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Impact of the introduction of GeneXpert on pulmonary tuberculosis detection trends in Guinea: analysis of the WHO “TB Burden” database (2000–2024)

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Impact of the introduction of GeneXpert on pulmonary tuberculosis detection trends in Guinea: analysis of the WHO “TB Burden” database (2000–2024)

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Abstract

Background: Tuberculosis screening is an essential first step in the early identification of cases, prevention of transmission, and initiation of prompt treatment. GeneXpert, introduced in Guinea in 2012, offers high sensitivity and specificity for tuberculosis diagnosis. The PNLT current policy is to expand the use of the GeneXpert test as the initial nationwide diagnostic test. Therefore, the objective of this study was to evaluate the impact of the introduction of GeneXpert on pulmonary tuberculosis detection trends in Guinea.

Methods: We conducted an ecological interrupted time-series study using 25 annual country-level observations (Guinea, 2000–2024). The introduction of GeneXpert MTB/RIF was considered the intervention. Tuberculosis incidence per 100,000 population and case detection rate were analysed using segmented linear regression to assess changes in level and trend after implementation. Subsequently, the "CausalImpact" package in R was used to estimate the causal effect of the intervention by comparing observed post-intervention outcomes with Bayesian model-based counterfactual predictions.

Results: The detection rate remained stable prior to the introduction of GeneXpert in 2012 ($\beta = 0.23$; $p = 0.526$) and showed no significant immediate change ($\beta = 0.57$; $p = 0.870$). In contrast, a gradual and significant increase in this rate was observed after the intervention ($\beta = 1.79$, $p = 0.001$). Regarding the incidence per 100,000 inhabitants, an upward trend was observed prior to 2012 ($\beta = 3.73$; $p < 0.001$), followed by a significant immediate drop upon the introduction of GeneXpert ($\beta = -12.60$; $p = 0.043$), with no significant change in the long-term trend ($\beta = -0.38$; $p = 0.646$). Bayesian CausalImpact analysis showed a mean increase in the detection rate of 13.96 pp following the introduction of GeneXpert, representing a relative rise of 27% (95% CI: 19–36%; $p = 0.001$).

Conclusion: These results support the expansion of this technology at the district level to improve the tuberculosis case detection system in Guinea. The results suggest the value of continuing to invest in tuberculosis diagnostic capacities in Guinea, particularly by expanding GeneXpert platform coverage and strengthening healthcare worker training to improve the case detection.

Background

Tuberculosis (TB) is a chronic infectious disease that remains one of the leading causes of morbidity and mortality, posing a threat to global health [1]. It remains a global public health problem, with 10.6 million new cases reported worldwide in 2022, according to the World Health Organization [2]. Although it is a preventable and treatable disease, tuberculosis infects approximately 25% of the global population, causing approximately 1.4 million deaths among people who are HIV-negative and 187,000 deaths among people living with HIV [3]. Without treatment, the mortality rate of tuberculosis is high (nearly 50%). With the treatments currently recommended by the WHO, approximately 85% of people with tuberculosis can be cured [4].

Geographically, 23% of the global tuberculosis burden in 2022 was located in Africa, a situation exacerbated by the advent of HIV/AIDS [5]. Despite considerable efforts since the establishment of the National Tuberculosis Control Program (PNLT) in 1990, tuberculosis remains a significant health problem in Guinea [6].

As in other sub-Saharan African countries, HIV has led to a resurgence of tuberculosis in Guinea, which is currently considered the leading opportunistic infection [7]. In 2018, a study on mortality factors among patients with tuberculosis in the capital city of Conakry found a case fatality rate of 14% [8].

Early and accurate diagnosis, which reduces the risk of transmission, is considered one of the most effective strategies for combating tuberculosis [9]. A delayed diagnosis can have negative consequences for patients, leading to a reduced quality of life and an increase in complications and mortality [10]. The diagnosis of pulmonary tuberculosis relies primarily on sputum examination, which can be difficult in patients who cannot produce sputum [11]. The reference method for diagnosing pulmonary tuberculosis is mycobacterial culture; however, this method is very slow, costly, and requires a well-equipped specialised laboratory [12]. The gap between traditional tuberculosis diagnostic methods and actual clinical needs calls for the development of new diagnostic methods that are accurate, rapid, and cost-effective [13].

Among these methods, the GeneXpert test has a high sensitivity and specificity for the definitive diagnosis of tuberculosis [14]. This test is currently recommended as a "first-line" rapid diagnostic test in endemic countries when rapid results are essential for diagnosing tuberculosis in HIV-infected patients or for the appropriate management of multidrug-resistant tuberculosis [15]. Owing to its very short turnaround time for results, it is of major interest in countries with a high prevalence of this disease [16].

In Guinea, the current PNLT policy is to expand the use of the GeneXpert test as the initial nationwide diagnostic tool [17]. A study conducted in 2015 at the National Reference Laboratory for Mycobacteria, based in the capital, confirmed the value of GeneXpert as a rapid diagnostic tool

for multidrug resistance, showing good concordance with phenotypic tests [18]. Nevertheless, despite these promising findings, the nationwide impact of this test has not been assessed.

Since its introduction, the number of machines has increased, and several areas across the country have received units to enable local tuberculosis diagnosis. However, other localities still lack this technology, which we believe contributes to the under-detection of tuberculosis cases. In this study, we aim to demonstrate the potential impact of this test on tuberculosis indicators and advocate for its availability in areas where it has not yet been implemented. The study's findings will serve as a basis for advocacy among policymakers and international organisations to expand the availability of GeneXpert nationwide.

Thus, the objective of this study was to evaluate the impact of GeneXpert introduction on pulmonary tuberculosis detection trends in Guinea.

II- Methods

Study type and period

This was an ecological interrupted time-series study based on secondary analysis of annual national aggregate TB indicators for Guinea, 2000–2024 to evaluate the impact of introducing GeneXpert in Guinea. The study compares the 2000–2011 period with the 2012–2024 period, as 2012 marked the rollout of GeneXpert in Guinea as a major diagnostic tool tests [18]. The analytical unit was year-country, not individual patients.

GeneXpert was introduced in Guinea in 2012 and has since been integrated into the national tuberculosis diagnostic system. Although the technology was progressively expanded across the country, 2012 was retained as the intervention point because it marked the first routine use of GeneXpert in tuberculosis diagnosis in Guinea.

We collected data on the introduction of GeneXpert in Guinea. For each year since 2012, we gathered information on the number of machines introduced and the number of sites in the country equipped with this technology for tuberculosis diagnosis. Data regarding the introduction of the test, the number of sites equipped with the technology, and the total number of machines available in the country for each year are provided in the supplementary file.

Data sources

The data used are derived from the WHO harmonised tuberculosis surveillance database titled "Estimates of the burden of tuberculosis in WHO countries." This database can be accessed via the link https://www.who.int/teams/global-tuberculosis-programme/data, then go to the "WHO TB burden estimates" section and finally download the database « **WHO TB burden** estimates ». The data were downloaded in Comma-Separated Values (CSV) format into Microsoft Excel on April 30, 2026. The CSV file contained 5,348 rows and 50 columns. As we were only interested in data for Guinea, we filtered the dataset to retain only those records. After filtering, 25 rows and 50 columns were obtained. The 25 rows represent the data for each year from 2000 to 2024. The data were aggregated to provide a comprehensive overview of the epidemiological trends [19].

Evaluation indicators

Overall, the database contains information on tuberculosis incidence and mortality, as well as indicators for assessing the program's performance and surveillance.

In low- and middle-income countries, surveillance data are prone to under-reporting. Consequently, we chose to analyse primarily those indicators based on WHO estimates; while these involve some uncertainty, they rely on robust methods and multiple data sources. These estimates provide a more accurate picture of the disease burden. Table I lists the indicators from the "WHO TB burden estimates" database used in the study, along with their associated labels.

The selection of these indicators was justified by their relevance to the research focus of this study. The chosen indicators allow the measurement of the overall disease burden, severity, program performance, and detection dynamics.

Table I: Indicators from the "WHO TB burden estimates" database used in the study, along with the associated labels

Indicator code	**Indicator labels**	**Indicator calculation methods** [20]
year	Year of notification	
Estimated incidence of tuberculosis		
e_inc_100k	Estimated incidence per 100,000 inhabitants	Total number of incident tuberculosis cases estimated by WHO / total population × 100,000
e_inc_num	Absolute number of estimated cases	The total number of incident tuberculosis cases was estimated by the WHO using the following formula: 1- Tuberculosis prevalence surveys 2- National tuberculosis prevalence survey combined with a country-specific dynamic model 3- Case notification data combined with expert opinion on case detection gaps 4- Notifications in high-income countries adjusted by a standard factor to account for under-reporting and under-diagnosis 5- Inventory studies, capture-recapture modelling
Gravity and Performance Program		
cfr_pct	Case fatality rate	Number of deaths from all causes among notified cases / Number of notified tuberculosis cases x 100
Monitoring indicators		
c_newinc_100k	Incidence per 100,000 inhabitants	Number of notified new tuberculosis cases / total population x 100,000
c_cdr	Case detection rate	Number of notified tuberculosis cases / Number of estimated tuberculosis cases x 100

The indicators " estimated incidence per 100,000 population" and " absolute number of estimated cases" are calculated by the WHO using data from multiple sources: national notifications, prevalence and mortality surveys, and sometimes expert opinion. They reflect an estimate of the actual disease burden in the population, including new cases and relapses. Consequently, this is a modelled value that provides a comprehensive overall picture of the incidence. In contrast, the indicator " incidence per 100,000 population" represents the notification rate of new tuberculosis cases per 100,000 inhabitants. It is derived from national surveillance systems and relies solely on data observed and reported by the country; it primarily reflects the performance of detection and notification systems [21]. Thus, the coexistence of the two incidence measures makes it possible to distinguish between the true burden of the disease (estimated incidence) and the health system's capacity to detect and report cases (new cases).

For each indicator, we plotted trends between 2000 and 2024 to compare variations before and after the implementation of GeneXpert in Guinea.

Data analysis

The data were analysed using R software (version 4.5.3), which comprised both descriptive and analytical components.

Descriptive section

Using the **"WHO TB burden estimates"** database, we plotted the annual trends for

- Estimated TB incidence in Guinea,
- Estimated number of TB cases in Guinea,
- Case fatality rate (expressed as a percentage),
- Incidence per 100,000 population, and
- TB case detection rate in Guinea.
- To further analyze program performance, we calculated the difference between the estimated incidence and the incidence per 100,000 population. This supplementary indicator allows for the visualisation of the gap between the actual disease burden and the cases effectively detected by the system in absolute terms. Although the detection rate is the standard indicator, the difference between these two metrics provides a concrete illustration of system improvement before and after the introduction of GeneXpert by highlighting the narrowing gap between the estimated and actual incidence. The smaller the difference, the more effective the system is for case detection.

The graphs presented in this descriptive section illustrate variations across the pre- and post-intervention periods, with a vertical line marking the year in which the test was introduced.

Analytical section

The analytical section comprises the following supplementary analyses.

Interrupted time series analysis using the segmented linear regression model

For this analysis, the dependent indicators were incidence per 100,000 population and case detection rate. We selected these two indicators for their complementarity: one provides information on disease dynamics, and the other reflects the system's detection efficiency.

The incidence per 100,000 population reflects the disease burden and allows for the assessment of transmission trends over time. The detection rate represents the performance of the surveillance and diagnostic systems, reflecting their capacity to identify and report TB cases. The independent variables were as follows: 1) time elapsed since 2000 (quantitative); 2) the intervention, capturing the immediate level change associated with the introduction of GeneXpert (binary: 0 before 2012, 1 after); and 3) time elapsed since the intervention (0 for 2012, 1 for 2013, 2 for 2014, etc.), allowing for the estimation of the slope change following the intervention.

This method enabled the estimation of the immediate effect of introducing GeneXpert.

The model is expressed as: $Yt = \beta0 + \beta1time + \beta2intervention + \beta3post\text{-}intervention + \varepsilon time$

where $\beta1$ is the slope of the time series, that is, the trend prior to the GeneXpert implementation.

$\beta2$ is the immediate change; and

$\beta3$ is the change in trend following GeneXpert deployment.

ε is the model error or residual (i.e. unexplained component).

A classic methodological issue with interrupted time series (ITS) analysis is residual autocorrelation, which manifests as a temporal dependency of the model errors. In time series data, consecutive observations tend to be more similar to one another than those that are further apart, a phenomenon known as autocorrelation [22]. In this case, the statistical tests were invalid, and the causal effects were overestimated. Therefore, the model validity was verified using the Durbin-Watson test, which detects potential residual autocorrelation. The test was interpreted as follows:

- Value close to 2: no autocorrelation
- Value less than 2: positive autocorrelation
- Value greater than 2: negative autocorrelation

The significance level for this test was set at 5%. %.

A graphical representation of the changes observed in the segmented linear regression was created to better assess these shifts in the data. This type of visualisation made it possible to evaluate trends prior to the introduction of GeneXpert, the immediate change at the time of the intervention, and the new trajectory following the rollout of GeneXpert.

Bayesian analysis of the CausalImpact package in R

Unlike the segmented linear regression model, the Bayesian approach used by CausalImpact is not a simple parametric equation. It relies on estimating a counterfactual scenario based on the dynamics of the observed time series, that is, how the response metric would have evolved following the intervention if it had never taken place. It thus generates a probability distribution of the expected outcome in the absence of the intervention and compares this with the data observed after the intervention, making it possible to estimate the effect attributable to the intervention along with its credible intervals [23]. The resulting graph consists of three panels. The first panel displays the data and counterfactual predictions for the post-intervention period. The second panel illustrates the difference between the observed data and the counterfactual predictions, which represents the point-in-time causal effect estimated by the model. The third panel sums the point-in-time contributions from the second panel, resulting in a graph of the intervention's cumulative effect [24]. For our analysis, the hypothesis to consider is that the time-series dynamics established prior to the intervention remain stable. This made it possible to quantify the effect of the intervention on the case detection rate while accounting for statistical uncertainty.

Ethical considerations

This study relied on public data that did not require specific procedures for obtaining. The data were compiled by the WHO and did not require individual consent.

Results

Description of the TB burden

Estimated incidence of tuberculosis

Figure 1 shows the trends in estimated incidence per 100,000 inhabitants and the absolute number of estimated tuberculosis cases in Guinea between 2000 and 2024, with a blue vertical line marking the introduction of GeneXpert in 2012. The estimated tuberculosis incidence increased between 2000 and 2010 and then began to decline. The introduction of GeneXpert in 2012 did not alter this trend, which continued thereafter. From 2015 onwards, the incidence rates remained stable. In contrast to the estimated incidence, the absolute number of estimated tuberculosis cases steadily increased. The introduction of the test did not change this trend, and the number continued to rise, exceeding the previous year's figure each year.

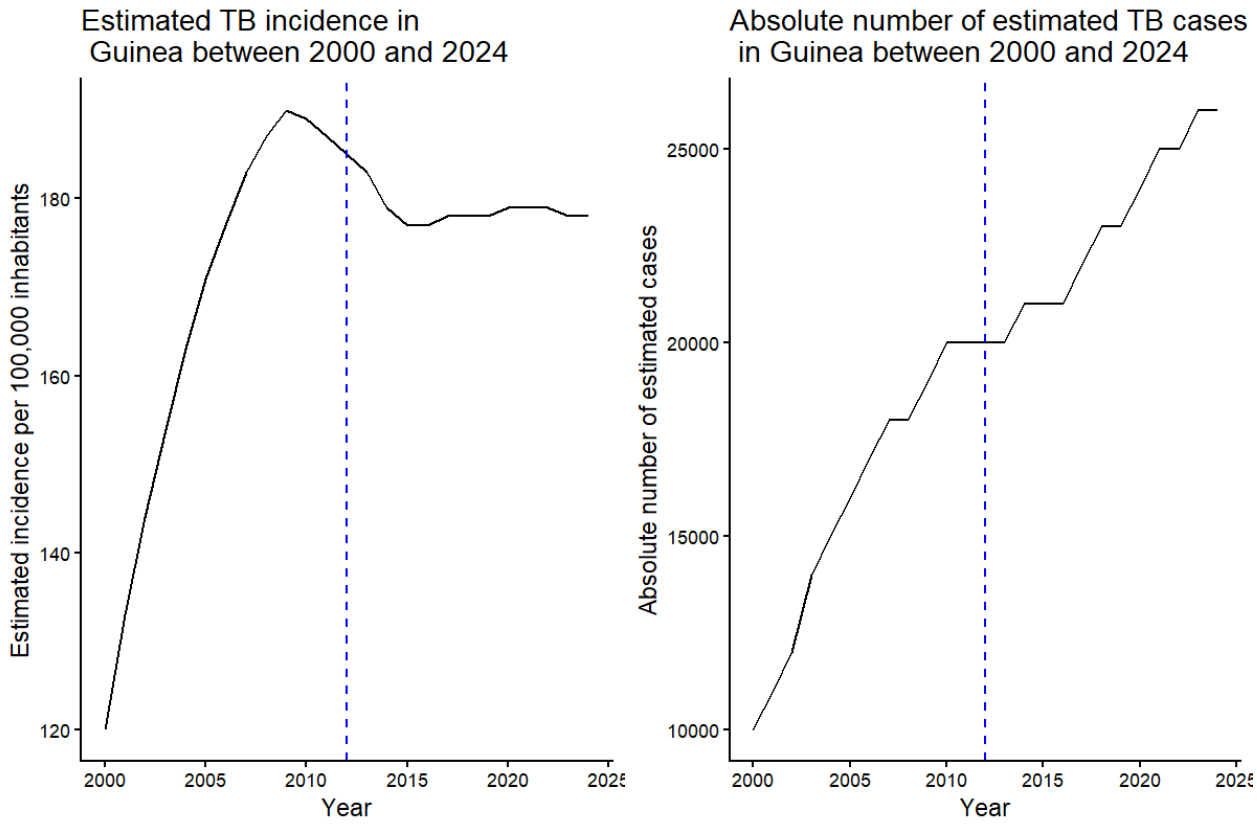


Figure 1: Trends in estimated incidence and absolute number of estimated tuberculosis cases in Guinea between 2000 and 2024; analysis of the WHO data.

Incidence per 100,000 inhabitants and case fatality rate

In Figure 2, we observe that the incidence per 100,000 inhabitants increased, showing an overall upward trend with fluctuations over the years. Regarding case fatality trends in Guinea between 2000 and 2024, fatality rates were rising prior to 2012, approaching 30%, with a peak around 2008. After 2012 (indicated by the blue vertical line), the fatality rate gradually declined from 2012 to 2019. In 2020, there was a slight increase, although the levels did not reach those observed during the pre-intervention period. Following this rise, the figures declined from 2020 to 2024.

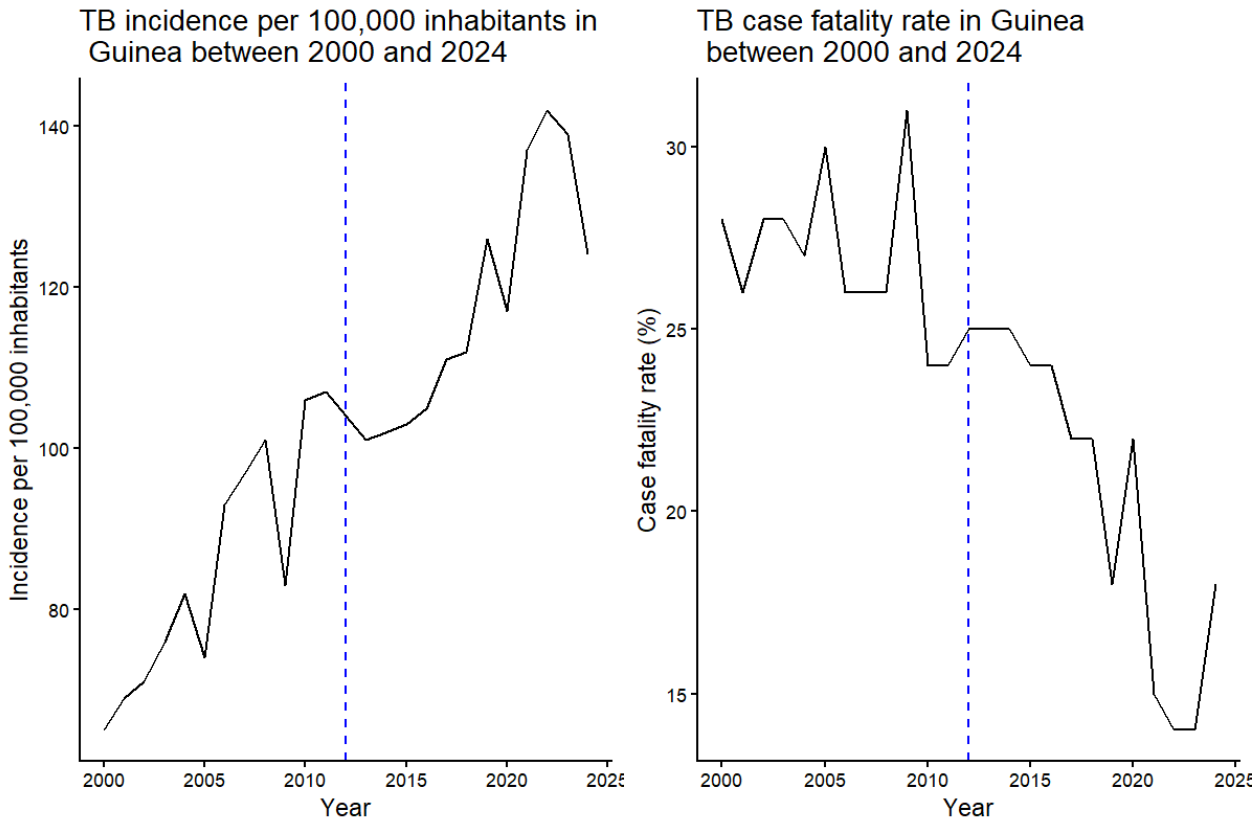


Figure 2: Trends in TB incidence per 100,000 inhabitants and case fatality in Guinea between 2000 and 2024 (WHO data)

Detection rate and difference between estimated incidence and incidence per 100,000 inhabitants

Figure 3 shows an upward trend in the detection rate, even after the introduction of GeneXpert testing. A comparison of the periods before and after the introduction of the test reveals greater fluctuation in the pre-introduction rates, with some figures falling below those of the previous year's rates. Conversely, following the introduction, the rate continued to rise, peaking in 2024. The trend in the incidence rate per 100,000 inhabitants following the introduction of GeneXpert

mirrored the trend in the tuberculosis case detection rate. Prior to the test's introduction, the incidence per 100,000 inhabitants was rising, whereas the detection rate fluctuated, showing low figures in certain years.

The introduction of the test was associated with improved detection, bringing the detection rate closer to the incidence rate per 100,000 inhabitants, which explains why the two curves appear similar after 2012. Similarly, the gap between the two incidence rates widened from 2000 to 2008. By 2020, the difference reached its lowest level, following a gradual decline since it was introduced.

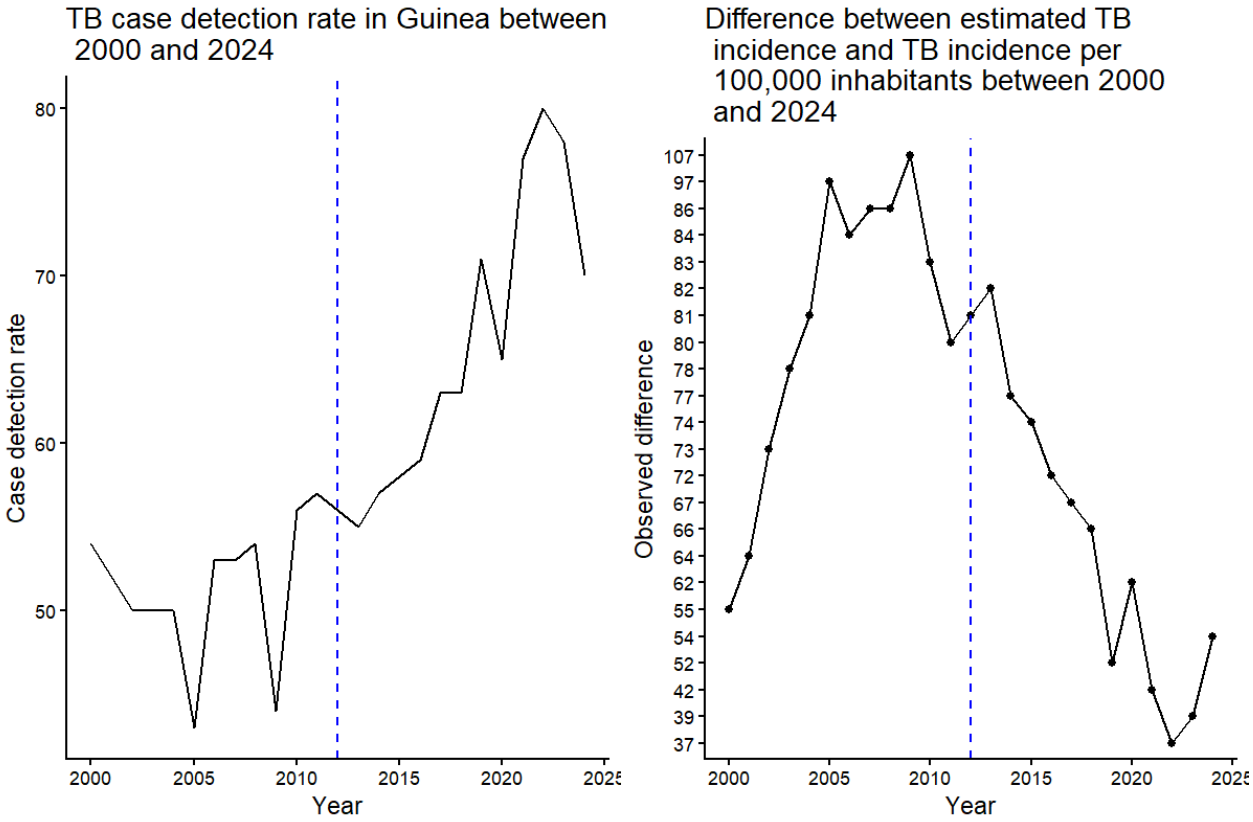


Figure 3: Trends in the tuberculosis detection rate and the difference between the estimated and reported incidence per 100,000 inhabitants in Guinea between 2000 and 2024 (WHO data).

Analytical section

Interrupted Time Series (ITS) analysis

The results of this analysis are presented in Table II.

Regarding the case detection rate, the pre-intervention slope was close to zero ($\beta 1 = 0.23$; 95% CI: -0.51 to 0.97; $p = 0.526$), indicating stability before the introduction of GeneXpert. No significant

immediate level change was observed following implementation (β2 = 0.57; 95% CI: -6.62 to 7.76; p = 0.870). However, the change in slope after the intervention was significantly positive (β3 = 1.79; 95% CI: 0.80 to 2.79; p = 0.001), indicating that the annual trend increased significantly after the introduction of GeneXpert. Consequently, the estimated post-intervention slope was 2.02 percentage points per year (β1 + β3 = 2.02), reflecting a progressive improvement in case detection over time following the introduction of GeneXpert in Guinea.

Regarding the incidence per 100,000 inhabitants, for each additional year prior to 2012, the incidence increased by an average of 3.73 cases per 100,000 inhabitants (95% CI = 2.48 – 4.99), all other factors being equal (p < 0.001), demonstrating a steady increase in cases before the intervention. In 2012, there was a distinct break, with a significant decrease of approximately 12.60 cases per 100,000 inhabitants (95% CI: -24.76 to -0.43; p = 0.043). After 2012, each additional year was associated with an average decrease of 0.38 cases per 100,000 inhabitants when the effect was adjusted for other variables in the model. However, this coefficient was not significant, suggesting a lack of long-term effect of the introduction of GeneXpert on the incidence per 100,000 inhabitants (p = 0.646).

Table II: Results of the segmented regression analysis of the tuberculosis case detection rate and incidence per 100,000 population in Guinea; analysis of WHO data.

	Case detection rate			**Incidence per 100,000 inhabitants**		
Features	**Beta**	**95% CI**	**p-value**	**Beta**	**95% CI**	**p-value**
Pre-intervention slope	0.23	-0.51 – 0.97	0.526	3.73	2.48 – 4.99	<0.001
Immediate change	0.57	-6.62 – 7.76	0.870	-12.60	-24.76 – -0.43	0.043
Change in slope	1.79	0.80 – 2.79	0.001	-0.38	-2.06 – 1.30	0.646

Abbreviation: CI = confidence interval

Figure 4 visually illustrates the changes observed through segmented regression. Prior to the intervention, the detection rate trend was relatively stable, corresponding to a non-significant pre-intervention slope. Following the introduction of GeneXpert, a gradual increase in the detection rate was observed, increasing from approximately 50% to approximately 80%. This aligns with the segmented linear regression results, which showed a significant change in the post-intervention slope. The second graph displays variations in the incidence of tuberculosis per 100,000 inhabitants over the study period. Before the rollout of GeneXpert, the trend was upward, corresponding to a significant pre-intervention slope. After the introduction, the indicator showed an immediate change and continued to rise, reaching approximately 140 per 100,000 population. However, the segmented linear regression indicated that the post-intervention slope was not significant.

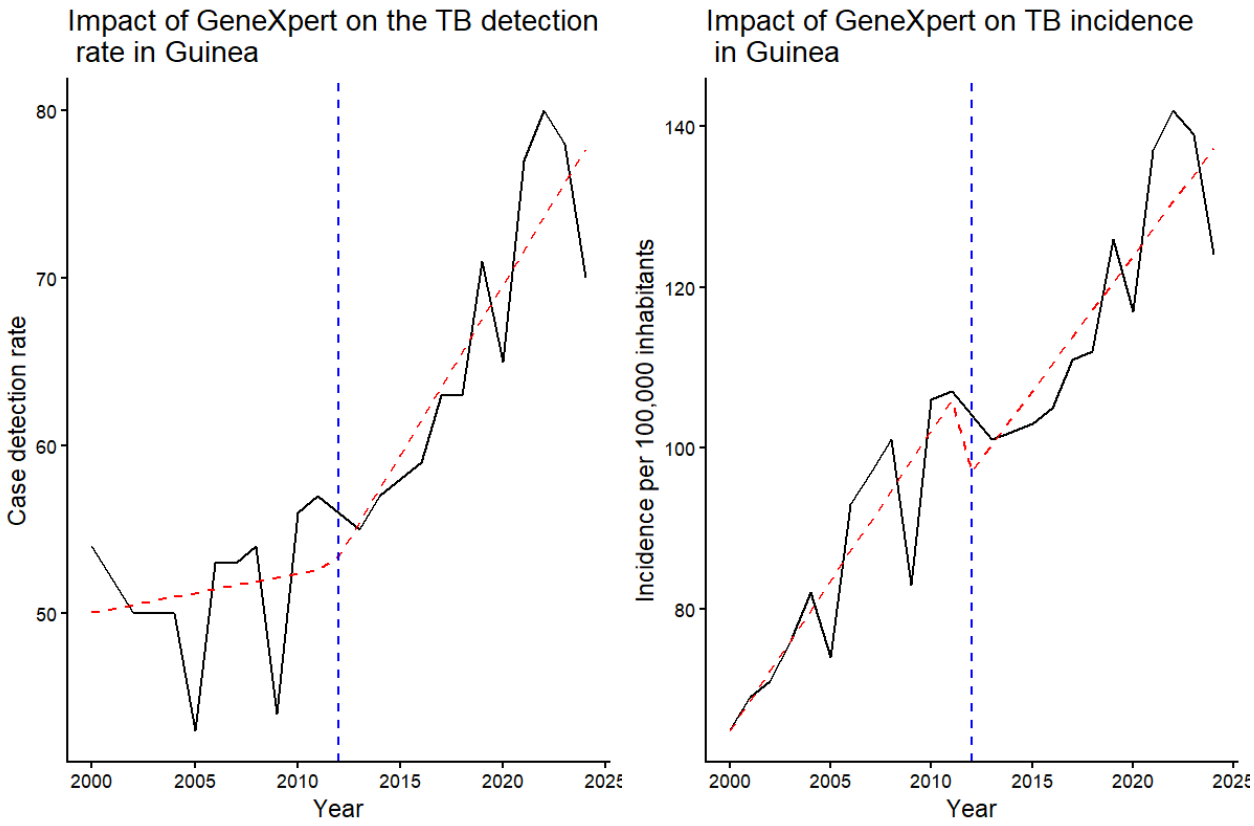


Figure 4: Interrupted time-series models for tuberculosis detection rate and incidence in Guinea, analysis of WHO data

Furthermore, the Durbin-Watson test applied to the segmented models yielded results close to 2.
Detection rate: DW = 1.9311, p-value = 0.1979
Incidence per 100,000 inhabitants: DW = 2.0518, p-value = 0.2963
These results indicate no evidence of significant residual autocorrelation in either of the models.

Bayesian approach with CausalImpact

Figure 5 presents the results of the ITS analysis using the Bayesian CausalImpact approach.

The top panel shows the observed trajectory of the tuberculosis detection rate (black line) compared with the trajectory estimated in the absence of intervention (blue area). After 2012 (the year GeneXpert was implemented), the observed values deviated from the expected trend.

The middle panel (pointwise) shows the effect of this introduction year by year, representing the difference between the observed values and the values expected in the absence of the intervention. After 2012, the effect became progressively positive and tended to increase annually.

Finally, the bottom panel (cumulative) shows the cumulative effect of the intervention over the entire post-2012 period. The dashed blue curve continuously increases, indicating that the impact

of the intervention increased over time. The graphs show the differences between the observed series and counterfactual predictions (in the absence of the intervention).

The numerical values are not directly visible on the curves and were calculated using the CausalImpact package with a Bayesian approach. The observed post-intervention case detection rate averaged 65.54%, compared with a model-predicted counterfactual rate of 51.58% (95% credible interval: 48.04%–55.04%). The estimated difference was 13.96 pp (95% CrI: 10.50–17.50), corresponding to a relative increase of 27% (95% CrI: 19%–36%). The posterior probability of a positive association was high (one-sided Bayesian tail-area probability, p = 0.001). However, in the absence of a concurrent control series, these findings should be interpreted as evidence of an association relative to the model-based counterfactual scenario, rather than as definitive proof of causality. They rely on the assumption that no major unmeasured co-interventions altered the outcome trends during the post-intervention period.

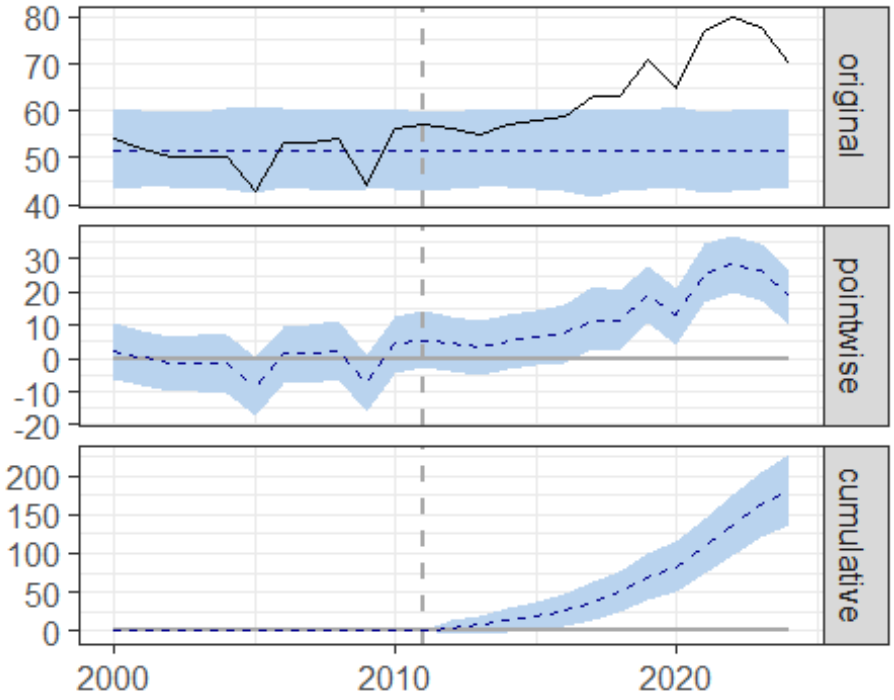


Figure 5: Analysis of the impact of introducing GeneXpert on tuberculosis detection rate in Guinea (CausalImpact), WHO data analysis.

Discussion

In this study, we analysed the impact of introducing GeneXpert on pulmonary tuberculosis detection trends in Guinea (2000–2024). We compared tuberculosis indicators from the WHO's "TB burden estimates" database. This database is publicly available on the WHO website and is derived from the organisation's harmonised tuberculosis surveillance data. This study aims to draw the attention of policymakers to the need to make this test available in areas of the country that have not yet received it.

To the best of our knowledge, this is the first study to combine time-series analysis with a Bayesian approach using CausalImpact to evaluate the impact of GeneXpert deployment in Guinea.

Our results show an improvement in the trends of the burden of tuberculosis following the introduction of the test in 2012. They showed a significant post-intervention change in the detection rate slope. Our results have important implications for clinical practice and public health.

Trends in case fatality

In our study, the case fatality rate decreased following the introduction of the test in 2012.

Similar results were reported in a 2022 study on the impact of GeneXpert in three African countries [25]. The authors analysed data from 2001 to 2019 and found that the estimated tuberculosis mortality rate decreased in all three countries after introducing the GeneXpert test. Treatment success rates also increased in the three countries following the test's introduction compared to the preceding period. Mortality rates can indirectly reflect the quality of care and timeliness of diagnosis. By enabling earlier detection of patients, GeneXpert allows for appropriate care with a lower risk of complications.

Effect on incidence per 100,000 inhabitants and detection rate

Both the reported tuberculosis incidence per 100,000 population and the case detection rate increased during the post-intervention period. These findings are consistent with improved tuberculosis detection and notifications. However, the observed changes cannot be attributed solely to GeneXpert, as other concurrent changes in tuberculosis control activities and surveillance may have also contributed.

A 2019 study in Madagascar concluded that using GeneXpert molecular tests to screen presumptive tuberculosis cases can significantly increase the number of cases reported at tuberculosis diagnostic centres [26]. Similar results were observed in a 2023 study in Ghana, where the introduction of the GeneXpert test for tuberculosis diagnosis led to a gradual increase in the number of bacteriologically confirmed cases [27].

This result indicates that the deployment of GeneXpert has enabled the country to improve its system for identifying and registering patients, likely by reducing the false negatives associated with traditional methods. This demonstrates the effectiveness of GeneXpert in improving the case detection rate.

Segmented linear regression analysis showed that the test did not produce an immediate effect, indicated by a non-significant coefficient, but did result in a significantly positive slope in the detection rate following the introduction of GeneXpert. The absence of an immediate effect may be attributed to the phased implementation of GeneXpert in Guinea. Although the technology was introduced in 2012, the scale-up of GeneXpert machines and testing sites occurred progressively, with a marked expansion beginning in 2017. Consequently, improvements in tuberculosis case detection were observed gradually over time rather than immediately after the introduction of the intervention.

This finding aligns with the results of a study showing that the introduction of the GeneXpert test increased tuberculosis screening in the settings studied, raising the rate from of the cohort of suspected tuberculosis cases compared to the baseline scenario [28]. This reflects a gradual improvement in the detection rate following the introduction of GeneXpert in Guinea.

Analysis result using a Bayesian approach

The Bayesian approach confirmed the results of the segmented regression, reinforcing the validity of the conclusions. The probability of observing this effect by chance was very low. This indicates that the effects were statistically significant. It can be considered causal, provided that the model assumptions hold true.

A study evaluating the health impact of implementing GeneXpert in five Southern African countries, Botswana, Lesotho, Namibia, South Africa, and Swaziland–concluded that, compared to the status quo, its implementation would avert tuberculosis cases and tuberculosis-related deaths in Southern Africa over the 10 years following its introduction, and would reduce prevalence by 2022, with more modest reductions in incidence [29]. This result supports the value of GeneXpert as a useful intervention for PNLT.

Strengths and limitations of the study

This study had certain limitations. The analyses relied on aggregated WHO data, which could have been affected by reporting delays or under-reporting and could not be validated against the National PNLT databases. The lack of regional data prevented the identification of the most heavily affected areas. Furthermore, as with any interrupted time-series analysis, concurrent factors, such as increased funding or tuberculosis control programs, may have influenced the results. Finally, certain operational constraints associated with GeneXpert use, such as cartridge availability and other logistical issues, were not considered in this study.

Despite these limitations, this study has several strengths. It addresses a major diagnostic innovation, the evaluation of which is essential for public health. The long observation period (2000–2024) allowed for a robust analysis of temporal trends. Additionally, the combined use of interrupted time-series analysis and the Bayesian CausalImpact approach represent a significant methodological asset. Finally, the data used were standardised and publicly accessible, ensuring the reproducibility of the results.

Conclusion

In summary, our study, based on an analysis of the WHO database on the tuberculosis burden across member countries, suggests a positive association between the phased rollout of GeneXpert in Guinea and improved detection trends for pulmonary tuberculosis. We found that the absolute number of estimated tuberculosis cases increased following the introduction, the case fatality rate declined, and both the detection rate and incidence per 100,000 inhabitants increased after 2012, the year the test was introduced. Interrupted time-series analysis revealed that the test did not have an immediate impact on the case detection rate but rather a gradual one. Bayesian analysis confirmed the findings of the interrupted time-series analysis, indicating a progressive improvement in the detection rate following the introduction of GeneXpert in Guinea.

These results support the nationwide expansion of this technology to enhance the performance of tuberculosis case detection systems. They also highlighted the need for further studies to better understand the challenges associated with tuberculosis control in the country.

Considering these findings, we propose the following studies as the next steps to supplement the available information:

- Studies on regional and prefectural disparities regarding GeneXpert in Guinea to identify priority areas for the deployment of new machines
- Operational studies to assess machine availability and staff training to understand the logistical constraints influencing GeneXpert effectiveness;

List of abbreviations

HIV: Human Immunodeficiency Virus

ITS: Interrupted Time Series

PNLT: National Tuberculosis Control Program

TB: Tuberculosis

WHO: World Health Organization

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The data analysed in this study are publicly available from the World Health Organization (WHO) Global Tuberculosis Programme database at https://www.who.int/teams/global-tuberculosis-programme/data. The datasets are openly accessible and can be used without prior authorisation.

Competing interests

The authors declare that this study was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

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Authors' contributions

TID, ASM, and KSB conceived and designed the study. TID and ASM developed the methodology, managed the dataset, performed the statistical analyses, interpreted the results, and drafted the initial manuscript. MBD, TS, AFT, AW, KSB, MT, ABT, and AAT contributed to the interpretation of the findings and provided important scientific and intellectual input throughout the study. MBD, TS, AFT, AW, MT, ABT, and AAT critically reviewed the manuscript for important intellectual content and contributed to its revision. All authors read, revised, and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

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