Simulation modeling and analysis of primary health center operations

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Abstract
We present discrete-event simulation models of the operations of primary health centers (PHCs) in the Indian context. Our PHC simulation models incorporate four types of patients seeking medical care: outpatients, inpatients, childbirth cases, and patients seeking antenatal care. A generic modeling approach was adopted to develop simulation models of PHC operations. This involved developing an archetype PHC simulation, which was then adapted to represent two other PHC configurations, differing in numbers of resources and types of services provided, encountered during PHC visits. A model representing a benchmark configuration conforming to government-mandated operational guidelines, with demand estimated from disease burden data and service times closer to international estimates (higher than observed), was also developed. Simulation outcomes for the three observed configurations indicate negligible patient waiting times and low resource utilization values at observed patient demand estimates. However, simulation outcomes for the benchmark configuration indicated significantly higher resource utilization. Simulation experiments to evaluate the effect of potential changes in operational patterns on reducing the utilization of stressed resources for the benchmark case were performed. Our analysis also motivated the development of simple analytical approximations of the average utilization of a server in a queueing system with characteristics similar to the PHC doctor/patient system. Our study represents the first step in an ongoing effort to establish the computational infrastructure required to analyze public health operations in India and can provide researchers in other settings with hierarchical health systems, a template for the development of simulation models of their primary healthcare facilities.

Keywords
Discrete-event simulation, public healthcare delivery, primary health center operations, healthcare simulation

1. Introduction
Providing quality healthcare services in India is a challenge, given the rapidly increasing demand due to the aging population, growing health-seeking behavior among the population due to increased awareness, and spurt in the burden of noncommunicable diseases (NCDs). This is exacerbated by the inadequate size of the public health workforce. These challenges are more pronounced in rural regions because of socioeconomic factors, such as increased poverty, illiteracy, and high levels of social inequality. The situation is further exacerbated because nearly 70% of the population resides in rural areas, which faces an acute shortage of trained medical staff. According to Jaiswal and Us Saba, nearly 70% of doctors in India are based in cities, whereas 70% of the demand arises from the villages. Additionally, in rural India, as few as 37% people have access to inpatient facilities within a 5-km distance, and only 68% have access to an outpatient department (OPD). Finally, despite the economic burden of availing private healthcare, only 20% of the people seeking outpatient care and 45% seeking inpatient care utilize public healthcare services.

Outside large public hospitals in urban metropolitan areas that provide highly specialized tertiary care (called superspecialty hospitals), the public health system in India comprises three levels of formal medical care: the primary health center (PHC, which offers primary care), the community health centre (CHC, which offers primary and limited secondary care), and the district hospital (DH, which offers comprehensive secondary and limited tertiary care). Further, smaller facilities known as subcenters...
(SCs) focus on public health awareness and immunization program and are present primarily in rural areas. PHCs form the basic unit of public healthcare delivery in India and represent the first point of contact for the patient with a formally trained medical doctor. Hence, as part of efforts to address the issues described in the previous paragraph and increase the utilization of public health services, there is increasing interest in strengthening primary healthcare delivery through establishing new PHCs, upgrading existing primary healthcare infrastructure and increasing medical personnel numbers. Specifically, the government has recently announced plans to create 150,000 health and wellness centers (HWCs) by financial year 2022. Under this scheme, all SCs and PHCs will be upgraded to HWCs to deliver universal and free comprehensive primary healthcare to the public. Although there has been a considerable increase in the number of PHCs across the country, that is, from 9115 during 1981–1985 to 25,650 in 2017, their operational effectiveness and influence on improving public health accessibility is not adequately quantified. In this backdrop, there is need for an assessment of the operational aspects of these facilities before more resources are invested in their upgradation and/or establishing new PHC infrastructure.

Further, an effort to comprehensively model public health operations in the Indian context would require developing simulation models of PHCs, given their foundational importance in the public health system (PHCs outnumber CHCs by a ratio of 5:1). Therefore, in this study, we focus on developing discrete-event simulation (DES) models of PHC operations as part of an ongoing effort to establish the computational infrastructure required to model and analyze public health operations in the Indian context. Our approach toward modeling and analyzing PHC operations can provide researchers and analysts in other countries with similar hierarchical public health systems with a template for developing models of similar primary/secondary healthcare facilities in their contexts. For example, the Ghanaian public healthcare system consists of five tiers (similar to the Indian system when SCs and superspeciality hospitals are also considered), with their “subdistrict” health centers being the equivalent of the Indian PHCs. Similarly, the public health system in Bangladesh is organized into four levels: community level healthcare (provided by the domiciliary health workers and community clinics), primary level healthcare (Union Health and Family Welfare Centers (UH&FWCs), and Upazila Health Complexes), secondary level healthcare (provided in district hospitals, general hospitals, etc.), and tertiary level healthcare (provided in postgraduate medical institutes and other large hospitals). UH&FWCs are the equivalent of Indian PHCs and house one staff member with formal medical training and support staff that focus on delivering limited curative outpatient care, maternal, and child healthcare.

In public health systems such as in India and the other countries described above, while there may be commonalities in operational patterns of these facilities because they are established according to operational guidelines specified by a central public health planning authority, there may also be significant differences in operational configurations between facilities. A generic modeling approach thus becomes an effective way to model such facilities, as the operational commonalities can be captured by a generic model developed by surveying multiple instances of these facilities. Subsequently, to capture the operational diversity in these facilities that is characteristic of such health systems, the surveyed facilities can be grouped into configuration classes, which can then be modeled by adapting/reusing the generic/archetypal simulation model. Thus, a key research contribution of our study is the demonstration of this approach for modeling PHCs, which can, as described above, prove useful for modeling hierarchical public health systems in other settings as well.

Our approach — the generic modeling approach — involved visiting multiple PHCs in a semiurban/rural district in North India and collecting data regarding their operational patterns. We then develop an archetypal or “generic” DES model of PHC operations based on the commonalities in PHC operations observed during our visits and subsequently adapt (reuse with modification) this generic model to represent the different operational configurations encountered in our visits. We then compare the performance of these existing PHC configurations with the performance of a benchmark configuration conforming to government-mandated operational guidelines with demand estimated from disease burden data and service times closer to international estimates, which are significantly higher than observed service times at the PHCs. Our literature search did not identify any studies that adopted, such an approach, driven by public health data and international healthcare delivery practice, toward operational benchmarking of such healthcare facilities. Thus, another research contribution of our study involves the demonstration of this approach.

The benchmarking exercise also motivated the conduct of simulation experiments to quantify how these PHC configurations respond to changes (increases) in demand and identify solutions to potentially improve operational efficiency under conditions of high demand. We anticipate that the model and such analyses can provide key stakeholders with a methodology to make informed decisions regarding changes in PHC/HWC operational guidelines or when upgrading or establishing existing/new PHCs/HWCs.

In the Indian context, to our knowledge, computational studies on the operational patterns and performance of PHCs have not been done before. Our research contribution in this context thus involves the estimation — via DESs — of operational outcomes, such as the average waiting
time of patients for various resources (e.g., doctors, pharmacy, and clinical laboratory), resource utilization levels across the PHC, and the proportions of childbirth patients who wait longer than a certain time threshold. Note that a DES is not strictly required to obtain rough estimates of average wait times. From the patient load and service time data, we collect for the PHC doctors, for example, one can anticipate negligible outpatient wait times. However, exact quantification of these wait times and resource utilization levels is not straightforward. For example, the outpatient care system consists of two queues in series—certain patients undergo an initial consultation with a nurse followed by consulting with the doctor, and the doctors themselves serve three types of patients with very different arrival rates. Further, the interaction between various queueing subsystems within the PHC—for example, the outpatient care, the pharmacy, and laboratory subsystems—yield somewhat counterintuitive results under certain conditions, as described in Section 4. Finally, developing PHC simulations represents the first step in establishing the computational infrastructure required to conduct other operational analyses of the public healthcare system (e.g., how would implementation of rigorously enforced referral mechanisms change operational outcomes across the public healthcare network in a district), with similar simulation models of CHCs and DHs to follow.

In the general healthcare delivery simulation context, although there are simulation studies that model patient flow in a single unit, such as the outpatient clinic, the emergency department (ED), or in multiple interdependent units (ED and inpatient department (IPD)) serving a single patient type, we found very limited work that utilizes a generic modeling approach for simulating primary healthcare delivery facilities that handle multiple patient types (with distinct clinical and operational flows through multiple facility units) and services (the PHC provides outpatient care, childbirth, antenatal services, limited inpatient care, pharmacy, and clinical laboratory services). Thus, another key research contribution of this study involves addressing the above research gap. Finally, we also develop two analytical approximations of the utilization of a server with characteristics similar to that of the PHC doctor (multiple job types, each with Markovian arrival rates and generally distributed service times) that resulted from the internal validation exercises that we conducted for the PHC simulations.

This article is organized as follows. In Section 2, we provide an overview of the relevant literature, and in Section 3, we elaborate on the generic modeling approach adopted in the study, PHC operational data collection, clinical and operational flow in PHCs, and input parameter estimation. In Section 4, we describe model validation efforts, key simulation outcomes, sensitivity and other operational analyses, and we conclude with a discussion of the study in Section 5.

2. Background and literature review

In this section, we provide a brief overview of PHCs and then describe the literature related to the application of DES in healthcare facility modeling. A brief overview of the public healthcare system in India is provided in Appendix A.

In India, PHCs are established to deliver integrated curative, promotive, and preventive healthcare services. They provide OPD services for 6 days a week and also operate 24-h emergency services. A PHC is intended to serve a population ranging from 30,000 persons in the plains and 20,000 persons in mountainous or heavily forested areas. Mainly outpatient services are rendered in a typical PHC; however, they house a delivery hut to assist in infant deliveries and have a small inpatient unit for patients requiring care and observation for brief periods. This could include, for instance, management of injuries and accidents, diarrhea, etc.

A typical PHC may house one or two doctors (decided based on the monthly childbirth load typical to the region), a pharmacist, one laboratory technician, three to four staff nurses working in shifts, and other nonmedical support staff. In addition to a delivery hut, a PHC must have four to six beds for catering to inpatients/emergency cases. Apart from these, PHCs are also responsible for community engagement, which is managed through SCs. Community engagement is driven by auxiliary nurse midwives (ANMs) or multipurpose health workers and involves creating awareness for hygiene and infectious diseases, maternal health, childcare, distribution of essential medicines/supplements, etc. PHCs can also refer patients who require more specialized or intensive care to the CHCs or the district hospital.

2.1. Related work

Simulation has been used in virtually all segments of the healthcare delivery analysis field. Simulation applications in healthcare include modeling for staffing decisions, facility design and location, patient flow, appointment scheduling, capacity allocation, and logistics. Comprehensive literature surveys on simulation applications in healthcare have been published. DES is the most widely used simulation methodology, and this is reflected in the publication of a number of survey articles regarding the use of DES in healthcare, which readers can refer to a comprehensive account of the relevant literature.

We begin by discussing a relevant review article by Günal and Pidd, who classified the relevant literature based on the healthcare unit modeled: accident and emergency (A&E) units (i.e., emergency/casualty/trauma units), inpatient facilities, outpatient clinics, other hospital units (intensive care units (ICUs), laboratories, etc.), and whole hospitals. Of particular relevance, the authors discussed
the study by Fetter and Thompson,\textsuperscript{29} who developed simulation models of hospital subsystems not specific to a facility and instead described them in general. The subsystems considered by them are: (a) maternity department, (b) OPD, and (c) surgical department. These subsystem simulation models were used for evaluating different operating policies and design changes.

There are numerous simulation articles that deal with modeling a specific unit of a healthcare facility, such as the OPD, IPD, ED, etc. More details regarding single unit simulations are available in the following articles on: (a) EDs,\textsuperscript{30–34} (b) inpatient facilities,\textsuperscript{35–37} and (c) outpatient clinics.\textsuperscript{38–40}

There has been a recent increase in the work on modeling: (a) multifacility units focusing on a single patient type, (b) whole facilities with the focus of analysis being a particular subsystem, and (c) facility subsystems serving multiple patient types.\textsuperscript{26} We discuss example studies of each type here. Of the first type, Revankar et al.\textsuperscript{41} developed a DES model for patients suffering from acute bacterial skin and skin structure infections. The model traced the treatment pathway of each patient through different departments – ED, IPD, and OPD. Hamid et al.\textsuperscript{42} focus on patients requiring elective open-heart surgery and develop a two-stage optimization and simulation approach to first mathematically determine optimal surgery schedules for the operating room, and then using DES determine the minimum number of beds in the downstream ICU to ensure an adequate patient service level. Of the second type, Lowery\textsuperscript{43} developed a simulation model of a tertiary care hospital with a focus on the surgical suite and critical care area. The objective of the work was to determine the optimum number of beds in the critical area of the community hospital. The simulation model was designed to represent the arrival of patients to, and their flows through, nine different units in the modeled hospital. Similarly, Grida and Zeid\textsuperscript{44} developed a systems dynamics simulation model of a medium-sized hospital with the focus of their analysis being identification of throughput improvement policies for the surgical department via a theory of constraints approach. Of the third type, Hasan et al.\textsuperscript{45} developed a DES of an ICU in a hospital catering to patients of multiple types from upstream hospital units, such as the ED, elective surgery, and emergency surgery. The objective of the study was to find suitable admissions and discharge policies to improve both patient and provider outcomes.

There is also a growing body of literature associated with the simulation of multidisciplinary clinics, which are healthcare units established to provide integrated care from multiple care disciplines to patients with a given condition.\textsuperscript{46–48} This is similar to the work by Revankar et al.,\textsuperscript{41} but is not limited to units within a larger facility (i.e., they can be standalone facilities as well). Examples of such studies include a simulation model of an “integrated practice unit” for treating patients with lower extremity pain,\textsuperscript{46} and a modeling study of a multidisciplinary clinic for treating basal cell carcinoma.\textsuperscript{47}

With respect to the above studies, there appears to be limited literature regarding whole facility simulation models that cater to multiple patient types with distinct clinical and operational flows through the facility (similar to PHCs). This is likely because most healthcare DES studies are undertaken to help analyze and/or solve specific problems associated with a facility, whereas our study aims to contribute toward establishing the computational infrastructure required to analyze the public health system in a region. Hence, a key research contribution of our work involves developing a more broad-based simulation of the entire set of medical care components within the facility, which incorporates all major patient types and their operational patterns within the simulation.

The widespread application of DES in healthcare implies substantial scope for its use in modeling and improving primary healthcare systems as well. Example studies include the use of DES for design of appointment scheduling systems for outpatient clinics, which see multiple types of outpatients,\textsuperscript{49} and the investigation of interactions between appointment scheduling policies and capacity allocation policies in an outpatient clinic with two patient types.\textsuperscript{50} However, as mentioned above, studies concerned with modeling and simulation of single primary care facilities handling multiple types of patients – in particular, a mix of inpatients and outpatients – appear to be scarce. We encountered only one article that reported the use of DES to assess the impact of upgrading primary healthcare centers into bigger family health units (FHUs).\textsuperscript{51} The authors modeled four types of consultations, viz. (a) medical, (b) emergency or acute, (c) nursing type 1, which mainly included diabetes and child or maternal care, and (d) nursing type 2 consultations dealing with vaccination and other types of nursing treatments. It is unclear as to whether the study considered inpatient care.

From the standpoint of the scope of services included in primary care facility simulations, our research contribution here involves the inclusion of limited inpatient care and childbirth care in our PHC models in addition to modeling general OPD consultations and emergency cases, as in the study by Fialho et al.\textsuperscript{51} Note that as discussed in Section 1, limited inpatient care and childbirth care services are likely to be offered in such primary care facilities in developing nations, given that access to more comprehensive and specialized care is likely to be limited in semiurban and rural regions.\textsuperscript{52}

Given our use of the generic modeling approach to develop the PHC simulation models, we also briefly discuss the related literature here. Many articles describe the development of generic/reconfigurable simulations in a general context\textsuperscript{53–58} and/or in healthcare settings.\textsuperscript{27,57,59,60} The above articles discuss the development of generic/
reconfigurable DES models for physician clinics,\textsuperscript{59,60} generic hospital simulation models,\textsuperscript{27} and that of their subunits.\textsuperscript{58,61} However, our search of the literature did not yield a study that demonstrated a generic modeling and model reuse approach for primary care centers that served multiple types of outpatients and inpatients. Moreover, we did not identify a study that categorized the surveyed facilities into different operational configurations and demonstrated, after the generic model is developed, the adaptation/reuse of the generic model to generate simulation models of these configurations.

A key research contribution of this paper thus involves addressing the above gap in the literature by providing a detailed demonstration of the implementation of the generic modeling approach to develop the PHC simulation models. In addition, we also demonstrate the adaptation of the archetypal PHC model to reflect the government mandate for PHC operations and idealized patient demand and outpatient consultation durations and compare the performance of the PHC configurations in actual operation to the performance of this benchmark configuration.

\subsection*{2.2. Indian context}

There is very limited literature available regarding modeling the delivery of public healthcare in India. Most existing articles report on infrastructure, cost of delivering healthcare services, shortages of medical personnel in primary and secondary care hospitals, customer satisfaction, and out of pocket expenditures. A review article by Pandve and Pandve,\textsuperscript{1} on primary healthcare services, describes the evolution of primary healthcare in India since independence.

Prinja et al.\textsuperscript{62} reported the total annual cost of delivering health services at the PHC and CHC level. Their research determined the per capita per year cost of the complete package of healthcare services delivered at a PHC and estimated it to be INR 170.8. The availability of infrastructure and personnel in the PHCs was studied in the work of Sriram\textsuperscript{8} for a district in the state of Andhra Pradesh. The author randomly selected 15 PHCs and compared the data with the standards mentioned in the Indian Public Health Standards (IPHS) guidelines.\textsuperscript{10} The work revealed that PHCs are deficient in both the human resources and the infrastructure required for day-to-day operations.

Mital\textsuperscript{63} conducted a queueing study for resource planning associated with medical staff and inpatient beds in a medium-sized hospital. The author used multichannel queueing models parameterized by patient arrival and service time data to compute average utilization estimates for inpatient beds and average lengths of stay were for male, female, and maternity wards.

In the Indian context, our literature search did not yield any study that computationally examined: (a) PHC operations, and (b) how their operational performance would respond to changes in demand and/or capacity. Moreover, there appears to be very limited healthcare facility simulations in general in the Indian context. Our study aims to address these gaps.

\section*{3. Model development}

In this section, we describe the development of DES models of PHC operations via the generic modeling approach. The DES models simulate provision of care to the following patient types: (a) outpatients, (b) inpatients and/or emergency cases, (c) childbirth patients, and (d) antenatal care (ANC) patients.

The resources in each PHC consist of doctors, nurses, the pharmacist, the laboratory with the laboratory technician, and inpatient and childbirth beds. Each resource is accessed by one or more of the above patient types. The number of doctors varies between one and two depending upon PHC configuration, as some PHCs have two doctors while others operate with a single doctor. Staff nurses are also categorized as resources. Moreover, the staff nurses are divided into two categories: (a) NCD trained staff nurse, who is present only during the OPD hours for conducting point-of-care tests and counseling related to NCDs (especially lifestyle diseases such as type 2 diabetes, hypertension, etc.) for patients above the age of 30; and (b) the staff nurse, who attends to inpatients or emergency cases and assists childbirth cases. Additionally, the in-house medical laboratory and pharmacy, with associated personnel, also remain available only during the OPD hours. We now describe the generic modeling process for the development of the PHC simulation models, including the operational data collected from PHCs.

\subsection*{3.1. Generic modeling approach and PHC operational data collection}

The generic modeling approach is a natural choice for developing simulation models of the PHCs. This is because the diverse health landscape of India implies that developing a broadly representative model of PHC operations would require surveying multiple instances of the facility of interest, identifying operational commonalities (and differences), and then conceptualizing and developing this archetypal model based on the information synthesized from the survey – essentially the generic modeling approach. We provide a brief overview of the generic modeling approach and the concept of model reuse below and place our PHC modeling effort within this context.

In their paper regarding generic modeling in the healthcare facility simulation context, Fletcher and Worthington\textsuperscript{57} propose a classification scheme for a simulation model based on the extent to which it effectively represents multiple facilities — that is, for determining the extent to which a simulation model is generic (referred to
in the paper as a model’s “genericity”). The authors suggest that the evaluation of a simulation model in terms of "genericity" must be done in terms of two key attributes: model abstraction and transportability, and model reuse. A simulation model may possess one of four levels of "genericity" in terms of model abstraction and transportability. These are, in descending order of genericity: level 1 — generic principle models not specific to an industry or a particular setting, such as general queueing models; level 2 — generic modeling frameworks or toolkits with models of units common to a specific industry (e.g., inpatient wards at hospitals, operating theatres), which can be leveraged to generate models of facilities of multiple types; level 3 — a generic model of a specific facility or process type (such as a generic model of A&E departments in the UK public health system, or outpatient clinics); and level 4 — models of a specific facility or process in a specific setting. In our case, the PHC models we develop clearly are of level 3, which also is the most commonly seen type in the literature — for example, the generic A&E model developed by Fletcher et al.\textsuperscript{64}

The notion of simulation model reuse was explored — albeit very briefly — in the context of generic modeling by Fletcher and Worthington\textsuperscript{57} and in detail by Robinson et al.\textsuperscript{54} Robinson et al.\textsuperscript{54} postulate a spectrum of model reuse, with the following key types: code segment reuse, function reuse, model component reuse, and full model reuse. They also note that reuse of a model may be done for similar purposes as the original instance (e.g., a generic PHC model developed for broad-based operational analysis may be adapted to model and analyze operations of a specific PHC encountered in a different location), or for a different purpose (e.g., to simulate implementation of patient referral or diversion mechanisms across a network of PHCs as in Fatma and Ramamohan\textsuperscript{65}). Note that model reuse — in particular, component and full model reuse — does not necessarily imply reuse completely devoid of modification. In fact, Robinson et al.\textsuperscript{54} suggest comparing the cost of adapting a model for reuse against that of de novo model development prior to opting for reuse.

In this context, we have developed a level 3 generic model of PHC operations, intending reuse in the same setting and in different settings, as well as reuse for both similar and different purposes. This also ties in with Fletcher and Worthington’s\textsuperscript{57} division of level 3 generic models into levels 3A and 3B, depending on the purpose and desired level of use. Level 3A models are meant to provide overarching insights regarding the facility’s operations and are intended for use by central planning stakeholders, whereas level 3B models are developed with multiple uses in mind (e.g., they can be adapted to model local instances of the facility) and hence may possess a higher degree of transportability. Overlap between these two types is possible, perhaps even desired, and the generic model we have developed achieves this overlap. We demonstrate this in the following sections where we describe experiments using the generic model to identify operational improvements in high-demand conditions that can be implemented on an overarching basis to existing and new PHCs regardless of configuration, and at the same time also modify the generic model to represent the PHCs with different operational configurations that we encountered in our data collection process. In Section 5, we also briefly discuss another case of reuse in the same setting, but for a different purpose — a use case relevant to the COVID-19 pandemic. In addition, even though the genericity of the PHC model that we develop extends only to public primary health facilities in the Indian context, reuse in different settings is also possible. As described in Section 1, because of similarities in hierarchical public health systems in the developing world, we anticipate that the generic PHC model can be considered for adaptation and reuse to model equivalent facilities in these settings as well.

Developing a generic model of a public health facility typically involves the following steps: (a) surveying a set of instances of the facility under consideration, involving operational data collection (patient flows, number of resources of each type, interarrival and services times for resources, etc.); (b) identifying operational commonalities across the facilities surveyed and conceptualizing the operational structure of the generic model based on these commonalities; and (c) parameterizing, programming, and validating the generic model. In the following paragraphs, we describe the implementation of each step in developing the PHC models and begin with describing our data collection visits.

We visited nine PHCs (out of 10 total) in a north Indian district with a mix of urban, semiurban, and rural populations to collect data regarding PHC operations. Permission to visit these PHCs and collect operational data was obtained from the district civil surgeon. Data collected included operational patterns (e.g., patient flow), staffing and resource levels (number of doctors, nurses, inpatient beds, etc.), patient arrival rates, and service time rates for different resources and patient types (doctors, outpatients, inpatients, clinical laboratories, staff nurses, etc.). This information is presented in Tables 1 and 2. Table 1 provides staffing information, the number of SCs associated with each PHC, and information regarding the services rendered at these facilities. Table 2 summarizes the data collected regarding service times per patient for different resources (e.g., doctor and laboratory). Here, we present this information as we were unable to identify literature that provided this (operational) data in the Indian context, and hence we anticipate that this information will benefit other researchers working on PHC and/or public healthcare operational policy.

Despite possessing institutional endorsement for the operational data collection, and also obtaining permission to collect PHC operational data from the district civil
suffered, we faced certain challenges regarding data collection during our visits. In most PHCs, staff were not fully cooperative and did not allow access to the PHC premises to the extent required to collect comprehensive datasets for patient loads, service times, etc. This discomfort was likely due to their unfamiliarity with research personnel seeking to observe precisely their service patterns and was alleviated only to a small degree by assurances that the data is anonymized. Moreover, because the precise entry and exit times of patients arriving to these PHCs and their subunits (e.g., time spent in the childbirth bed) were not maintained by the PHC administration, we recorded service times for multiple resources with a stopwatch in PHCs where we were provided the requisite access. Data collection in this manner was not possible for inpatient and childbirth care, and hence these service times were estimated based on discussions with doctors and nurses. However, even for outpatient services, we were not allowed to record associated service times in some PHCs (PHCs 7, 8, and 9). Furthermore, even in PHCs 1–6, we were not able to record more than 10–15 observations at each resource before the staff requested us to stop. We faced similar restrictions in collecting data regarding outpatient interarrival times as well. Therefore, for patient load data, we were either provided brief snapshots of handwritten records regarding daily outpatient loads at a few PHCs, or at PHCs where such access was not provided, the patient load data were determined based on discussions with the medical staff (doctors, nurses, and pharmacists). For example, at one of the PHCs, we were provided access to daily outpatient loads recorded for 5–6 days, and at another PHC, we were only told that the outpatient load varied between 120 and 150 patients/day. Due to this, we were unable to observe — and hence could not incorporate in our models — any seasonal variation in patient load, or thinning effects (decrease in patient load as operating hours near closing time) that might be present in the PHCs. However, given that we capture the basic operational flow in the PHCs and the overarching patient loads and service rates are captured in the input parameters, further refinements regarding seasonal or weekly variations in patient load, thinning effects, etc. can easily be incorporated.

We note that in certain PHCs, key operational and/or medical staff were not available. For example, four PHCs did not have a pharmacist, and five functioned without laboratory technicians. The four PHCs, which did not have a pharmacist as shown in Table 1, operated the pharmacy with the help of the staff nurse or the ANM associated with one of the SCs associated with the PHC.

In Table 2, the consultation time for doctors — the time the doctor spends with outpatients — was recorded for most PHCs using a stopwatch. Overall, 60 observations made during the OPD hours were used for determining the distribution of the doctor’s service time. Similarly, observations for the time spent by the patients at the clinical laboratory for point-of-care tests and at the pharmacy were also recorded. More details regarding the parameterization of the simulation using this data are provided in Section 3.4.

We now describe the conceptualization of the generic model and other configurations based on the data collected above.

3.2. PHC model configurations and parameter estimation

It is evident from Table 1 that a variety of PHC configurations are currently in operation, and hence a single simulation model would not be able to capture this operational diversity. However, it was also evident that while PHCs differ in terms of staffing levels (e.g., number of doctors), services offered (e.g., presence/absence of childbirth services), and patient load (e.g., outpatient and inpatient demand), approximately the same operational pattern is followed for a given patient type and service. Therefore, we developed a model of patient care operations in an archetypal or generic PHC and modified the archetypal

| Table 1. Data summary of staffing level, patient load, and other facilities at PHCs. |
|-----------------------------------------------|---------------|-----------------|------------------|-----------------|-----------------|-----------------|
| PHC visited | No. of doctors | No. of nurses | Patients/day | Monthly childbirth load | 24 × 7 facility | No. of associated SCs | Laboratory technician | Pharmacy manager |
| PHC-1 | 2 | 4 | 80–100 | 20–40 | Yes | 7 | 1 | 1 |
| PHC-2 | 1 | 4 | 50–70 | N/A | No | 5 | 0 | 0 |
| PHC-3 | 2 | 4 | 60–80 | N/A | Yes | 6 | 1 | 1 |
| PHC-4 | 1 | 4 | 35–60 | 5–20 | Yes | 8 | 0 | 0 |
| PHC-5 | 2 | 6 | 120–140 | 15–25 | Yes | 7 | 1 | 0 |
| PHC-6 | 2 | 4 | 30–50 | 10–12 | Yes | 6 | 0 | 1 |
| PHC-7 | 2 | 4 | 50–80 | N/A | No | 3 | 0 | 0 |
| PHC-8 | 1 | 3 | 60–80 | 15–20 | Yes | 7 | 0 | 1 |
| PHC-9 | 2 | 3 | 120–150 | 30–50 | Yes | 5 | 1 | 1 |

PHC does not handle childbirth patients. N/A: not applicable; No.: number; PHC: primary health center; SC: subcenter.
model to generate simulation models of other PHC configurations encountered in our visits. The archetypal model was created based on our observations of a set of PHCs that most closely resembled the guidelines for PHC operations prescribed by the Indian government. Overall, we created three PHC configurations to broadly capture essential characteristics of the types of PHCs we encountered in our visits: one archetypal configuration, and two other configurations created by modifying the archetypal model. These configurations were developed based on key characteristics that affect operational outcomes: the number of doctors in the PHC, and whether they offer childbirth and ANC. In addition, we have also created a configuration corresponding more closely to government-mandated PHC operational guidelines. This is done to present a comparison of the operational performance of the PHC configurations encountered during our visits and a configuration conforming more closely to government-mandated guidelines (which the archetypal/generic model also does), but with demand more closely following publicly available disease burden data, and doctor consultation times for outpatients closer to those observed internationally and in private facilities. We henceforth refer to this configuration as the “benchmark” configuration. Note that this benchmark configuration differs from the archetypal configuration only in the outpatient load and the doctor’s consultation time for outpatients. However, we still consider it to represent a separate configuration because the process of estimating the patient load for this configuration was significantly different and more involved than for the other configurations. Further, because we consider this configuration to represent an idealized benchmark case, we also assume higher consultation times for outpatients with the doctors — as will be discussed in Section 5, larger service times have been found to correlate with perceptions of higher quality by patients. More details regarding the patient demand estimation process are provided in Section 3.2.1. The essential facts regarding these configurations are presented in Table 3.

Configuration 1 represents the archetypal PHC operational pattern, as it is closest to the government mandate, with two doctors, daily observed outpatient load similar to demand estimated based on national disease incidence data (for more details, see Section 3.2.1), and provision of childbirth and ANC facilities. Furthermore, it represents the superset of services and resource levels associated with other PHC configurations, and hence we decided to designate this configuration as the generic/archetypal model. PHCs 1, 5, and 9 from Table 1 can be considered as being represented by this configuration. PHC 6 may also be represented by this configuration if resource levels alone are considered; however, the patient load at this PHC is unusually low. Configuration 2 is developed to represent the cases where only one doctor is operating with a relatively lower patient load. These facilities also provide care to childbirth and ANC patients. PHCs 4 and 8 can be considered as represented by this configuration. Configuration 3

| PHC visited | Doctor (seconds): mean (SD) | Laboratory (seconds): mean (SD) | Pharmacy (seconds): mean (SD) |
|------------|-----------------------------|-------------------------------|-----------------------------|
| PHC-1      | 60 (18.9)                   | 232.6 (62.8)                  | 127.1 (13.4)                |
| PHC-2      | 62.1 (25.5)                 | N/A                           | 142.8 (53.4)                |
| PHC-3      | 53.2 (11.5)                 | 187.9 (33.3)                  | 160.7 (56.2)                |
| PHC-4      | 47.5 (10.37)                | N/A                           | 128.3 (39.2)                |
| PHC-5      | 47.8 (13.6)                 | 200.5 (52.8)                  | 94.66 (33.3)                |
| PHC-6      | 50 (9.5)                    | N/A                           | 91.4 (23.2)                 |
| Overall    | 53.4 (12.2)                 | 207 (52.9)                    | 124.6 (51.8)                |

N/A: not applicable; PHC: primary health center; SD: standard deviation.

| Table 3. PHC configurations. |
|-----------------------------|
| Configuration | OPD/IPD/Childbirth/ANC interarrival time (min) | Number of doctors | Number of nurses |
|---------------|-----------------------------------------------|-------------------|------------------|
| Configuration-1 (generic)  | 4/2880/1440/1440 | 2 | 4 |
| Configuration-2       | 9/2880/2880/2880 | 1 | 4 |
| Configuration-3       | 9/2880/NA/NA | 1 | 4 |
| Configuration-4 (benchmark) | 3/2880/1440/1440 | 2 | 4 |

All configurations have six inpatient beds and one childbirth room (with a single bed).ANC: antenatal care; IPD: inpatient department; NA: not applicable; OPD: outpatient department; PHC: primary health center. The nurses work in shifts — that is, each nurse works alone in an 8-h shift.

190Simulation: Transactions of the Society for Modeling and Simulation International 98(3)
was developed to represent cases where childbirth and ANC care facilities are not present. Given the low patient load at these PHCs (PHCs 2, 3, and 7) and the fact that the PHC guidelines\textsuperscript{10} prescribe that only a single doctor is required if childbirth case load is less than 20 patients a month, we assumed that only a single doctor would operate in this configuration, similar to the case of PHC 2. We now describe the development of the benchmark PHC configuration.

### 3.2.1. Benchmark PHC configuration

A key difference between the configurations described in the previous sections and the benchmark configuration is the patient load. Given that the PHC was set up to handle primary care in India, and that only up to 30\% of current demand is addressed in public facilities, it is reasonable to assume that primary care demand at a PHC would be substantially larger than the average observed demand under conditions of greater trust in the public healthcare delivery system. Hence, we have modeled the benchmark configuration to be a type-B PHC, that is, with two doctors. Hence, for this configuration type, in addition to two doctors, we assume one NCD nurse, four staff nurses working individually in consecutive 8-h shifts, one laboratory technician, one pharmacist, and six inpatient beds and one labor room available 24 h a day. PHCs are expected to have a minimum attendance of 40 patients per day per doctor as per the PHC guidelines,\textsuperscript{10} but these guidelines do not provide any information regarding the actual demand placed on the PHCs.

Hence, we estimated the demand for primary care using morbidity data from the Brookings India report.\textsuperscript{66} We used the disease incidence data reported for a 10-month period in India from the Brookings report\textsuperscript{66} to estimate the number of people seeking medical care in the district where the PHCs we visited were located. Later, using the percentage contribution of each disease to the total morbidity and the diseases that can be addressed at PHCs (identified by consulting PHC doctors), we estimated the daily demand for primary care. However, given that patients can visit PHCs, CHCs, and DHs for receiving primary care, we then needed to estimate the fraction of the primary care demand that was addressed at PHCs. In the absence of data from the literature for estimating this, we assumed that the primary care demand is equally distributed among PHCs, CHCs, and the DHs. We made this assumption because even through CHCs and the DH provide secondary and tertiary care (respectively) in addition to primary care, they have greater capacity as well, in terms of both the number of medical personnel and physical infrastructure (e.g., beds and larger premises). The total demand for primary care for the entire district was estimated as 8560 patients per day, distributed uniformly across all the facilities. This yielded a patient load of roughly 570 per day seeking primary care at each PHC. However, considering only approximately 30\% of the population utilize public healthcare facilities,\textsuperscript{67} the final estimated patient load is approximately 170 patients per day.

We estimated the annual childbirth load a PHC may experience based on the birth rate for the district under consideration. Furthermore, we then used data (37.6\% births delivered in public hospitals) from the National Family Health Survey\textsuperscript{68} to estimate the number of deliveries in public hospitals. We then assumed that out of these public facilities, PHCs get only 20\% of the birth cases because: (a) PHCs are mostly located in the rural/remote areas with sparse population, and (b) CHCs and DHs are better equipped in terms of facilities and staff and are located in relatively more thickly populated areas. This assumption is in line with the observations made during our visits, wherein we witnessed relatively low childbirth load in the PHCs. The estimated childbirth load was approximately one childbirth case per day. Additionally, in the absence of information in the PHC guidelines regarding inpatient load, the inpatient interarrival time is taken to be one per 2 days because, in keeping with the modeling assumption of higher-than-observed demand for the benchmark configuration, we assumed it to be slightly greater than the observed load (8–12 per month).

With regard to the consultation time with PHC doctors in the benchmark configuration, there is substantial variation seen across the globe. Studies report that consultation time with primary care doctors varied from 43 s in Bangladesh to nearly 22 min in Sweden.\textsuperscript{69,70} Irving et al.\textsuperscript{69} claimed that in 18 countries, comprising half of the global population, mean consultation time with primary care physicians was less than 5 min per patient. Given that we develop this configuration to represent a benchmark in terms of quality of care as well, we set the consultation times with doctors to be higher than that actually observed because of correlations of outpatient consultation durations with patient perceptions of quality of care at PHCs (more details in Section 5). However, in India, because high consultation durations (e.g., exceeding 10 min) are likely to be difficult to implement due to the high demand, we have assumed the consultation time to be normally distributed with a mean of 5 min and standard deviation of 1 min with a lower bound fixed at 2 min. Finally, the duration of post-childbirth stay in hospital is adopted from the PHC guidelines\textsuperscript{10} in which a minimum stay of 48 h is required. However, during the discussion with the doctors and the nurses, we found that childbirth patients after the delivery rarely stay for more than 24 h in the hospital and in general their length of stay lasts between 4 and 24 h. Consequently, for our model, we have used a uniform distribution between 4 and 24 h of stay. The nurse, laboratory, and pharmacist service time distributions and the inpatient bed length of stay are assumed to be similar to...
that estimated from the data collected during our PHC visits.

3.3. Patient flow

We now describe the patient flow in the archetypal PHC (configuration 1). Figure 1 shows the patient flow for the archetypal PHC. All PHC resources — doctors, NCD nurses, staff nurses, pharmacy, and the laboratory — are shared by all patient types, where applicable.

3.3.1. Outpatient department. All the outpatients first go to the OPD room for a consultation and then are directed to the laboratory or to the pharmacy accordingly. In the OPD room, patients who are 30 years of age or above are directed for NCD-related checks with the NCD nurse before consulting the doctor. Patients of age less than 30 years consult with the doctor directly. NCD checks involve recording patient medical history — blood pressure, body temperature, and weight measurements — and on some occasions, providing diet counseling and other such instructions.

After consulting the doctor, patients either go to the laboratory for tests, or they exit the PHC through the pharmacy. At the laboratory, two kinds of tests are typically performed: tests for which reports are generated in approximately 5–10 min, and others for which more than a few hours are required to generate reports. These are collected at a later date, and the associated patients are treated as new patients when they visit again since they are required to follow the regular flow in the facility. Patients requiring tests of the former category immediately go back to the OPD and leave through the pharmacy after registration as depicted by the dotted line in the figure, and the latter group of patients return for consultation the next day. A point of note here is that those outpatients who require laboratory tests do not spend more than a few seconds when they first consult the doctor. This means that the doctor sends these patients immediately upon arrival to the laboratory for conduct of their tests, typically based on prior history with the patient. It is only when these patients collect their reports and return to the doctor (5–10 min after the test is conducted if it is a point-of-care test, or the next day if they undergo more complex tests) that the doctor conducts a full-fledged consultation. Therefore, even though patients consult the doctor twice during a single visit, the actual time spent with the doctor is effectively equal to that of a single visit.

Furthermore, all outpatients invariably visit the pharmacy for registration (and provision of drugs if required) from where they exit the precinct. In the registration process, patient details are recorded, and a nominal fee (INR 5/10) is charged in some PHCs.

3.3.2. Inpatient department. The PHC was established with the view to provide primary care and has no provisions for intensive inpatient care. Thus, the patients who are admitted on an inpatient basis comprise those with ailments that require care for less than 24 h and if necessary are then referred to the CHCs or the DH. The average number of inpatient admissions varies widely across PHCs and also depends on the season — for example, the number of patients suffering from dengue fever or malaria increase during the monsoon months. When an inpatient arrives, they first check whether the doctor is available. If the doctor is available, they are first attended to by the doctor and then by the staff nurse, and if not they are attended to by the staff nurse until the doctor becomes available. The length of stay for inpatients in PHCs is usually for a period of 4–6 h and rarely exceeds 8 h. The nurse in charge of the IPD monitors the patient at regular intervals, provides medication, and maintains relevant records for each patient.

We note here that the inpatients have nonpreemptive priority in comparison to outpatients with regard to consulting with the doctor — that is, if the doctor is busy with an outpatient when an inpatient arrives, the inpatient moves to the head of the outpatient queue. The doctor then attends to the inpatient once they are finished consulting with the outpatient.

3.3.3. Childbirth patients. According to the norms of the Ministry of Health and Family Welfare, if the number of deliveries exceeds 20 per month, the PHC has to be
ANC is provided to pregnant women before childbirth. According to the IPhS\textsuperscript{10} guidelines, pregnant women are advised to make four visits to the facility for routine examinations, medication, and counseling. The visit schedule is adopted from these guidelines wherein the first visit will be within 12 weeks of pregnancy, followed by the second visit between 14 and 26 weeks, third and fourth visits are scheduled between 28 and 34 weeks, and the fourth between 36 weeks and term. The staff nurse provides the ANC during these visits. In the simulation, the next visit of an ANC patient is scheduled upon their arrival in the PHC for their current visit, and the number of visits they make is tracked to ensure it does not exceed four.

Upon the first visit, the staff nurse will make a registration card for the ANC patient and perform the predefined set of examinations and counsels the patient. ANC visits happen only during the OPD hours. Once ANC patients complete the examination, they undergo routine laboratory tests which, in most cases, are conducted in the PHC laboratory. They then exit the system through the pharmacy after collecting any medications or supplements.

### 3.4. Estimation of simulation parameters

In Table 4, we present model input parameter estimates with their associated probability distribution. We used 60 observations each for the doctor, pharmacy, and lab service duration, recorded using a stopwatch during our PHC visits, for estimating the associated input parameters. As described in Section 3.2, because we were unable to collect more than 10–15 observations of service time for a given resource, we had to pool service time observations across PHCs to obtain a sample of reasonable size. Goodness-of-fit tests for various distributions for each resource service duration were conducted on the Minitab statistical analysis software, State College, PA, and the Anderson–Darling statistic was utilized to identify the best-fitting distribution. The normal distribution best fit the service duration data for all three parameters (with negative values truncated at the minimum observed service durations during our visits; more details are provided in Appendix B): doctor consultation time, pharmacy service time, and point-of-care tests at the laboratory. Note that the laboratory service time includes the time for interacting with the patient, collecting their sample, storing the sample, and recording patient and sample details. In other words, it represents the time between entry of the patient inside the laboratory and their exit. The laboratory reports for a given patient are generated approximately 5–10 min after sample collection; however, the time taken by the patient to pick up the report is negligible, and hence we do not include this within the laboratory service time. The service time distributions at the doctor, laboratory, and pharmacy are provided in Appendix B.

The number of patients of each type (outpatients, inpatients, etc.) arriving in different PHCs were estimated using the data maintained at the facilities and also based on discussions with doctors and other associated staff. Patient arrival (for all four patient types, and for each configuration) is modeled by using an exponential distribution for the interarrival time. The average interarrival times (and consequently the average number of patients) at each configuration were estimated in the following manner. The number of outpatients visiting configuration 1 PHCs (PHCs 1, 5, and 9) range from 80 to 150 patients per day. These include patients visiting for the first time for a given case of illness as well as patients visiting for follow-up consultations on a previous case. Thus, we assumed that approximately 125 patients visit a given day for these PHC configurations, which include 90 first-visit patients, 20% patients on their first follow-up, and 10% visiting for their second follow-up, yield approximately 126 patients.
Therefore, the interarrival time of 4 min at configuration 1 PHCs corresponds to first-time visits, with follow-up visits scheduled at the same time on any day between the next 3 and 8 days. With regard to the childbirth patient load at configuration 1, the number of cases range between 15 and 50 per month, and therefore we assumed the childbirth patient load to be 30 per month (close to the average of the range), corresponding to approximately one case per day. For estimating the inpatient load, we could access inpatient data load from only three PHCs, and in these, the average monthly patient load varied from 2 to 21 patients across an 8-month time horizon. Additionally, based on discussions with nurses and doctors across all PHCs, we determined that almost all PHCs experience low inpatient loads, ranging from 10 to 15 patients per month. Thus, we assumed that on average 15 patients will seek inpatient care at the PHC across all the configurations.

We modeled configurations 2 and 3 to have similar patient loads and resource levels (except for childbirth and ANC services) to illustrate the difference that offering childbirth and ANC services makes to operational outcomes. Hence, we discuss their parameterization together. With regard to outpatient load at configurations 2 and 3, we see that their daily outpatient loads vary between 35 and 80. The outpatient load was therefore estimated to approximately equal to the midpoint of this range (approximately 55 patients per day, including follow-up visits), and hence the interarrival rate was also estimated in a manner similar to that configuration 1. The childbirth load at PHCs 4 and 8 (configuration 2) ranged from 5 to 20, and hence the childbirth load for this configuration was estimated to be close to the mean on the higher side, to be one case every alternate day.

Later, for assigning ages to outpatients (to determine which patients are required to visit the NCD nurse), we utilized Census 2011 data to estimate the proportion of the population aged less than 30 years. Thus, those aged 30 years and above were directed to the NCD nurse before consulting the doctor. Furthermore, we assumed that an outpatient makes a maximum of two follow-up visits to the PHC after the first visit, considering the facility only provides primary care; in other words, a patient can make a maximum of three visits to a PHC. Additionally, in the absence of published information regarding the proportion of patients requiring follow-up visits, we assumed that 20% and 10% of the incoming outpatients would make two and three visits, respectively.

As for the inpatient, ANC, and childbirth cases, length of stay estimates was obtained from discussions with doctors, nurses, and also from relevant published data. The length of stay of inpatients is estimated based on discussions with the nurses and doctors because we could not access inpatient records for length of stay. For childbirth patients, considerable variation in the length of stay across facilities was reported by the nurses and the doctors. For these patients as well, because we could not access records for length of stay, we assumed a uniform distribution for the patient stay based on our interaction with the

| Parameter                              | Value (min) | Probability distribution | Method                                      |
|----------------------------------------|-------------|-------------------------|---------------------------------------------|
| Doctor (OPD) consultation time         | Mean = 0.87, SD = 0.21 | Normal                  | Data collection (stopwatch)                 |
| Pharmacy service time                  | Mean = 2.08, SD = 0.72 | Normal                  | Data collection (stopwatch)                 |
| Laboratory service time                | Mean = 3.45, SD = 0.82 | Normal                  | Data collection (stopwatch)                 |
| Nurse (NCD check) service duration     | Min = 2, max = 5      | Uniform                 | Data collection (nurse discussion) + limited observations collected |
| Doctor (inpatient) service time        | Min = 10, max = 30   | Uniform                 | Data collection (doctor discussion)          |
| Nurse (inpatient) service time         | Min = 30, max = 60   | Uniform                 | Data collection (nurse discussion)          |
| Nurse (childbirth) service duration    | Min = 120, max = 240 | Uniform                 | Data collection (nurse discussion)          |
| Inpatient bed length of stay           | Low = 60, high = 360, mode = 180 | Triangular | Data collection (doctor and nurse discussion) |
| Labor bed length of stay               | Min = 300, max = 600 | Uniform                 | Data collection (doctor and nurse discussion) |
| Doctor (childbirth) service time       | Min = 30, max = 60   | Uniform                 | Data collection (doctor and nurse discussion) |
| Childbirth patient bed length of stay  | Min = 240, max = 1440| Uniform                 | Doctor and nurse discussion, IPHS guidelines10 |
| ANC visits                             | Four visits         | Deterministic           | IPHS guidelines10                            |

ANC: antenatal care; NCD: noncommunicable disease; IPHS: Indian Public Health Standards; OPD: outpatient department.
concerned staff in the PHCs. In addition, the duration of labor for childbirth cases varies substantially from case to case.\textsuperscript{71} In the data collection exercise, the doctors and nurses reported that the duration of labor could vary between 6 and 10 h (assumed to follow a uniform distribution in the model), which we found to be consistent with the findings published in the literature.\textsuperscript{72,73}

We did not encounter any ANC case during our visits, and the time estimates informed by the staff nurses were inconsistent and varied considerably from PHC to PHC. Hence, we have used estimates of ANC durations from the work of Both et al.\textsuperscript{74} They measured the time taken per patient by the nurses for providing ANC services in their article. Similarly, for NCD checks, we were able to record a very small number of observations because of staff apprehension that doing so would disrupt provision of care, and hence, we held discussions with the nurses to estimate their service duration.

### 3.4.1. Model assumptions

Here, we list the assumptions made for the simulation model.

- The outpatient unit runs for 6 h/day, and all the outpatients who arrive from morning 8 am to 2 pm consult with the doctor.
- All the resources and staff remain fully available during operations.
- The performance of the staff, in terms of their service time parameters, does not change with time during shifts, and they are available throughout the shifts without breaks.
- There is one staff nurse per shift (8-h shift); thus in a day, three nurses work in tandem, whereas the fourth nurse has a night off.
- Each nurse does administrative work of approximately 1 h per shift.
- Pharmacy and laboratory are available continuously during the outpatient unit hours.
- Doctors do not attend to the patients (inpatient/childbirth cases) after outpatient unit hours.
- Doctors also perform administrative work – for example, paperwork associated with running the PHC. Based on discussions with the doctors, the administrative work is taken as normally distributed variable with a mean value of 100 min and a standard deviation of 20 min.
- All the outpatients go to the pharmacy after consulting the doctor.
- We only consider patient care provided on a direct basis in our models. For example, doctors are responsible for organizing various health camps and conduct field visits as part of public health outreach program, and because the nature of these program changes from period to period based on government policies, we do not include these in our studies.

### 4. Simulation experiments and results

The PHC simulation was programmed using the Python programming language on the Pycharm IntelliJ, JetBrains Distributions s.r.o., Praha 4, Czech Republic, integrated development environment. Python’s Salabim package (Ruud van der Haam, Turriers, Provence-Alpes-Côte d’Azur, France),\textsuperscript{75} which is a third-party package developed for DES, was used in programming the model. The simulation was run for 365 days, with a warm-up period of 180 days. The warm-up period, per usual simulation practice, was run with the same set of patient arrival and service rates as in the steady-state period (see Tables 3 and 4). The duration of the warm-up period was chosen to allow a sufficient amount of time for the simulation outcomes to achieve steady state. Results from 100 replication runs were collected for all computational experiments. All computational experiments were performed on a workstation with a quad-core Intel Xeon processor (Intel Corporation, Santa Clara, CA), base frequency of 3.7 GHz, and 16 gigabytes of RAM. Completing 100 replications required approximately 43 min and 45 s. The software for the generic PHC model (configuration 1) is available at this location: https://github.com/shoaibioe/PHC-/blob/main/PHC.py.

We begin by discussing our efforts to validate the results of our models and extract analytical insights related to queueing systems that form part of the PHC models.

#### 4.1. Model validation and queueing analysis

We were unable to perform external validation of the simulation model by comparing its outcomes to, for example, operational outcomes published in the literature, because we were unable to identify any previously published data in the Indian context regarding PHC operational outcomes, such as average outpatient waiting time, utilization of doctors, staff nurses, etc. However, the outcomes generated by the model for all configurations were in good agreement with those observed during our visits to the PHCs. For example, the waiting times observed for outpatients visiting configuration 1 PHCs were negligible, and the utilization of all resources as observed in terms was also well below 50%.

In addition, we were able to compare the estimates of time spent waiting in the outpatient queue and doctor’s utilization generated by our model to the corresponding estimate obtained from primary data collected from a visit to the primary care unit of a similar public health facility in another district. We measured the average time spent waiting in the outpatient queue before consulting the primary care doctor for 40 patients and compared it to the estimates generated by our simulation model for configuration 1, the PHC closest in operational patterns to the primary care unit facility. The observed waiting time was estimated to
be approximately 20.03 s with a standard deviation of nearly 20 s, caused by the presence of a large number of observed waiting times of 0 s (42.5% of outpatients observed during our visit had 0 s waiting times, and the maximum waiting time observed was 84 s). The simulated average waiting times generated for configuration 1 was negligible (< 5 s), thereby indicating that our simulations appear to capture PHC operational outcomes reasonably well. Furthermore, the doctor’s utilization was estimated to be approximately 20% during our visit, in comparison to the corresponding estimate of approximately 25% for configuration 1.

From the perspective of internal validation (i.e., ensuring the simulation was implemented correctly by comparing simulation outcomes to analytical estimates), we also compared the doctor’s average utilization estimates from the simulation models to the corresponding analytical estimates obtained using queueing theory concepts. In the subsequent analysis, we consider the utilization of the doctor to be a random variable, to reflect the fact that in steady-state operations of the PHC, the measurement of utilization over different time periods will yield slightly different estimates of the doctor’s utilization. In steady state, we can assume that these estimates are iid and have expected value $\bar{\rho}_d$ and standard deviation $\sigma_d$. Given this view of the doctor’s utilization, we assume that the best estimate of $\rho_d$ can be generated by an accurate simulation of PHC operations run for a sufficiently long duration.

We computed the average utilization of doctors, ignoring their administrative work, from the simulation models and compared the results with analytically computed average utilization estimates. The parameters of the analytical queueing system from which we estimate the server’s (the doctor’s) average utilization remain the same as that of the simulation model – that is, the doctor serves outpatients, inpatients, and childbirth cases, each with exponentially distributed interarrival times and corresponding general (nonexponential) service time distributions, as given in Table 4. The analytical estimate of the average utilization of a server in such a queueing system is computed by summing the average utilizations estimated assuming each patient type was the only patient type arriving in the system. This is given below:

$$\rho_a = \rho_o + \rho_i + \rho_c$$

Here, $\rho_o$ represents the analytical estimate of the average utilization of the doctor under demand from three types of patients, and $\rho_o$, $\rho_i$, and $\rho_c$ represent the average utilization values for the doctor assuming the doctor handles demand for care from only outpatients, inpatients, and childbirth cases, respectively. $\rho_o$, $\rho_i$, and $\rho_c$ are estimated in the usual manner; that is, as the ratios of the average service durations $\mu_o$, $\mu_i$, and $\mu_c$, respectively, and the corresponding average interarrival times $\lambda_o$, $\lambda_i$, and $\lambda_c$. The comparisons between the average utilization estimates for the doctors from each configuration (denoted by $\hat{\rho}_d$) with $\rho_d$ are summarized in Table 5. Note that $\rho_d$ was generated by assuming no outpatient revisits and administrative work to simplify the exercise. We conducted one sample $t$-test to check whether the analytical estimates of $\rho_d$ lay within the interval $(\bar{\rho}_d - k_o \hat{\sigma}_d, \bar{\rho}_d + k_o \hat{\sigma}_d)$, where $k_o$ is chosen to reflect the maximum allowable deviation from $\rho_d$. Thus, we do not check whether the analytical estimates lie within a confidence interval associated with the sampling distribution of $\rho_d$, and instead check whether it lies within an acceptable range around $\rho_d$ within the distribution of the utilization. We adopt this approach because in steady state, the value of $\hat{\sigma}_d$ is very small (as expected), and hence checking against the sampling distribution of $\rho_d$ would be unduly restrictive. The results of this exercise are summarized in Table 5.

We see from the results in Table 5, that the $\hat{\rho}_d$ and $\rho_d$ estimates are statistically similar for all configurations except for the benchmark case. Even in this case, the difference between the analytical and simulation estimates is $< 4.0\%$.

The above exercise for performing internal validation of our simulation outcomes also motivated us to develop two analytical approximations for the utilization of the server in the queueing system represented by the doctor providing service to outpatients, inpatients, and childbirth patients. The development, simulation-based validation, and avenues of use of these analytical approximations are described in detail in Appendix C.

While the analytical results in Appendix C are applicable to general multiclass queueing systems where there are significant disparities between the arrival and/or service rates of one job class relative to others, they were developed based on our observation of the simulation outcomes for the queueing system represented by the doctor’s service of outpatients, inpatients, and childbirth patients. Therefore, the numerical verification of these analytical results using our PHC simulation can also be considered to be another level of internal validation of our simulation models – that is, if the simulations lacked internal validity, the verification exercise would have yielded results contradictory to those in Theorems C.1 and C.2.
4.2. Simulation outcomes

The results from the simulation models of the as-is and benchmark configurations are presented in Table 6. It is evident that all as-is configurations are substantially underutilized when compared to the benchmark configuration. In the case of the benchmark configuration, the higher demand (nearly 30% higher than configuration 1, the as-is configuration with the highest demand) and the higher average doctor service time for outpatients (more than five times that in the as-is configurations) is the main cause for the increase in resource utilization. In the case of configurations 2 and 3, the increase in the doctor’s utilization despite the decrease in outpatient load is explained by the fact that only one doctor is present during the OPD hours. The operational implication of utilization estimates exceeding 1.0 is that the resource under consideration spends time over and above their designated work hours in completing care provision to patients who arrive during their work hours. For example, the utilization estimate of 1.142 for the doctor in the benchmark configuration implies that the doctor spends approximately 14% more time than their designated work hours in providing care to all patients who arrive during their work hours.

It is also clear from Table 6 that inpatient as well as labor bed utilization values are low in all cases. Despite the low values of the labor bed utilization, we see that a significant fraction of childbirth patients are referred elsewhere. This occurs because these patients happen to visit the facility while the labor bed is occupied by another childbirth patient and are referred elsewhere when their waiting time exceeds 2 h. This could thus indicate that at least one of the inpatient beds could be converted into a second labor bed. We explore this in simulation experiments in the following sections.

The higher values of resource utilizations for the benchmark configuration are a cause for concern, as the patient demand was estimated assuming that only 30% of the total patient load is addressed in public facilities. If the proportion of patients seeking care at public facilities increases (e.g., to 50%), then it is clear that the current capacity of the PHC (at an “ideal” mean service time of 5 min for the doctor) is not sufficient to effectively address the demand. This indicates a need for expanding either the capacity of the PHC in terms of adding sufficient medical personnel, exploring alternative operational patterns, or establishing new PHCs. We explore the first and second options in the following sections, as the third is outside the scope of the paper.

4.3. Sensitivity analysis and configuration optimization

In this section, we conduct sensitivity analyses for the generic PHC model — that is, the configuration 1 PHCs. The sensitivity analysis involves determining how PHC operational outcomes (e.g., average outpatient waiting time and resource utilization) respond to changes in demand, which are modeled by varying outpatient, childbirth, and inpatient case arrival rates. The doctor’s average service time for outpatients is varied from the default estimate of

| Simulation outcome | Configuration-1 (2/130/0.5/1/1/6/1)a | Configuration-2 (1/60/0.5/0.5/0.5/6/1)b | Configuration-3 (1/60/0.5/0/0/6/0)a | Benchmark case (2/170/0.5/1/1/6/1)a |
|--------------------|---------------------------------------|----------------------------------------|---------------------------------------|---------------------------------------|
| Mean (SD)          | Doctor utilization                    | 0.268 (0.003)                          | 0.372 (0.004)                         | 0.354 (0.002)                         | 1.142 (0.006)                         |
|                    | NCD nurse utilization                 | 0.865 (0.011)                          | 0.469 (0.005)                         | 0.468 (0.005)                         | 1.232 (0.019)                         |
|                    | Staff nurse utilization               | 0.323 (0.008)                          | 0.243 (0.006)                         | 0.16 (0.001)                          | 0.322 (0.008)                         |
|                    | Pharmacist utilization                | 0.643 (0.004)                          | 0.288 (0.003)                         | 0.289 (0.003)                         | 0.855 (0.005)                         |
|                    | Lab utilization                       | 0.559 (0.008)                          | 0.254 (0.004)                         | 0.239 (0.004)                         | 0.736 (0.011)                         |
|                    | Inpatient bed utilization             | 0.093 (0.004)                          | 0.055 (0.003)                         | 0.011 (0.001)                         | 0.093 (0.004)                         |
|                    | Labor bed utilization                 | 0.283 (0.01)                           | 0.153 (0.009)                         | Not applicable                        | 0.281 (0.012)                         |
|                    | Mean length of OPD queue              | 0 (0)                                  | 0.007 (0.001)                         | 0.001 (0)                             | 0.817 (0.027)                         |
|                    | (number of patients)                  |                                        |                                        |                                        |                                        |
|                    | OPD queue waiting time (min)          | 0.009 (0.004)                          | 0.171 (0.032)                         | 0.034 (0.001)                         | 6.789 (0.268)                         |
|                    | (number of patients)                  |                                        |                                        |                                        |                                        |
|                    | Mean length of pharmacy queue         | 0.09 (0.002)                           | 0.01 (0.001)                          | 0.009 (0)                            | 0.15 (0.002)                          |
|                    | (number of patients)                  |                                        |                                        |                                        |                                        |
|                    | Pharmacy queue waiting time (min)     | 1.025 (0.021)                          | 0.244 (0.008)                         | 0.232 (0.006)                         | 1.282 (0.018)                         |
|                    | (number of patients)                  |                                        |                                        |                                        |                                        |
|                    | Mean length of Lab queue              | 0.094 (0.003)                          | 0.012 (0.001)                         | 0.011 (0)                            | 0.188 (0.001)                         |
|                    | (number of patients)                  |                                        |                                        |                                        |                                        |
|                    | Lab queue waiting time (min)          | 2.084 (0.054)                          | 0.606 (0.023)                         | 0.571 (0.02)                         | 3.135 (0.005)                         |
|                    | Fraction of childbirth cases referred | 0.156 (0.019)                          | 0.088 (0.022)                         | Not applicable                        | 0.157 (0.18)                         |

ANC: antenatal care; IPD: inpatient department; NCD: noncommunicable disease; OPD: outpatient department; PHC: primary health center; aNumber of doctors/OPD cases/IPD cases/childbirth/ANC (patients)/inpatient beds/labor room.

Shoaib and Ramamohan 197
slightly less than 1–2.5 min and 5 min. We did not vary the outpatient service time beyond 5 min because as discussed earlier in Section 3.2.1 service times comparable to that seen in developed nations (10–20 min per consultation) is unlikely to be viable at current capacity levels in the Indian context due to the high patient demand. Hence, we increase the doctor’s average outpatient consultation time to a maximum equal to that assumed for the benchmark configuration (5 min). We also consider an intermediate average outpatient consultation time of 2.5 min.

Similarly, the outpatient arrival rate was varied to a maximum of 170 patients per day, equal to that in the benchmark configuration. The estimation of the outpatient arrival rate for this configuration is described in detail in Section 3.3.1. Similarly, for the second set of sensitivity analyses, the inpatient, childbirth, and ANC patient arrival rates were at maximum doubled given that a significant proportion (approximately 16%) of childbirth patients were being referred elsewhere even at the current childbirth patient arrival rates. The results of these experiments are presented in Figures 2 and 3. In these figures, we only present outcomes that change significantly when the parameters that are the subject of the sensitivity analysis are varied.

As expected, resource utilization increases with increases in outpatient load. However, we see that doctor and nurse utilizations (Figure 2(a) and (b)) exceed 100% only in one case — that is, when outpatient load is 170 patients per day and doctor service time is at its highest value (mean of 5 min per patient). This indicates that if maintaining a service time of 5 min is not feasible in the Indian context, increasing the average service time to at least 2.5 min from the current estimate (< 1 min/patient) is well within the current capacity limits. However, if it is imperative to maintain a 5-min mean service time per patient, then more resources must be added to reduce doctor and NCD nurse utilization. The NCD nurse utilization in particular is a cause for concern; however, a potential solution could involve having the staff nurse assist with NCD checks given their relatively lower utilization. We explore this in simulation experiments described in the subsequent paragraphs.

Interestingly, at each outpatient arrival rate, as the doctor consultation time decreases the waiting time before pharmacy increases as indicated in Figure 2(d). This occurs because at lower consultation times, more patients reach the pharmacy in a given time duration and thus results in slightly longer waiting times. However, since the number of patients remain the same, the pharmacist utilization does not change.

From the sensitivity analyses depicted in Figure 3(a) to (d), we see that increase in inpatient, childbirth and ANC case demand does not affect the doctor’s utilization significantly because the major portion of the doctor’s time is

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**Figure 2.** Sensitivity analyses for the configuration 1 PHC around average outpatient load at different doctor’s outpatient consultation time (min): (a) impact on doctor’s utilization, (b) impact on the NCD nurse’s utilization, (c) impact on the average waiting time (min) in the OPD, and (d) impact on the average waiting time (min) in the pharmacy.

Note: The doctor’s consultation time does not impact this outcome. SD represents standard deviation.
consumed by outpatient demand. However, staff nurse utilization, depicted in Figure 3(b), increases substantially as the staff nurse is primarily responsible for attending to childbirth and inpatient cases. We also note that waiting times for outpatient-related resources (laboratory, OPD consultation, etc. – not depicted in Figure 3(a) to (d)) increase marginally because the associated resources are also required by inpatient/childbirth/ANC cases, which increase in number in the above scenarios. In addition, as mentioned previously, the substantial proportion of childbirth cases that are referred elsewhere due to labor bed unavailability is cause for concern (27% when the average number of childbirth cases per day is increased to 2).

In the subsequent sections, we discuss some potential solutions through which operational outcomes for both medical personnel and patients can be improved.

4.3.1. Doctor’s utilization. The sensitivity analyses reveal that at an average outpatient load of 170 patients per day, the utilization of doctors increases substantially with increases in the mean service time and exceeds 100% at an average consultation time of 5 min per patient, implying that doctors may stay longer than the designated working hours to serve all patients arriving within the designated working hours. To address this, we experimented with letting the staff nurse (whose utilization is approximately 32%) take over the administrative work. This led to a 12% drop in the utilization level, which implied that the doctor’s utilization still exceeded 100%. Implementing this measure resulted in increasing the staff nurse utilization to nearly 40%. Therefore, we then considered a situation wherein the staff nurses require minimal intervention in childbirth cases. We assumed that in 50% of childbirth cases, staff nurses require no intervention by the doctor, require only one-third of the typical amount of intervention in 30% of cases, and require full intervention in the remaining 20% of cases. This led to a decrease of the doctor’s utilization to 101% (a further decrease of approximately 1%), and an increase in the nurse’s utilization to 40%. The nurse’s utilization does not change significantly because the nurse attends to the patient irrespective of the presence of the doctor. Thus, while this reduction in administrative and childbirth work improves the doctor’s utilization, it does not address the issue entirely, as the doctor’s utilization remains at 100% (in stochastic conditions, utilizations of less than 100% are recommended).

Finally, we also investigated the effect of stationing an additional doctor in the PHC. This yielded an average utilization of well below 100% for each doctor. This indicates that additional doctors can be rotated in from less busy PHCs (perhaps from configuration 2 PHCs) to a busier PHC when required.
Furthermore, in addition to the administrative work, when average utilization of the NCD nurse decreases to 100% administrative work alone is assigned to the staff nurse, the nurse assisting with NCD checks for outpatients. When the work performed by the NCD nurse and/or (b) the staff nurse assists with the administrative (iat = 9 min). The NCD nurse utilization can be addressed loads, utilization remains at 61% (iat = 6 min) and 47%
interarrival time (iat) is 3 min, and at lower outpatient nurse utilization exceeds 100% (123%) when outpatient cause for concern. We see from Figure 2(b) that NCD utilization, the NCD nurse utilization presented the most case load increases, more labor beds will be required.

4.3.2. Labor and inpatient bed utilization. In the simulation model, beds are divided into two categories: labor and inpatient beds. For inpatient ward beds, the utilization is 7%–10%. These are utilized by inpatients and the childbirth patients after the labor period is completed. However, as seen from sensitivity outcomes, changing inpatient and childbirth case arrival rates do not significantly increase their utilization levels, with a maximum utilization of 20%. We also observe that if the number of beds is reduced to four from six, the utilization level is observed to be approximately 33% even under higher demand conditions (two inpatient and childbirth cases per day).

Labor bed utilization is nearly 28% for configuration 1 PHCs. However, because there is only a single labor bed and labor bed utilization times are relatively high, a significant fraction of patients are referred elsewhere. For minimizing the number of childbirth cases referred elsewhere due to the occupied delivery bed, one of the inpatient beds was converted into an additional labor bed. The results of this investigation are depicted in Figure 4, which show the change in the fraction of cases referred elsewhere and labor bed utilization by adding one extra labor bed at different childbirth patient loads. The results show a significant drop in the fraction of cases referred elsewhere; however, as expected, it is evident that as the childbirth case load increases, more labor beds will be required.

4.3.3. NCD nurse utilization. From the standpoint of nurse utilization, the NCD nurse utilization presented the most cause for concern. We see from Figure 2(b) that NCD nurse utilization exceeds 100% (123%) when outpatient interarrival time (iat) is 3 min, and at lower outpatient loads, utilization remains at 61% (iat = 6 min) and 47% (iat = 9 min). The NCD nurse utilization can be addressed by (a) having the staff nurse assist with the administrative work performed by the NCD nurse and/or (b) the staff nurse assisting with NCD checks for outpatients. When the administrative work alone is assigned to the staff nurse, the average utilization of the NCD nurse decreases to 100%. Furthermore, in addition to the administrative work, when the staff nurse assisted for NCD checks (for 10% cases), the utilization of NCD nurse dropped to 71%. Thus, it could be a viable solution to assign administrative work to the staff nurses and also take their assistance for NCD checks, wherever possible, in the case of high-demand PHC configurations.

5. Discussion and conclusions

In this work, we study the operations of PHCs via the method of DES. We develop the PHC DESs by visiting nine PHCs in a north Indian district and collecting operational data from each PHC. Our key findings from the PHC visits include the following: (a) while operational patterns around provision of patient care are similar across PHCs (enabling the development of a generic PHC model), a variety of operational configurations in terms of services offered and medical staffing levels, beyond the two configurations mandated by the Indian government, appear to operate; (b) not all PHCs follow the minimum staffing requirements mandated by the government; and (c) the inpatient, outpatient, and childbirth case load at PHCs appear on average to be lesser than demand estimated from the disease burden data; however, significant variation in demand is also observed between PHCs. We also note that our visits were limited only to a single district. Although we conducted limited additional visits to primary healthcare facilities in other districts for collection of data to validate the model and observed similar patterns, generalization of our observations to PHCs across the diverse and vast health landscape of India must be made with appropriate caution. The generic modeling approach that we have adopted can provide some relief here—given the diversity in the operational configurations of PHCs that we encountered in this district (e.g., compare PHCs 4–6 in Table 1), and the fact that the government guidelines for PHC configurations are applicable on a national level, it is likely that one of the configuration models that we have developed will be similar to PHC configurations encountered in other districts across the country.

Our simulation outcomes indicate that the medical personnel, with the exception of the NCD nurse, are underutilized in the PHC. This is likely due to both low demand conditions, and the high service rate of the medical personnel—in particular that of the doctors (average service times < 1 min for outpatients). The low service times we have observed in our PHC visits is consistent with service times that have been observed across India. Thus, if only medical care and administrative duties are considered, low utilization conditions are likely to be encountered in other Indian PHCs as well.

A few studies have been published that investigate factors that affect patient perceptions of quality of care at public and private hospitals, and in the relatively recent past,
factors that drive why patients bypass PHCs.\textsuperscript{78,79} Narang\textsuperscript{77} studied the impact of a variety of factors affecting patients’ perceptions of quality of health services in both public and private hospitals in a large Indian city. Prominent among the factors that patients perceived as important was the time spent by doctors at these facilities during consultations. The most influential factors, however, were adequate clinical examination and the compassion and respect shown by care providers to patients, with adequate clinical examination potentially correlated with sufficient time provided to patients. On all these factors, private hospitals performed better than public hospitals, with public hospitals performing better only on accessibility. Similarly, in a qualitative study by Ramani et al.\textsuperscript{79} where the authors interviewed both care providers (doctors) and patients who accessed PHCs, patients expressed that insufficient attention was a key factor in their bypassing PHCs. Rao and Sheffel\textsuperscript{78} investigated the impact of clinician competence and structural quality of PHCs (availability of drugs, physician absenteeism, etc.) on patients bypassing PHCs and determined that increasing provider competence (measured by accuracy of diagnosis) and structural quality reduced bypassing only up to a certain extent. This was despite the fact that patient costs were half of that in private facilities. This suggests that in addition to accuracy of diagnosis, as determined by Narang\textsuperscript{77} and Ramani et al.,\textsuperscript{79} sufficient attention and the manner of providing care may improve patient perceptions of quality of care at PHCs. Prior research has also established that increased perceptions of quality of care lead to increased demand, as demonstrated in both India\textsuperscript{78} and in other developing countries.\textsuperscript{79–82}

In this context, our PHC simulation models can prove useful, as demonstrated by the sensitivity analyses and configuration optimization experiments in Section 4.3. For example, as the sensitivity analyses with consultation times for doctors closer to international levels showed PHC resources become stressed even when only 30% of current healthcare demand is addressed at a PHC. Furthermore, we also find that a significant proportion of childbirth patients (approximately 16%–28% when the number of childbirth cases per day varies from 1 to 2) wait longer than 2 h before receiving admission into the childbirth facility (bed) at a PHC. In response to these operational issues at higher demand levels, we have also demonstrated how the PHC models can be used to evaluate strategies for reconfiguring PHC resources to address the demand effectively prior to actually implementing them as shown in Sections 4.3.1–4.3.3. This ties into the Indian government’s program of upgrading PHCs into HWCs and establishing an additional 150,000 HWCs. The findings from this study may be useful in specifying medical personnel numbers or childbirth room capacities (e.g., convert a few inpatient beds to childbirth beds) at these new/upgraded facilities. For example, if quality of care is to be increased in the upgraded PHCs or new HWCs by establishing guidelines regarding consultation durations, then the capacity of these individual facilities may also need to be expanded to accommodate both existing levels of demand and the increased levels of demand that may be experienced if quality of care increases.

From a more general methodological standpoint, the key research contribution of this study involves providing a proof of concept for modeling primary healthcare delivery units that are part of large hierarchical public health systems operating in underserved settings. In particular, our approach toward capturing the operational diversity of PHCs by applying a generic modeling and reconfigurable simulation approach to capture key operational characteristics could provide researchers studying other hierarchical health systems with a template toward modeling primary healthcare delivery. This could also assist in developing simulations of the network of PHCs in a given region. Simulations of the network of PHCs in a region can be used for many types of operational analyses associated with policy changes in healthcare administration in the region. For example, Fatma and Ramamohan\textsuperscript{65} utilize the PHC models presented in this paper to develop a simulation of the network of PHCs in the district under consideration. Afterward, they demonstrated how the issue of increased wait times before admission to the childbirth facility in a PHC could be alleviated by diverting patients based on real-time predictions of their wait times generated at the time childbirth patients arrive at the PHC seeking admission. Similarly, in another working paper, we develop a simulation of the network of PHCs, CHCs, a DH, and a makeshift COVID-19 care center to determine how the public health system responds to COVID-19 case-loads under a specific pandemic response strategy. In the pandemic response strategy that we simulate, developed in collaboration with a clinical expert, the PHCs serve as testing and triaging centers for symptomatic patients with suspected COVID-19, wherein they are advised home isolation or hospitalization depending upon the severity of their illness after diagnosis and triage. We adapt the PHC models that we present here to include testing and triaging pathways for suspected COVID-19 patients. Note that this operationalization of PHCs as COVID-19 testing and triage centers is consistent with our recent visits to primary urban health centers (the equivalent of PHCs in urban metropolitan areas), and with the experiences of clinicians with expertise in COVID-19 management regarding the role PHCs are playing in the pandemic response strategy of the public health system.

The above studies illustrate the reusable nature of the generic PHC model that we have developed – specifically, they represent full model adaptation and reuse in the same setting, but for a different purpose. In contrast, the creation of simulation models of configurations 2 and 3 represent full model reuse in the same setting and for the same purpose (analysis of PHC operations). For example, in Fatma
and Ramamohan, a real-time delay prediction and diversification module was added to the PHC models that we present here, and in the latter study described above, COVID-19 testing and triaging pathways were added. These modified individual PHC models were then integrated into the network of public health facilities within the district.

Our simulation models also contribute to the whole healthcare facility simulation literature, with our search of the literature not yielding any other study that considered a primary care facility that serves outpatients, inpatients, childbirth cases, and ANC patients. Finally, as described in Section 4.1 and Appendix C, we introduce simple approximations for the estimation of the utilization of a server (the PHC doctor in our model) with multiple job classes with significantly different exponential interarrival times and/or general service times and also derive straightforward conditions under which the approximation is likely to hold. In particular, our proposed approach toward the conversion of the queueing system represented by the PHC doctor to an M/G/1 system makes its analysis significantly more tractable, in terms of analytical estimation of average time spent in the system, waiting time, and average number of patients in the queue.

A challenge in developing such simulation models in the Indian context is obtaining adequate access to the facilities under consideration for a sufficiently long period of time to collect data required to fit distributions for every input parameter of the simulation. For instance, given the limited data maintained for inpatient length of stays, we were unable to observe inpatient admissions long enough to collect sufficient data to find the best-fitting distribution for inpatient length of stay. In such cases, we estimated these parameters based on our discussions with key medical personnel. We anticipate that the model will have to be updated when data for these parameters become available. Moreover, we note that we have only included resources and operations associated with provision of medical care and hence have not included maintenance/cleaning personnel, etc.

Overall, our work establishes the computational infrastructure required to analyze the operational capacity and performance of PHCs, and we anticipate that other researchers, policymakers, and other stakeholders in health capacity planning will be able to utilize and/or adapt our simulation models to analyze PHC operations in their contexts.

Appendices
Appendix A

Overview of public health system in India. Public healthcare delivery in India is provided at four levels in the district (in increasing order of extent of services provided): (a) the subcenter (SC), (b) the primary health center (PHC), (c) the community health center (CHC), and (d) the district hospital (DH). The primary healthcare infrastructure in India is designed as a three-tier system. Three tiers are SC at the base, PHC in the middle, and CHC at the top. The SC is the first contact point between the primary care system and community; it covers a population of 5000 persons and is limited to a coverage of 3000 persons in hilly or tribal areas. An SC is manned by at least one auxiliary nurse midwife (ANM) and provides maternal and child care services, nutritional care, and immunization among other services intended to improve population health. PHCs are small hospitals with one or two medical doctors who serve as the first point of contact between society and healthcare provided by formally trained doctors. CHCs were established to provide both primary and secondary care to the community. It was envisaged that people who require specialized care could access a CHC directly or if required, by referral from a PHC. A CHC is mandated to be a thirty-bedded hospital with four specialized doctors—in surgery, medicine, gynecology, and pediatrics—and supported by 21 paramedical and other staff. It acts as a referral unit for four or more PHCs.

DHs are bigger hospitals in comparison to PHCs and CHCs, and were established to provide comprehensive secondary care and limited tertiary care. Per operational guidelines for DHs, each district is mandated to have a DH with the number of beds in the hospital ranging from 75 to 500, based on the population size and the geography of the district. Services provided at the DH are categorized as essential (general medicine, general surgery, ophthalmology, intensive care units, and radiology), desirable (dermatology, radiotherapy, dialysis service, etc.), and superspecialties (such as neurosurgery).

Appendix B

Estimation of service time parameters. For determining the distribution of the doctor’s consultation time with outpatients, 60 observations were recorded across six PHCs as per Table 2, and two outlier service time values were identified and removed from this dataset. Figure B1(a) depicts the histogram for the data. We conducted the Anderson–Darling (AD) normality test using the Minitab software, State College, PA, and observed a p-value of 0.466 and an AD statistic of 0.348. Histogram plots are shown in Figure B1(b) and (c), respectively, for similar data collected for the laboratory and the pharmacy service times. With regard to the normality test for the laboratory service time, a p-value of 0.265 and an AD statistic of 0.465 was reported. From the 60 observations for the pharmacy service time recorded in the PHCs we visited, three outlier values were removed, and then the AD normality test was conducted which yielded a p-value of 0.327 and an AD statistic of 0.413.

With regard to negative values from the estimated normal distribution for the doctor’s consultation time for outpatients, we truncate normal distribution at 30 s, the lowest consultation time observed during our data collection.
process. Similarly, the distributions of the pharmacy and laboratory service times are truncated at 40 s and 120 s, respectively, both of which are approximately equal to the lowest service times observed during the data collection exercise.

Appendix C

Analytical approximations for the doctor’s utilization. In this section, we utilize the notation defined in Section 4.1. First, we investigate the extent to which \( \rho_o \) approximates \( \rho_d \), given that outpatient arrival rates are nearly three orders of magnitude larger than inpatient and childbirth patient arrival rates. We derived the result below using the notion of the “domination factor,” the extent to which one job type dominates the other job types in terms of average arrival rates, service rates, or utilization in general. For example, the domination factor for outpatients in our queueing system can be expressed as follows: 

\[
d_o = \frac{\rho_o}{\rho_o + \rho_i + \rho_c}.
\]

The domination factor may also represent a belief regarding the extent to which one job type dominates other job types, where data for precisely estimating each term in the above equation may not be available.

**Theorem C.1.** Consider a queueing system with a single server and \( n \) types of jobs, with Poisson arrivals (with average arrival rates \( \lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_n \)) and general service times for each job type (with corresponding average service rates \( \mu_1, \mu_2, \mu_3, \ldots, \mu_n \)). Let the utilization of the server be a random variable with a symmetric and unimodal distribution \( f_d \) with expected value \( \rho_d \) and standard deviation \( \sigma_d \), which may be estimated by a simulation in steady state that yields a single estimate of utilization in each replication. Let the estimated (from the simulation) values of \( \rho_d \) and \( \sigma_d \) be \( \hat{\rho}_d \) and standard deviation \( \hat{\sigma}_d \).
Further, let $\rho_1, \rho_2, \rho_3, \ldots, \rho_n$ represent the average utilizations of the server, with $\rho_i = \frac{k_i}{\mu_i}$ ($i = 1-n$), if only a single type of job was considered for the system. Without loss of generality, let the first job ($i = 1$) be the dominant job type. Then $\rho_d$ can be approximated by $\rho_1$ at an $\alpha$ level of significance if $d_1 = \sum_{i=1}^{n} \frac{\rho_i}{\rho_1} > \frac{\rho_1 - k_a^2 \delta_d}{\rho_d}$. 

Proof. Let the average utilization estimated from the simulation be $\hat{\rho}_d$ (we assume one replication of the simulation yields a single steady-state estimate of utilization). Let the standard deviation of the utilization be denoted as $\hat{\delta}_d$. Then if $f_d$ represents the distribution of the doctor’s utilization, we say that $\rho_1$ approximates $\rho_d$ with an $\alpha$ level of significance if $\rho_1 \in I$, where $I = (f_d^{-1}\left(\frac{\alpha}{2}\right), f_d^{-1}(1 - \frac{\alpha}{2}))$.

We now derive the conditions under which $\rho_1 \in I$. 

Let $f_d^{-1}\left(\frac{\alpha}{2}\right) = \hat{\rho}_d - k_2 \hat{\delta}_d$ and $f_d^{-1}(1 - \frac{\alpha}{2}) = \hat{\rho}_d + k_2 \hat{\delta}_d$. If $f_d$ is symmetric and unimodal, then $k_2 = k(1 - \frac{\alpha}{2}) = k_\alpha$. We make the simplifying assumption that $f_d$ is symmetric and unimodal for the remainder of our analysis. Thus, the problem reduces to deriving the condition under which $\rho_1 \in I$, where $I = (\hat{\rho}_d - k_\alpha \hat{\delta}_d, \hat{\rho}_d + k_\alpha \hat{\delta}_d)$.

This is possible only if $|\hat{\rho}_d - \rho_1| < k_\alpha \hat{\delta}_d$.

Now, $\rho_d > \rho_1$, and therefore it is reasonable to assume that in steady state $\hat{\rho}_d > \rho_1$ (more details in subsequent section). Therefore, we write $|\hat{\rho}_d - \rho_1| = \hat{\rho}_d - \rho_1$.

Therefore, $\rho_1 \in I$ if $\hat{\rho}_d - \rho_1 < k_\alpha \hat{\delta}_d$, that is, if $\rho_1 > \hat{\rho}_d - k_\alpha \hat{\delta}_d$.

Now $\rho_1 = d_1 \sum\limits_{i=1}^{n} \rho_i = d_1 \rho_\alpha$, and therefore $\hat{\rho}_d - d_1 \rho_\alpha < k_\alpha \hat{\delta}_d$.

This implies that $\rho_1 \in I$ if $d_1 > \frac{\hat{\rho}_d - k_\alpha \hat{\delta}_d}{\rho_\alpha}$. Now, we can assume that $|\hat{\rho}_d - \rho_\alpha| = 0$ (this is seen in Table C1 below and is also based on the analytical properties of the queueing system under consideration that $\rho_\alpha$ is the best analytical estimator of $\rho_d$, whereas $\hat{\rho}_d$ can be considered to be the best empirical estimator of $\rho_d$), and hence the above result can be written as $\rho_1 \in I$ if $d_1 > \frac{\hat{\rho}_d - k_\alpha \hat{\delta}_d}{\rho_\alpha}$.

The above approximation may be useful in situations where reasonably accurate arrival and service data is available for the dominant job type, but similar data is not available for the less frequent job types. This is applicable to the service system corresponding to the doctor in the PHC, where primary data is available for the doctor’s consultation time for outpatients, whereas only point estimates (without uncertainty information) based on discussions with the medical staff are available for the arrival and service rates associated with inpatients and childbirth patients. In such a situation, our approximations can be used in the following manner: if there is reason to believe that one job type dominates other job types by a certain extent – for instance, its arrival rate is such that between 85% and 90% of jobs are contributed by this job type, and service rates for all jobs are approximately the same, then the utilization of this job type lies within $k_\alpha \sigma_d$ of $\rho_d$ with probability $1 - \alpha$ if the condition in the above theorem is satisfied. Here, $\alpha$ can be chosen such that $k_\alpha \sigma_d$ represents the desired maximum allowable deviation (e.g., 5%) from $\rho_d$. Satisfying the condition described by Theorem C.1 can just involve checking whether $d_1 > 1 - \frac{\hat{\rho}_d}{\rho_\alpha}$. Thus, for the above example, if the domination factor $d_1$ is believed (or estimated) to be between 85% and 90%, and the server’s utilization is required to be approximated with a maximum of 5% error, then $k_\alpha \sigma_d = 0.05$, and thus in this case, the approximation cannot be used for any value of $d_1$ in the above range ($d_1 = 85 - 90\%$). The results in Table C1 reflect this. For three configurations (1, 2, and the benchmark case) because the inpatient and childbirth service times are significantly higher (one and two orders of magnitude higher than outpatient service times), $d_\sigma < 0.95$ for these three configurations, and hence by Theorem C.1, $\rho_\alpha$ cannot be used to approximate $\rho_d$ with probability $1 - \alpha$, and the results in Table C1 verify this. However, we note that even in these cases, the difference between $\rho_\alpha$ and $\rho_d$ is at maximum approximately 13%. For configuration 3, because childbirth services are not offered, $d_\sigma > 0.95$, and hence, by Theorem C.1 (supported by the numerical evidence), it approximates $\rho_d$ with probability $1 - \alpha$.

We also explored the conversion of this system to an M/G/1 system by treating the less frequently arriving patient types as nonpreemptive “setup” jobs, following the approach indicated in Hopp and Spearman. This approach not only yields another approximation of $\rho_d$ (denoted by $\rho_{\text{opp}}$) via the conversion of this system to an M/G/1 queueing system but also yields estimates for average outpatient waiting time, time spent in the system, etc. We now describe in detail how this conversion is achieved.

We describe the analysis of the server and the dominant job type in this queueing system by converting it to an M/G/1 system, which is a significantly simpler system to analyze than the queueing system with multiple types of jobs with nonpreemptive priority. This approach may be useful when the server and one particular job type (ideally the dominant job type) is the focus of the analysis, because the simplification of this system comes at the cost of information regarding waiting times and time spent in the system for the other job types.

We first consider the case when only one other patient type other than outpatients are served by the doctor. We achieve the conversion to an M/G/1 system by applying the approach provided in Hopp and Spearman for calculation of effective process time of a machine when setups need to be performed between jobs. In our system, the “jobs” represent the dominant job type, and the “setups” represent all other job types. Let $\lambda_1$ denote the average arrival rate of the dominant job type and $\mu_1$ represent its service rate. Therefore, we define average utilization as $\rho_1 = \frac{\lambda_1}{\mu_1}$. Arrival of other job types can be thought of as
the arrival of setups that can be attended to immediately after the current job (e.g., the dominant job type) is processed. If the rate of arrival of other job types (setups) is denoted by \( \lambda_i (i = 2 - n) \), we can calculate the average number of dominant jobs after which a setup arrives. We denote this by \( N_i \). Then, following the analysis presented in Hopp and Spearman,\(^83\) the effective average process time of the doctor for outpatients, including inpatients (setups), becomes:

\[
\frac{1}{\mu_1} = \frac{1}{\mu_1} + \frac{1}{\mu_N}, \text{ where } \frac{1}{\mu_N} \text{ is the mean service time for setup } i.
\]

Therefore, it is clear that \( \mu_1 < \mu_1 \), and hence \( \rho_1 > \rho_1 \). It is then reasonable to assume that if a large number of replicates observations of the doctor’s utilization are obtained under steady-state simulation conditions, \( \hat{\rho}_d \) will also be greater than \( \rho_1 \).

Note that \( \rho_1 \) can be further modified by considering the arrival of next job type as another type of setup, and thus the impact of all other nondominant job types can be incorporated into the values of \( \mu_1 \) and \( \rho_1 \). Let the average utilization of the server of such an M/G/1 system be denoted by \( \rho_{ap} \). Note that \( \rho_{ap} \) takes the other patient types into account and hence is likely to be a better approximation of \( \rho_d \) than \( \rho_1 \). We derive the following condition that \( \rho_{ap} \) must satisfy to be a valid approximation of \( \rho_d \).

**Theorem C.2.** Let \( \rho_{ap} \) be an approximation of \( \rho_d \) in the queueing system as described in Theorem C.1, and define

\[
r = \frac{k_{o,d}}{\rho_d}.
\]

Then \( \rho_{ap} \) approximates \( \rho_d \) at an \( \alpha \) level of significance if

\[
d_1 \in \left( \frac{(1-r)\rho_1}{\rho_{ap}}, \frac{(1-r)\rho_1}{\rho_{ap}}, 1 \right),
\]

where

\[
d_1 = \sum_{i=1}^{p_i} \rho_i.
\]

**Proof.** Let \( \rho_{ap} \) be any approximation of \( \rho_d \) that takes into account the impact of nondominant job types. \( \rho_{ap} \) approximates \( \rho_d \) at an \( \alpha \) level of significance if

\[
|\hat{\rho}_d - \rho_{ap}| < k_{o,d}\delta.
\]

We have

\[
r = \frac{k_{o,d}}{\rho_d},
\]

therefore \( \rho_{ap} \) approximates \( \rho_d \) at an \( \alpha \) level of significance if

\[
\rho_{ap} \in (\hat{\rho}_d - \rho_{ap}, \hat{\rho}_d + \rho_{ap}n).
\]

Now, given that

\[
\sum_{i=1}^{p_i} \rho_i
\]

can replace \( \rho_{ap} \) with \( \rho_1/d_1 \) above. Rearranging terms completes the proof.

We suggest that the above approximation can also be used when the focus of interest is the server’s utilization and outcomes related to the dominant job type (e.g., average dominant job type waiting time and time spent in the system). This may be useful in situations where a focus may have limited access to literature regarding queueing systems with jobs of different priorities, and in this case, the more common Kingman approximations\(^84\) for the average wait time, length of stay, and number of entities in an M/G/1 queueing system may be used. The above representation of the system can be used in situations where in a manner similar to the case when \( \rho_1 \) approximates \( \rho_d \), \( d_1 \) and \( p_i \) are known with a high degree of accuracy, and \( \lambda_i \) and \( \mu_i \) for the remaining jobs are known with lower accuracy. For example, the M/G/1 approximation may be applied in a situation with \( n \) job types, if it is known that:

1. (a) nondominant job types arrive on average after \( k \) dominant jobs are processed and (b) detailed information (e.g., primary or secondary data) regarding service times for these job types is not available, and it is only known that on average they require a certain fraction of the service time of the dominant job type.

The numerical results in Table C1 suggest that, as expected, \( \rho_{ap} \) is a significantly better approximator of \( \rho_d \) than \( \rho_1 \). Even for condition 2, wherein the condition in Theorem C.2 is not satisfied by \( d_1 \), we see that the difference between \( \rho_{ap} \) and \( \hat{\rho}_d \) is approximately 9.4%, lower than the corresponding Table C1 maximum difference of approximately 13% for \( \rho_1 \).

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**References**

1. Pandve H and Pandve T. Primary healthcare system in India: evolution and challenges. *Int J Heal Syst Disaster Manag* 2014; 1: 125–128.
2. The World Bank. India’s poverty profile, www.worldbank.org/en/news/infographic/2016/05/27/india-s-poverty-profile (2016, accessed 10 August 2019).
3. Aubron C, Lehoux H and Lucas C. Poverty and inequality in rural India: reflections based on two agrarian system analyses in the state of Gujarat. *EchoGéo* 2015; 32: 1–21.
4. PTI. Literacy rate at 71% in rural India, 86% in urban: Survey. *The Economic Times*, 30 June 2015, https://economictimes.indiatimes.com/news/economy/indicators/literacy-rate-at-71-in-rural-india-86-in-urban-survey/articleshow/47886609.cms (2015, accessed 10 August 2019).
5. Government of India M of HA. Census of India, http://www.censusindia.gov.in/2011census/population_enumeration.html (2011, accessed 8 August 2019).
6. Jaiswal B and Us Saba N. Indian healthcare system: issues and challenges. *Int J Res Appl Sci Eng Technol* 2014; 2: 195–201.
7. KPMG-OPPI. *Report on healthcare access initiatives*. Report, India, August 2016, https://www.indiopi.org/委/wp-content/uploads/2019/12/Report-on-healthcare-access-initiatives-For-web.pdf (2016, accessed 10 August 2019).
8. Sriram S. Availability of infrastructure and manpower for primary care centers in a district in Andhra Pradesh, India. *J Fam Med Prim Care* 2018; 7: 1256–1262.
9. Government of India M of H and FW. Indian Public Health Standards (IPHS) guidelines for district hospitals (101 to 500
Bedded) revised 2012, http://nhm.gov.in/images/pdf/guidelines/iph traveller-guidelines-2012/district-hospital.pdf (2012, accessed 1 August 2019).

10. Government of India M of H and FW. Indian Public Health Standards (IPHS) guidelines for primary health centres revised 2012, http://nhm.gov.in/images/pdf/guidelines/iph/ iph-revised-guidelines-2012/primary-health-centres.pdf (2012, accessed 1 August 2019).

11. Government of India M of H and FW. Indian Public Health Standards (IPHS) guidelines for community health centres revised 2012, http://nhm.gov.in/images/pdf/guidelines/iph/ iph-revised-guidelines-2012/community-health-centres.pdf (2012, accessed 1 August 2019).

12. Ved RR, Gupta G and Singh S. India’s health and wellness centres: realizing universal health coverage through comprehensive primary health care. WHO South-East Asia J Public Heal 2019; 8: 18–20.

13. Government of India M of H and FW. National Health Profile 2018, http://www.cbhidghs.nic.in/WriteReadData/ 1892s/BeforeChapter1.pdf (2018, accessed 5 August 2019).

14. Government of India M of H and FW. National Health Profile 2019, http://www.cbhidghs.nic.in/WriteReadData/ 1892s/8603321691572511495.pdf (2019, accessed 5 January 2020).

15. Fatma N, Shoaib M, Mustafee N, et al. Primary healthcare delivery network simulation using stochastic metamodels. In: Bae K, Feng B, Lazarova-Molnar S, et al. (eds) Proceedings of the 2020 winter simulation conference, Orlando, FL, USA, 14-18 December 2020, paper no. 20607060, pp.818–829. Piscataway, NJ: IEEE.

16. Awoonor-Williams JK, Tindana P, Dalinjong PA, et al. Does the operations of the National Health Insurance Scheme (NHIS) in Ghana align with the goals of primary health care? Perspectives of key stakeholders in northern Ghana. BMC Int Health Hum Rights 2016; 16: 1–11.

17. Alvarado MM, Cotten TG, Ntiamo L, et al. Modeling and simulation of oncology clinic operations in discrete event system specification. Simulation 2018; 94: 105–121.

18. Lee S, Min D, Ryu JH, et al. A simulation study of appointment scheduling in outpatient clinics: open access and overbooking. Simulation 2013; 89: 1459–1473.

19. Bedoya-Valencia L and Kirac E. Evaluating alternative resource allocation in an emergency department using discrete event simulation. Simulation 2016; 92: 1041–1051.

20. Ashby M, Ferrin D, Miller M, et al. Discrete event simulation: optimizing patient flow and redesign in a replacement facility. In: Mason S, Hill R, Monch L, et al. (eds) Proceedings of the 2008 winter simulation conference, Miami, FL, USA, 7–10 December 2008, paper no. 10441856, pp.1632–1636. Piscataway, NJ: IEEE.

21. England W and Roberts SD. Applications of computer simulation to health care. In: Proceedings of the 10th conference on winter simulation, Miami Beach, FL, USA, December 1978, pp.665–667. Piscataway, NJ: IEEE.

22. Jun AJB, Jacobson SH and Swisher JR. Application of discrete-event simulation in health care clinics: a survey. J Oper Res Soc 1999; 50: 109–123.

23. Fone D, Hollinghurst S, Temple M, et al. Systematic review of the use and value of computer simulation modelling in population health and health care delivery. J Public Health Med 2003; 25: 325–335.

24. Brailsford SC, Harper PR and Pitt M. An analysis of the academic literature on simulation and modelling in health care. J Simul 2009; 3: 130–140.

25. Mieleczarek B and Uzialko-Mydlikowska J. Application of computer simulation modeling in the health care sector: a survey. Simulation 2012; 88: 197–216.

26. Zhang X. Application of discrete event simulation in health care: a systematic review. BMC Health Serv Res 2018; 18: 1–11.

27. Günal MM and Pidd M. Discrete event simulation for performance modelling in health care: a review of the literature. J Simul 2010; 4: 42–51.

28. Thorwarth M and Arisha A. Application of discrete-event simulation in health care: a review. Report, Technological University Dublin, 2009, https://arrow.dit.ie/buschinreps/3.

29. Fetter RB and Thompson JD. The simulation of hospital systems. Oper Res 1965; 13: 689–711.

30. Ferrin DM, Miller MJ and McBroom DL. Maximizing hospital financial impact and emergency department throughput with simulation. In: Henderson S, Biller B, Hsieh M, et al. (eds) Proceedings of the 2007 winter simulation conference, Washington, DC, USA. Paper no. 9847901, pp.1566–1573. Piscataway, NJ: IEEE.

31. Ruohonen T, Neittaanmäki P and Teittinen J. Simulation model for improving the operation of the emergency department of special health care. In: Perrone L, Wieland F, Liu J, et al. (eds) Proceedings of the 2006 winter simulation conference, Monterey, CA, USA, 3–6 December 2006, paper no. 9463213, pp.453–458. Piscataway, NJ: IEEE.

32. Sinreich D and Marmor YN. A simple and intuitive simulation tool for analyzing the performance of emergency departments. In: Ingalls R, Rossetti M, Smith J, et al. (eds) Proceedings of the 2004 winter simulation conference, Washington, DC, USA, 5–8 December 2004, paper no. 8401360, pp.1994–2002. Piscataway, NJ: IEEE.

33. Yousefi M, Yousefi M and Fogliatto FS. Simulation-based optimization methods applied in hospital emergency departments: a systematic review. Simulation 2020; 96: 791–806.

34. Srinivas S, Nazareth RP and Shoiratullah M. Modeling and analysis of business process reengineering strategies for improving emergency department efficiency. Simulation 2021; 97: 3–18.

35. McLean S and Millard P. Modelling in-patient bed usage behaviour in a department of geriatric medicine. Methods Inf Med 1993; 32: 79–81.

36. Marshall A, Vasilakis C and El-Darzi E. Length of stay-resource allocation in an emergency department using discrete-event simulation: optimizing patient flow and redesign in a replacement facility. In: Mason S, Hill R, Monch L, et al. (eds) Proceedings of the 2008 winter simulation conference, Miami, FL, USA, 7–10 December 2008, paper no. 10441856, pp.1632–1636. Piscataway, NJ: IEEE.

37. Harrison GW, Shafer A and Macky M. Modelling variability in hospital bed occupancy. Health Care Manag Sci 2005; 8: 213–220.

38. Yousefi M, Yousefi M and Fogliatto FS. Simulation-based optimization methods applied in hospital emergency departments: a systematic review. Simulation 2020; 96: 791–806.

39. Guo M, Wagner M and West C. Outpatient clinic scheduling – a simulation approach. In: Ingalls R, Rossetti M, Smith J, et al. (eds) Proceedings of the 2004 winter simulation conference, El Dorado, CA, USA, 4–7 December 2004, paper no. 8401360, pp.1994–2002. Piscataway, NJ: IEEE.

40. Ruohonen T, Neittaanmäki P and Teittinen J. Simulation model for improving the operation of the emergency department of special health care. In: Perrone L, Wieland F, Liu J, et al. (eds) Proceedings of the 2006 winter simulation conference, Monterey, CA, USA, 3–6 December 2006, paper no. 9463213, pp.453–458. Piscataway, NJ: IEEE.

41. Sinreich D and Marmor YN. A simple and intuitive simulation tool for analyzing the performance of emergency departments. In: Ingalls R, Rossetti M, Smith J, et al. (eds) Proceedings of the 2004 winter simulation conference, Washington, DC, USA, 5–8 December 2004, paper no. 8401360, pp.1994–2002. Piscataway, NJ: IEEE.

42. Yousefi M, Yousefi M and Fogliatto FS. Simulation-based optimization methods applied in hospital emergency departments: a systematic review. Simulation 2020; 96: 791–806.

43. Srinivas S, Nazareth RP and Shoiratullah M. Modeling and analysis of business process reengineering strategies for improving emergency department efficiency. Simulation 2021; 97: 3–18.

44. McLean S and Millard P. Modelling in-patient bed usage behaviour in a department of geriatric medicine. Methods Inf Med 1993; 32: 79–81.

45. Marshall A, Vasilakis C and El-Darzi E. Length of stay-resource allocation in an emergency department using discrete-event simulation: optimizing patient flow and redesign in a replacement facility. In: Mason S, Hill R, Monch L, et al. (eds) Proceedings of the 2008 winter simulation conference, Miami, FL, USA, 7–10 December 2008, paper no. 10441856, pp.1632–1636. Piscataway, NJ: IEEE.

46. Harrison GW, Shafer A and Macky M. Modelling variability in hospital bed occupancy. Health Care Manag Sci 2005; 8: 213–220.

47. Yousefi M, Yousefi M and Fogliatto FS. Simulation-based optimization methods applied in hospital emergency departments: a systematic review. Simulation 2020; 96: 791–806.

48. Guo M, Wagner M and West C. Outpatient clinic scheduling – a simulation approach. In: Ingalls R, Rossetti M, Smith J, et al. (eds) Proceedings of the 2004 winter simulation conference, El Dorado, CA, USA, 4–7 December 2004, paper no. 8401360, pp.1994–2002. Piscataway, NJ: IEEE.
55. Pidd M and Carvalho A. Simulation software: not the same yesterday, today or forever. J Simul 2006; 1: 7–20.

56. Kaylani A, Mollaghasemi M, Cope D, et al. A generic environment for modelling future launch operations – GEM- FLO: A success story in generic modelling. J Oper Res Soc 2008; 59: 1312–1320.

57. Fletcher A and Worthington D. What is a ‘generic’ hospital model? A comparison of ‘generic’ and ‘specific’ hospital models of emergency patient flows. Health Care Manag Sci 2009; 12: 374–391.

58. Penn ML, Monks T, Kazmierska AA, et al. Towards generic modelling of hospital wards: reuse and redevelopment of simple models. J Simul 2019; 14: 107–118.

59. Swisher JR, Jacobson SH, Jun JB, et al. Modeling and analyzing a physician clinic environment using discrete-event (visual) simulation. Comput Oper Res 2001; 28: 105–125.

60. Mustafee N, Williams DM, Hughes F, et al. Simulation-based study of hematology outpatient clinics with focus on model reusability. In: Jain S, Creasey R, Himmelspach J, et al. (eds) Proceedings of the 2011 winter simulation conference, Phoenix, AZ, USA, 11–14 December 2011, paper no. 12541542, pp.1178–1189. Piscataway, NJ: IEEE.

61. Weerawat W, Pichtilamken J and Subsombat P. A generic discrete-event simulation model for. J Healthc Eng 2013; 4: 285–305.

62. Prinja S, Gupta A, Verma R, et al. Cost of delivering health care services in public sector primary and community health centres in North India. PLoS One 2016; 11: e0169086.

63. Mital KM. Queuing analysis for outpatient and inpatient services: a case study. Manag Decis 2010; 48: 419–439.

64. Fletcher A, Halsall D, Huxham S, et al. The DH accident and emergency department model: a national generic model used locally. J Oper Res Soc 2007; 58: 1554–1562.

65. Fatma N and Ramamoohan V. Patient diversion across primary health centers using real time delay predictors, https://arxiv.org/abs/2101.11074 (2021).

66. Ravi S, Ahluwalia R and Bergkvist S. Health and morbidity in India (2004–2014). Report, Brookings India Res Pap No 092016, August 2016.

67. Government of India M of S and PI. Key indicators of social consumption in india health, 71st round, http://mospi.nic.in/sites/default/files/publication_reports/nss_rep574.pdf. (2019, accessed 5 September 2019).

68. International Institute for Population Sciences (IIPS), ICF. National Family Health Survey (NFHS-4) 2015-16, http://rhoips.org/nfhs/nfhs-4Reports/India.pdf (2017, accessed 25 January 2017).

69. Irving G, Neves AL, Dambha-Miller H, et al. International variations in primary care physician consultation time: a systematic review of 67 countries. BMJ Open 2017; 7: e017902.

70. Ahmad BA, Khairatul K and Farnaza A. An assessment of patient waiting and consultation time in a primary healthcare centre. BMC Health Serv Res 2018; 223: 123–132.
73. Pitchaimuthu N and Bhaskaran S. Labor pattern among primigravida in local population. J Obstet Gynecol India 2018; 68: 482–486.

74. V Both C, Fleßa S, Makuwani A, et al. How much time do health services spend on antenatal care? Implications for the introduction of the focused antenatal care model in Tanzania. BMC Pregnancy Childbirth 2006; 6: 22.

75. van der Ham R. Salabim: discrete event simulation and animation in python. J Open Source Softw 2018; 3: 767.

76. Kleinrock L. A conservation law for a wide class of queueing disciplines. Nav Res Logist Q 1965; 12: 181–192.

77. Narang R. Measuring perceived quality of health care services in India. Int J Health Care Qual Assur 2010; 23: 171–186.

78. Rao KD and Sheffel A. Quality of clinical care and bypassing of primary health centers in India. Soc Sci Med 2018; 207: 80–88.

79. Ramani S, Sivakami M and Gilson L. How context affects implementation of the primary health care approach: an analysis of what happened to primary health centres in India. BMJ Glob Heal 2019; 3: e001381.

80. Litvack JI and Bodart C. User fees plus quality equals improved access to health care: results of a field experiment in Cameroon. Soc Sci Med 1993; 37: 369–383.

81. Andaleeb SS. Public and private hospitals in Bangladesh: improved access to health care: results of a field experiment in Bangladesh. BMJ Global Health 2019; 3: e001381.

82. Akin JS and Hutchinson P. Health-care facility choice and the phenomenon of bypassing. Health Policy Plan 1999; 14: 33–41.

83. Hopp WJ and Spearman ML. Factory physics: foundations of manufacturing and health economics. 2nd ed. Boston, MA: Irwin/McGraw-Hill, 2011.

84. Shortle JF, Thompson JM and Gross D. Fundamentals of queueing theory. 5th ed. Hoboken, NJ: John Wiley & Sons, 2017.