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Brief communication

Incorporating patient reporting patterns to evaluate spatially targeted TB interventions

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ABSTRACT

Purpose: Tuberculosis (TB) is geographically heterogeneous, and geographic targeting can improve the impact of TB interventions. However, standard TB notification data may not sufficiently capture this heterogeneity. Better understanding of patient reporting patterns (discrepancies between residence and place of presentation) may improve our ability to use notifications to appropriately target interventions.

Methods: Using demographic data and TB reports from Dhaka North City Corporation and Dhaka South City Corporation, we identified wards of high TB incidence and developed a TB transmission model. We calibrated the model to patient-level data from selected wards under four different reporting pattern assumptions and estimated the relative impact of targeted versus untargeted active case finding.

Results: The impact of geographically targeted interventions varied substantially depending on reporting pattern assumptions. The relative reduction in TB incidence, comparing targeted with untargeted active case finding in Dhaka North City Corporation, was 1.20, assuming weak correlation between reporting and residence, versus 2.45, assuming perfect correlation. Similar patterns were observed in Dhaka South City Corporation (1.03 vs. 2.08).

Conclusions: Movement of individuals seeking TB diagnoses may substantially affect ward-level TB transmission. Better understanding of patient reporting patterns can improve estimates of the impact of targeted interventions in reducing TB incidence. Incorporating high-quality patient-level data is critical to optimizing TB interventions.

Background

Tuberculosis (TB) is the leading infectious cause of morbidity and mortality worlwide. Although the past few years have seen a large increase in TB control efforts in high-burden countries, several studies have shown that TB burden is geographically heterogeneous, which can undermine the effectiveness of such interventions [1]. Therefore, when implementing TB interventions, it may be more effective to target areas of high TB incidence (i.e., "hotspots") as opposed to the general population [2,3]. By distinguishing hotspots from the general population, spatial targeting concentrates interventions such as active screening, preventive therapy, or vaccine campaigns within a geographically restricted population (e.g., neighborhood, subdistrict) to maximize the

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impact of the resources and effort spent in reducing disease incidence.

To estimate the spatial distribution of TB cases in a population, most models use standard TB notification data collected from TB reporting centers. However, such data, defined by the locations of these centers, may not necessarily reflect where individuals with TB live, where people become infected with TB, or where transmission frequently occurs (e.g., slums, workplaces, public transit, etc.) [4,5]. Considering that TB is an airborne disease, such mobility could have a substantial impact on the distribution of TB transmission and the effectiveness of spatially targeted TB control measures, particularly in urban areas and at smaller spatial resolutions [6].

Methods

Overview

In this study, we explored the effect of one measure of patient mobility, specifically discrepancies between patient reporting and residence, on the projected population-level impact of geographically targeted TB interventions [6]. Our primary outcome was the 10-year relative reduction in TB incidence through active case finding (ACF), comparing a hotspot-targeted strategy (approximately 50% coverage across high-incidence wards) with an untargeted strategy (10% population-wide coverage). A relative reduction greater than 1.0 indicates that a hotspot-targeted strategy would reduce TB incidence more than an untargeted strategy of equal intensity after 10 years of continuous implementation, whereas a relative reduction less than 1.0 would favor the untargeted strategy.

Generally, ACF—which may include combinations of symptom interviews, chest radiography, sputum smear, and molecular testing—aims to detect infectious individuals earlier in their disease course to both avert transmission and improve treatment outcomes. We conceptualized ACF as an intervention that could reduce time to diagnosis by one-third in 10% of individuals with prevalent TB receiving the intervention each year [7,8]. We evaluated the impact of this stylized intervention using a previously published mathematical model of TB transmission in Dhaka, Bangladesh [6]. In this model, each ward's population was stratified into three compartments: TB uninfected, latent TB infection, or active TB disease. Latently infected populations could develop active TB disease either via reactivation or via reinfection followed by primary progression.

Setting

Dhaka City Corporations, Bangladesh (population: 8.9 million in 2011) consisted of 90 wards as of 2018, divided into Dhaka North City Corporation (DNCC, 36 wards) and Dhaka South City Corporation (DSCC, 54 wards) [9]. Wards are the lowest administrative unit in Bangladesh, with an average population of 100,000 people.

Data source

In Bangladesh, patients report to TB reporting centers for treatment, which are located in nearly all wards. These centers notify the National TB Control Program of new TB diagnoses using a standardized reporting form and provide TB treatment to patients via Bangladesh's Directly Observed Therapy, Short-Course program. We extracted ward-level TB notification data in 2014 and 2017 and used these to generate estimates of ward-level TB notification rates [6], calculated as the number of notified TB cases within each ward divided by the population of the ward (estimated using the 2011 national census and an assumed 5% annual growth rate). Wards with the highest TB notification rates (whose cumulative populations comprised approximately 20% of the total population in each city corporation: six wards in DNCC and 12 in DSCC) were selected for "geographic targeting". We compared the impact of ACF in these wards alone with ACF in Dhaka City Corporations as a whole, assuming that the additional number of people diagnosed and treated for prevalent TB was the same in both strategies.

To account for discrepancies between where TB cases are notified and where they live, we extracted the residential addresses of 3512 patients diagnosed with TB from selected reporting centers in one DNCC ward and five DSCC wards between 2017 and 2018. For each of the six wards, we estimated the percentage of patients who reported TB in the same, adjacent, or distant (noncontiguous) wards from which they lived. We used the wards with the highest and lowest correlations between patient reporting and residence to inform two scenarios as described in the following.

Scenarios

- *Strong correlation scenario:* assumes 50% of patients report TB in their ward of residence, 37% report in adjacent wards, and 13% report in distant wards.
- *Weak correlation scenario*: assumes 18% of patients report TB in their ward of residence, 12% report in adjacent wards, and 70% report in distant wards.

In addition, we considered hypothetical scenarios of *perfect correlation* and *constant incidence* across all wards for purposes of comparison.

- *Perfect correlation scenario:* assumes 100% of patients report TB in their ward of residence.
- *Constant incidence scenario:* assumes TB notification rates are uniform across wards in DNCC and DSCC, regardless of reporting.

Sensitivity analysis

We considered three different transmission levels that could reasonably reflect the observed epidemiology of TB in Dhaka: low (in which 56% and 44% of incident cases in DNCC were due to recent transmission and reinfection, respectively, compared with 71% and 29% in DSCC), moderate (70% and 30% in DNCC; 82% and 18% in DSCC), and high (79% and 21% in DNCC; 88% and 12% in DSCC).

Results

The impact of geographically targeted interventions varied substantially depending on correlation between reporting and residence. Generally, the relative impact of hotspot-targeted ACF was greatest when the correlation between locations of reporting and residence was higher, regardless of transmission level. Assuming a moderate level of transmission, the relative reduction (RR) in TB incidence, comparing targeted to untargeted ACF in DNCC, was 1.20 for the weak correlation scenario, 1.82 assuming strong correlation, and 2.45 assuming perfect correlation (Fig. 1). Similar patterns were seen in DSCC (1.03 vs. 1.50 and 2.08). In the scenario of constant incidence (with no correlation between location of reporting and location of residence), targeted ACF was consistently less effective than untargeted ACF (RR 0.88 in DNCC, 0.94 in DSCC). Assuming higher underlying TB transmission, these associations were more pronounced (e.g., RR 1.90 for strong correlation scenario in DNCC).

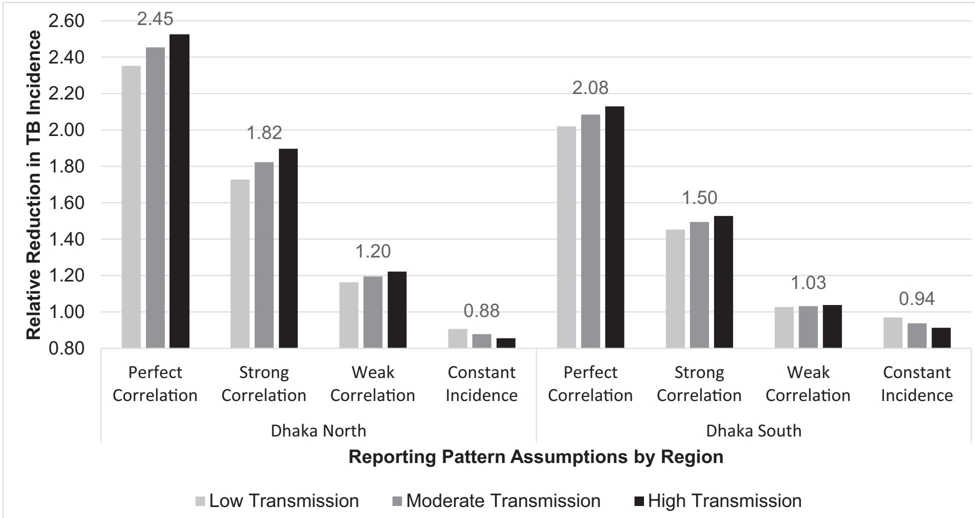

Fig. 1. Relative reduction in TB incidence, comparing targeted to untargeted active case finding (ACF) in Dhaka North City Corporation (DNCC) and Dhaka South City Corporation (DSCC), under four different reporting pattern scenarios and three different levels of transmission (low, moderate, high). "Perfect correlation" assumes 100% of patients report TB where they live. "Constant incidence" assumes all wards in DNCC and DSCC, independently, have the same incidence rate. "Strong correlation" assumes 50% of patients report TB in their ward of residence, 37% report in adjacent wards, and 13% report in distant wards. "Weak correlation" assumes 18% of patients report TB in their ward of residence, 12% report in adjacent wards, and 70% report in distant wards. For example, assuming perfect correlation between reporting and residence and a moderate level of TB transmission, a relative reduction of 2.45 in DNCC indicates that an ACF intervention targeted to high-incidence wards would reduce TB incidence 2.45 times more than an untargeted strategy of equal intensity after 10 years of continuous implementation.

Discussion

Using patient-level data from selected reporting centers in wards across Dhaka, Bangladesh, we explored how assumptions regarding patient reporting patterns could mask the underlying epidemiology of TB in an urban setting and thus affect the projected impact of geographically targeted TB interventions, such as ACF. For example, we found that, if one neglects to account for underlying patient mobility and assumes that patients live strictly in the wards in which they are diagnosed with TB, interventions targeted to high-incidence wards might appear to be more effective than they will actually be in practice. Should significant discrepancies exist between available data and actual patterns of interward mobility, a universal approach may be preferred to one that is targeted on the basis of those data. Conversely, if discrepancies between reporting and residence are minimal, the collection and integration of patient-level data into TB transmission models may refine our understanding of where TB hotspots (and contact networks of TB cases) are located and inform the targeted delivery and evaluation of TB interventions in these areas.

As with any modeling analysis, our study had certain limitations. We collected data from TB reporting centers; however, reported TB does not encompass all TB cases within a population, and such missed cases also contribute to transmission. In addition, our patient-level data were sampled from only six wards and thus may not be representative of the entire population. A comprehensive assessment of reporting patterns across DNCC and DSCC could address this limitation. Furthermore, discrepancies between patient reporting and residence may not reflect the full scope of movement of individuals seeking TB diagnoses, particularly in urban settings; additional metrics of mobility, such as the purpose of migration, frequency and duration of travel, and mode of transportation, could be highly informative as well [10].

In summary, our results illustrate how a better understanding of patient reporting patterns can help improve the interpretation of notification data and thus the impact of targeted interventions, particularly in settings like Dhaka, Bangladesh, where the location of TB reporting centers may be used in lieu of patients' place of residence because of logistical challenges and available resources. In such situations, the ability to accurately identify high-incidence hotspots, assess reporting patterns, and incorporate high-quality patient-level data (e.g., movement of individuals seeking TB diagnoses) at an appropriate and actionable spatial scale, such as at the ward level in Dhaka, Bangladesh, is critical to reducing TB incidence. Without such information, discrepancies between available notification data and actual mobility patterns may reduce the relative impact of geographically targeted interventions by a factor of 50% or more.

CRediT authorship contribution statement

Isabella Gomes: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **Mehdi Reja:** Resources, Data curation, Writing - review & editing, Supervision. **Sourya Shrestha:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration. **Jeffrey Pennington:** Methodology, Validation, Software. **Youngji Jo:** Methodology, Validation, Investigation, Writing - review & editing. **Yeonsoo Baik:** Methodology, Validation, Investigation, Writing - review & editing. **Shamiul Islam:** Resources, Writing - review & editing. **Ahmadul Hasan Khan:** Resources, Writing - review & editing. **Abu Jamil Faisel:** Resources, Writing - review & editing. **Oscar Cordon:** Resources, Writing - review & editing. **Tapash Roy:** Resources, Writing - review & editing. **Pedro Suarez:** Resources, Writing - review & editing. **Hamidah Hussain:** Resources, Writing - original draft, Writing - review & editing, Supervision, Funding acquisition. **David Dowdy:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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