	59%	59%	23%
F	Export data [15]	54%	82%	82%	**100%**
	Analyse results [16]	49%	78%	78%	**100%**
	Report results [17]	3%	3%	3%	2%

Note: Numbers in brackets correspond to the task numbering, see Fig. 1. Bold is used to identify bottleneck tasks (utilization equal to 100%).

Table 2: **Percent utilisation for each step in the process for Schedules 1–4.**

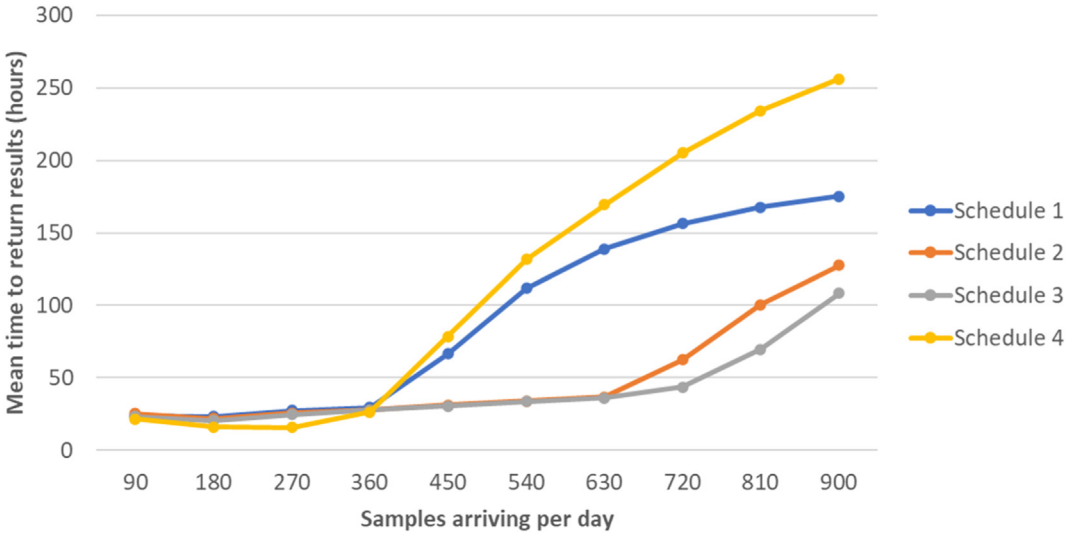

Fig. 5: **Mean times for reporting the results, with different staff schedules and numbers of arriving samples**.

over time, for reagent shortages of varying lengths: from a one-day shortage up to a five-day shortage. The average time to return results with one-day shortage (orange line) is very similar to the baseline scenario with no shortage (blue line). This one-day shortage has minimal impact because the staff dedicated to extracting RNA are not fully utilised and the bottleneck is elsewhere. For any shortage longer than one day, the time to return results goes up sharply, close to 150 h on day 6 after a 5-day delay, since there are so many samples in the system waiting for testing. As there is some spare capacity in the RNA extraction step, as soon as reagents become available again the system can eventually "catch up", but it takes several weeks to do so (more

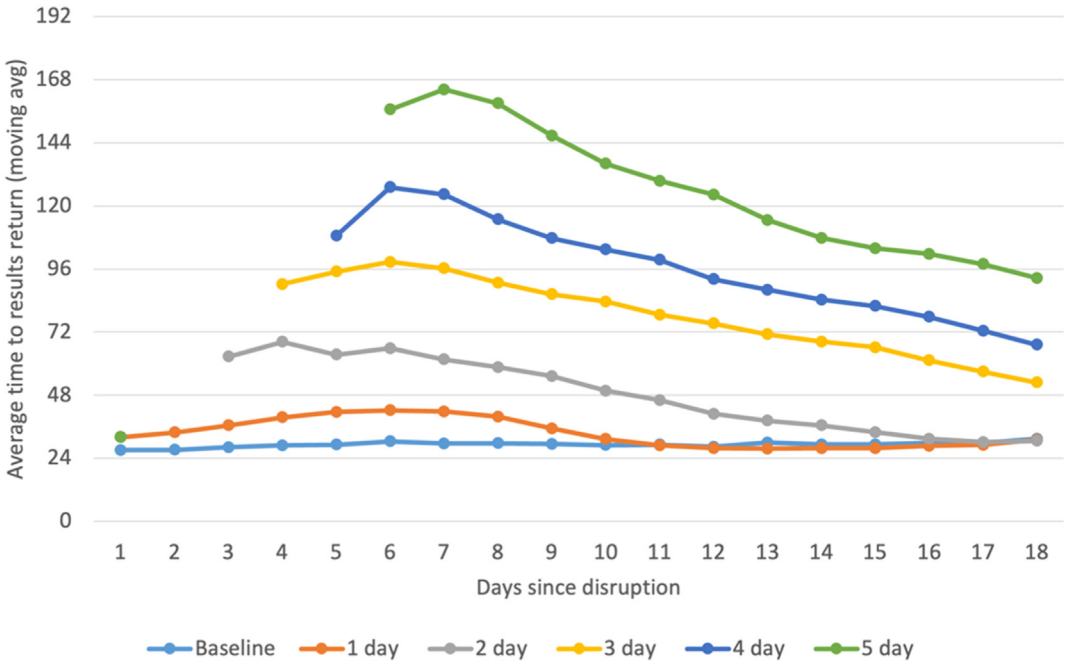

Fig. 6: **Average time to return results after a shortage of RNA extraction reagents lasting varying lengths of time**. The first one or two days after the end of the shortage show the longest time to return results, then the system slowly recovers to its original performance. (Results based on the historical sample arrival data, approximately 630 samples per day).

than two weeks for a 2-day shortage, and longer for the others). Note that we expect the same pattern (Fig. 6) for shortages of the real time PCR assay reagent since the real time PCR step (Step E14) comes right after extraction (Step E13).

A less severe but more common problem is a shortage of the specific kit required to perform automatic extraction. When this kit is not available, automatic extraction cannot be performed, but RNA can still be extracted manually if other reagents are available. However, manual extraction is a much slower process than automatic extraction. Fig. 7 shows the mean time to return results when no automatic extraction kit is available and manual extraction is employed instead. We observed that the mean time to return results starts increasing when the number of samples is greater than 540 per day, for the baseline scenario without automatic extraction (AE). When comparing the results of the baseline scenario with and without automatic extraction, we also observed that the increase is linear and reaches up to six times the time to report results when automatic extraction is employed. However, Fig. 7 also shows that by changing the schedules of the staff to add more time for manual RNA extraction (Schedule 5 without AE), it is possible to mitigate the problems resulting from the shortage of automatic extraction kits.

Introduction of automation

This section analyses the potential benefits of introducing automation into the process, at two points. The first experiment introduces bar coding (BC) for the identification of samples that would then shift from the existing manual data entry (Step C) to automatic. We expected such automation to dramatically decrease the processing time from 30 s to 1.25 s, based on data from the Maryland laboratory.[20] For these experiments, we assumed that barcodes are used consistently by the laboratory and its upstream clients, including all sample collection sites. The second experiment is the automation of sample transfer (Step E9). This consists of using a robotic liquid handler that automatically transfers the samples instead of doing the transfer manually. (We used the same reference times and machines as in the study by El Hage and colleagues).[20] For these experiments, we assumed the baseline scenario and varied the number of staff available. We also utilised a comparison with a state-of-the-art laboratory in Maryland, USA, as a benchmark to show the performance that highly automated processes can achieve.[20]

Barcoding could enable significant improvements (Fig. 8). The figure shows the mean time to report results for our baseline scenario with 8 staff (with and without BC) and with 7 staff members (with and without BC). Introducing BC decreases the mean time to report results, especially when many samples must be processed. For example, when 900 samples arrive per day and there are 8 staff, introducing barcoding lowers the time to return results from 70 h (dashed blue line) to less than 48 (solid blue line). Barcoding has limited impact, however, when the number of samples per day is smaller—i.e., well within the laboratory's capacity (for example, 720 or fewer samples per day).

Fig. 9 shows that the addition of a robotic liquid handler (automating sample transfer) creates a large improvement in performance, especially when the number of samples per day is high. For example, with seven staff, and a demand of 720 samples per day, this automation improved reporting time from a mean of more than 60 h to just under 24. In comparison, adding a staff member (without adding

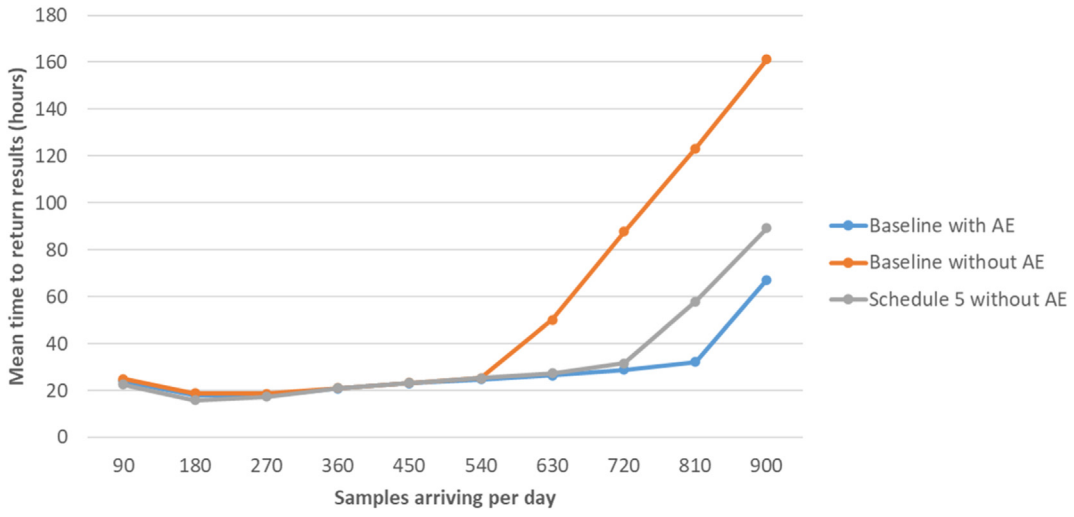

Fig. 7: **Average time to return results when there is a shortage of the automatic extraction kit (AE), and manual extraction is used instead.**

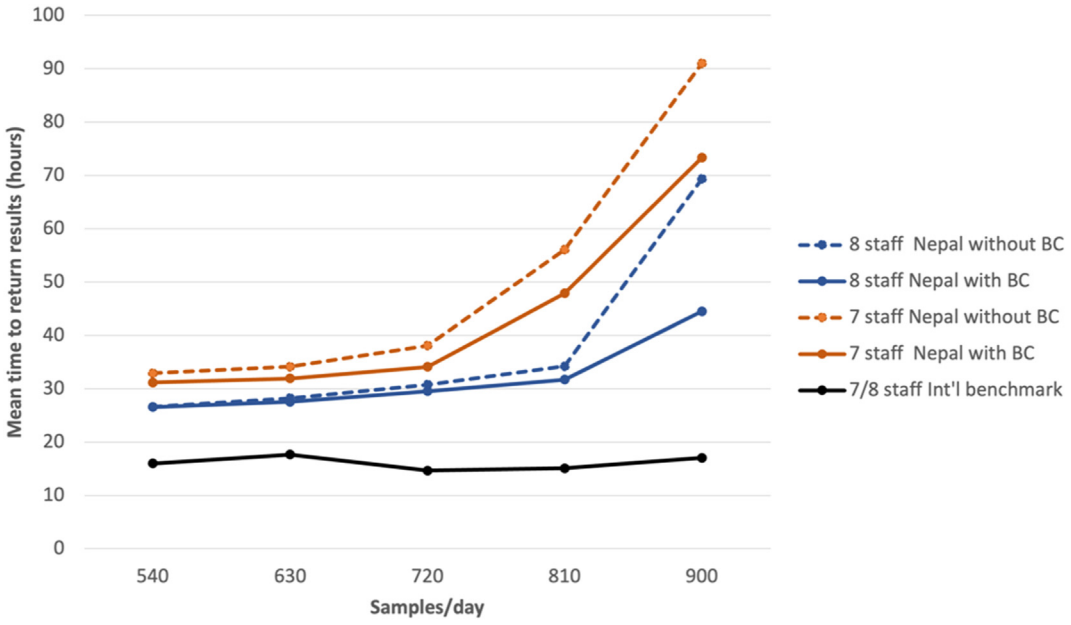

Fig. 8: **Changes in mean time to report results when bar coding is available.**

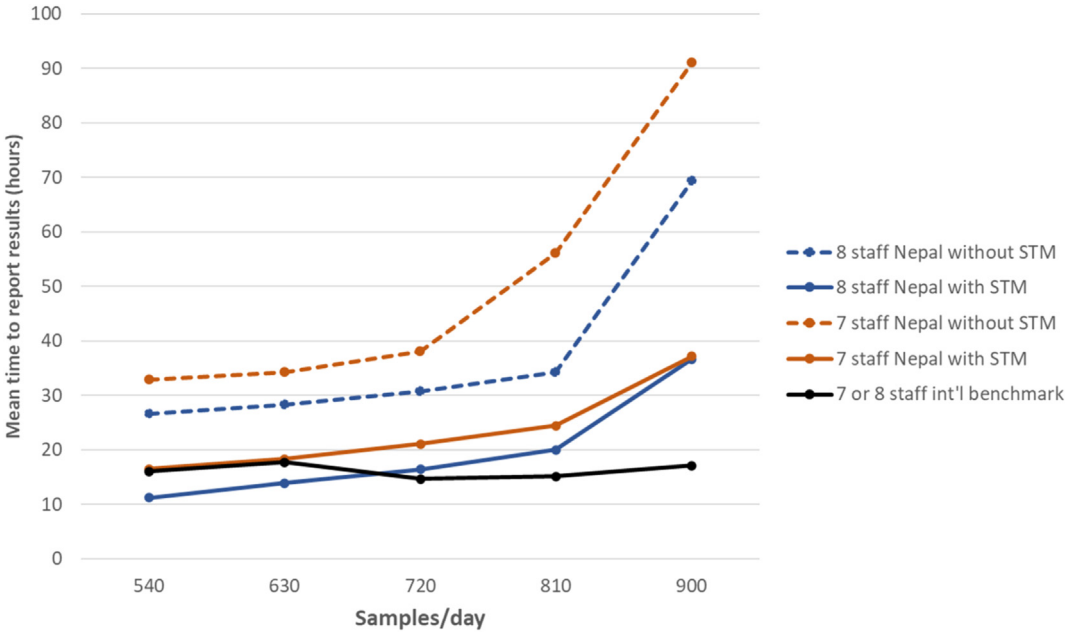

Fig. 9: **Changes in mean reporting time for introduction of automated sample transfer machine, compared to the addition of staff and the international benchmark laboratory.**

automation) is somewhat less effective: reporting time drops only to about 32 h. We observed exactly the same behaviour as when introducing BC. Introduction of automation at this step clearly improves the process and relieves pressure from the system.

Even higher levels of automation enable even better performance. A comparison with the benchmark laboratory in Maryland, where nearly all tasks are automated, showed that the laboratory can process any number of samples, up to 900, without any increase in reporting time.

Discussion

In this paper, we answered the following questions pertaining to standard COVID-19 laboratories in Nepal: (i) what is the laboratory's capacity to return results within 48 h, in terms of number of samples per day; (ii) what are the bottlenecks in the processing of COVID-19 samples; (iii) what is the impact of disruptions in reagent availability; and (iv) what is the benefit of investment in automation? The following paragraphs discuss the answers. In the process of analysing these questions, we evaluated methods for mitigating the impact of bottlenecks and disruptions, and more generally we identified several key factors that drive the performance and resilience of the system. Our experiments also allowed us to derive managerial insights about assessing laboratory capacity, the role of staffing, and the drivers of bottlenecks.

(i) Assessing system capacity may be more complex than managers expect. Estimating capacity based on expected throughput, using average processing times, is inadequate in this context, since processing and arrival time variability and wait times have an impact on capacity. Simulation models capture much more of the complexity of the real system, enabling a better assessment of capacity. This is important because the notion of capacity is intimately related to the service level. For example, in this paper, we assessed the capacity to process 95% of arriving samples within 48 h. This target was agreed with the experts, but other laboratories may have different goals: e.g., 90% or 95% of the results returned within 24 h. Answering relatively simple questions about laboratory capacity requires a quantitative tool such as the simulation model here presented. Further, our model allowed the identification of non-linear relationships between resources and laboratory capacity that might result in unexpected efficiency gains.

Another key insight from our analysis is the importance of staff scheduling in determining laboratory performance. Even relatively minor changes in the allocation of staff across laboratory tasks can strongly impact performance: in one case, such a change pushed the mean time to report results from less than 48 h to more than 150 h. This represents an opportunity: laboratories might be able to increase performance by simply re-allocating staff. Similarly, disruptions such as shortages of extraction kits can be partially mitigated by changing the staff schedules. Modifying staff schedules may require other considerations outside the scope of this project, such as contracts, financial concerns, and staff preferences, but could be well worth the effort.

(ii) Contrary to earlier work on an American laboratory,[20] we do not find that any single step is consistently a bottleneck in the process. Instead, the allocation and scheduling of staff determines where bottlenecks occur in our representation of the standard laboratory in Nepal. This difference is likely due to the lower level of automation in Nepal laboratories. When automation is high (as in the American laboratory),[20] the process is less labour-intensive, and bottlenecks may be determined by equipment availability rather than staff schedules. In Nepal, where many steps are performed manually, the availability of staff rather than equipment drives bottlenecks.

(iii) Shortages of extraction kits and real time PCR reagents have been a major concern everywhere throughout the COVID-19 pandemic.[29] Thanks to some spare capacity in the extraction step, our standard laboratory in Nepal can recover from even multi-day reagent shortages. Changing staff schedules can also mitigate some of the resulting problems by allocating extra staff to steps that are slower (e.g., when manual rather than automatic extraction is required) or have bigger backlogs (e.g., directly after a reagent shortage has been resolved). The implication is that laboratories should consider maintaining some spare capacity and flexibility in staff schedules, to be resilient to disruptions. Additional studies could estimate the amount of redundancy, and its associated costs required to enable various levels of resilience.

(iv) Our results also provide a basis for considering investments in expanding capacity. Investing in barcoding or equipment for automatic sample transfer can indeed improve capacity, but it is only useful when the demand for testing is very high—and when barcodes are utilised uniformly across the entire testing process. Indeed, our results also suggest the value of a related investment: coordinating processes not only within the laboratory but also with those who collect samples, such that registration is accomplished upon sample collection and not needed at the laboratory (as for the internally sourced samples in our model). This would speed up results return and free up some registration staff for other duties. Finally, our results suggest the potential pitfalls of making uninformed investments. Our results show that adding one staff member does not necessarily lead to a linear increase in capacity; it depends on many other factors, such as economies of scale, staff schedules, and the details of the process. Generally, evaluating potential investments with models like ours can help decision-makers to most usefully allocate scarce funds. For example, our results suggest that staff reallocation, which costs relatively little, could significantly improve performance, perhaps obviating the need for an investment in another staff member or expensive automation equipment.

Implementing any of these potential changes would require substantial cooperation and investment from stakeholders in Nepal, whose resources are already strained. We hope that our analysis provides the evidence for holding such discussions and making informed decisions on policy changes and investments. Such discussions should also consider the long-term sustainability of these investments. Our analysis focused on urgent pandemic-driven needs to expand capacity and improve resilience. Beyond the pandemic, however, such a large capacity might no longer be needed, so the long-term sustainability of investments—such as their applicability for other ongoing health conditions such as dengue or cholera—should be carefully evaluated in future work.

It is also worth considering the generalisability of these results to other laboratories and to other diseases. Regarding the latter, many steps in the testing process are similar for some other diseases of interest, such as human papillomavirus, so similar simulation methods can be used to evaluate testing in such cases.[13] Regarding the former—generalisability to other contexts—it is clear from the prior literature (see the Introduction to this paper) that the specific findings from this type of analysis, such as bottlenecks or the required number of staff, are different in different contexts. While the process flow is fundamentally the same in all these cases, the specific quantities (such as number of samples, daily capacities, and time to return results) and the methods of implementation (such as automated versus manual) are not directly exchangeable. This underlines the importance of conducting studies for each context, as we have done for Nepal, to extract specific insights to improve performance and resilience.

At the same time, several of our general insights are likely to be valuable in laboratories with similar reliance on manual processes with low levels of automation. First, such laboratories should pay careful attention to staff scheduling because (i) it can have a major impact on laboratory capacity and performance; and (ii) it can be a source of resilience, since shifting staff schedules can help to mitigate disruptions. Second, if a significant expansion in capacity is required, automation can be very impactful. Third, estimating capacity based on averages alone may be misleading since it fails to capture the complexity of the system. These results can inspire other laboratories to examine their own operations to estimate capacity and optimise staff scheduling before making other, more expensive, investments.

Our work has several limitations. First, the results shown here assume no decline in quality (i.e., rise in inconclusive result rate) and no disruptions to the process, such as machine breakdowns and staff no-shows. This assumption seems unrealistic even for the baseline scenario, let alone in the likely situation of worsening quality with increasing pressure on equipment and staff. Relatedly, our results also assume sufficiently skilled and experienced staff; this may not be the case if new staff were recruited to address the increasing demand during the peaks of the epidemic. Unfortunately, no reliable data exist to characterise these issues. We expect that the capacity would be decreased, and the turnaround times increased as these problems worsen. Our models would allow adjustment for these nuances by adding specific parameters, constant or not, reflecting such issues as staff turnover, learning curves, machine breakdowns, and suboptimal quality.

In developing alternative staff schedules, we have assumed that we can move scientific staff to perform tasks that are below their level of skill, such as data entry. This might not be possible in some settings given rigid contractual arrangements and obligations. It might not even be financially viable or optimal given different payment arrangements among laboratory staff; private laboratories would be particularly sensitive to this argument. We did not have access to data on costs, but our results could be easily extended if data were available to address financial scenarios. We also assumed that staff may only switch tasks once per hour. Our results are based on staff schedules that were developed manually using a heuristic algorithm that attempts to find the best schedule for any given set of staff. This process represents the current state of the art, but an optimisation approach should be developed in future work to find a guaranteed best schedule.

Future work could explore the sensitivity of laboratory performance to the limitations described above, such as the assumption of skilled staff availability. These analyses were beyond the scope of this short project, but the model remains available to explore additional scenarios and inform interventions to improve laboratory performance. We recommend collecting data to explore the sensitivity of the results to constraints in staff availability and skill levels, to process disruptions, and to rising reprocessing rates, since these problems are likely to arise in practice. At this point, we raise the required caveat that for such complex and adaptive system the range of evolving scenarios is entirely uncertain and consequently impossible to model exhaustively.

Since the data were collected amidst the high pressure of a global pandemic, there is a risk that the data are incomplete or biased toward the larger and more resource-rich laboratories. However, the data from sources 2 through 4 was largely complete: for example, the situation reports (Data Source 3) were missing only 3% of values, half of those from a single laboratory (of the 77 laboratories reporting), for the three-week period analysed in this paper. Our analysis found high consistency in the reported values across these three weeks, suggesting reasonable quality. The combination of data from across the system with expert input helped to triangulate and validate the data and the model parameters inferred from it. Nevertheless, we cannot rule out the possibility of problems with the data affecting our results.

The model has also left out some aspects of the testing process, including sample collection and transportation to the laboratory at the start of the process, and the transmission of results from laboratory to patients or doctors. Further, our work only addresses a limited number of scenarios reflecting immediate challenges in laboratory operations during the pandemic, and a limited set of performance metrics (turnaround times and utilisation rates). Selecting the scenarios and performance metrics to run must follow policy priorities, data availability, and resources for simulation analysis. Future work could explore additional performance measures such as cost, subject to data availability. Future work could also test additional scenarios reflecting resource availability to implement changes, ideally prior to specific planning and development efforts. For example, we could investigate the impact of automating results reporting. We could examine the impact of several improvements simultaneously, e.g., the addition of BC and automated sample transfer, or the effects of multiple impacts affecting the process simultaneously, e.g., lack of reagents and a large volume of samples. We could examine the impact of pooling samples to conserve reagent.[30] To extend our analysis to the country's entire network, we would need to integrate our models and results with those of the studies by Bakker and colleagues[3] and Krishnan and colleagues.[4] Finally, future work should see the integration of our within-laboratory model with others targeting the rest of the laboratory system and beyond, including other response pillars intimately related to the laboratory network's performance, such as contact tracing and surveillance among others. Such an exercise could consider stated objectives and trade-offs (e.g., improving efficiency, reducing access inequalities, sustainability), adding resource implications, workforce and supply chain considerations, and partners' priorities (such as private laboratories, animal health facilities, and those of the community whom the network aspires to serve).

In general, we did not examine the feasibility and long-term sustainability of the suggested solutions to the challenges. Some of them, such as repurposing laboratory staff, would demand minimal resources but may require some changes in policies and stakeholder cooperation. Others, such as automation, are likely to require substantial investments as well. A formal cost and feasibility study, outside the scope of our work, would be required.

The identified areas for improvement and the scope of this analysis should not preclude passing judgement on a general, if perhaps insufficiently recognised fact: the rapid growth of the network, from one laboratory in early 2020 able to conduct real time PCR testing, the National Public Health Laboratory, to more than 70 at the end of that year, and the parallel development of the complex system, including the trained workforce and the supply chain, which supported it well for the most part. In future pandemics, models like ours could support the refinement of these systems to provide greater performance and resilience with fewer resources.

Contributors

FLC: conceptualisation, data collection, data verification, analysis, application of methodology, conclusions, manuscript production.

NL, EG: conceptualisation, data verification, analysis, application of methodology, conclusions, manuscript production.

HB, PKK, JG: conceptualisation, data verification, analysis, methodology validation, manuscript review.

AG: project lead, conceptualisation, manuscript review.

RJ, LS, NB, SS, RM, PJ: domain expertise, data validation, manuscript review.

RS, DN: local and regional domain expertise, data validation, manuscript review.

VJDRV: project lead, conceptualisation, manuscript review.

Data sharing statement

Data was retrieved and is available from publicly available websites provided by MoHP Nepal (https://covid19.mohp.gov.np/situation-report).

Declaration of interests

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.lansea.2025.100584.

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