Epidemiological Analysis of Tuberculosis Relapses in Morocco: Leveraging Artificial Intelligence for Predictive Modeling

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Abstract: Tuberculosis remains a major public health problem. In most cases, appropriate and correctly administered anti-tuberculosis treatment leads to recovery. However, the presence of certain factors increases the risk of relapses. This study aims to analyze the epidemiological profile of tuberculosis relapses and discuss the results of treatments at the tuberculosis diagnostic center in Khémisset, Morocco. A total of 274 cases of tuberculosis relapse were reported during the study period. The average age of patients was 44.7 years ±18.1. Of these patients, 65.3% were male, giving a male-to-female ratio of 1.9. Of the relapses, 21.9% were extrapulmonary and 78.1% were pulmonary, of these, 71.5% were confirmed bacteriologically. The treatment success rate was 74.3%, the death rate, 7.8%, 9% of patients were lost to follow-up, the failure rate, 4.1% and 3.4% of patients became drug-resistant. Integrating artificial intelligence into the diagnosis and monitoring of tuberculosis treatment could significantly enhance public health initiatives in the fight against the disease.

Keywords : Tuberculosis, epidemiology, relapse, artificial intelligence

1 Introduction

Tuberculosis remains a serious public health issue in many parts of the world, including areas where it appears to be under control. This contagious disease often results in relapses, significantly increasing the risk of death or serious complications for those affected. However, the risk factors involved are not yet fully understood, which makes it difficult to implement effective prevention strategies [1]. The severity of national TB epidemics varies widely from country to country, and national notification rates range from less than five to more than 500 new cases or relapses per 100,000 population per [2]. People who have recovered from tuberculosis may suffer from the disease again. Tuberculosis relapse rates can vary depending on variety of parameters such as the quality of initial treatment received, patient adherence to treatment, drug resistance, and the prevalence of tuberculosis in the community [3]. Studies on TB relapse have several foundations. TB is curable disease, but it can become serious and life-threatening if not treated properly [4]. Understanding the causes and mechanisms of recurrence after successful treatment is essential for developing new correction and treatment strategies. Moreover, tuberculosis is a contagious and highly infective disease, thus we should carefully estimate the recidivism risk to control and prevent it in curative sense, Khémisset province, in Morocco, the number of new cases is more than 100 for every 100000 habitants, with a relapse rate of 38% ± 10.

Resistance to anti-tuberculosis drugs is a growing problem that reduces the effectiveness of current treatments. It complicates standard treatment protocols and patient management. In addition, managing this disease is complicated by the fact that many people relapse after successfully completing treatment. These issues demonstrate the usefulness of predictive models, as they enable therapeutic decisions to be made by anticipating the evolution of patient's condition during the treatment period [5]. Deep learning and machine learning algorithms make decisions in a similar way to humans. It is therefore possible to predict the worsening of this disease [6]. In light of these recent challenges, there is now a push to use AI in epidemiological studies, public health research and data analysis. This approach enables a more targeted and personalized integration of biology, health, and information technologies, representing one of the key improvements in this area [7].

The current study aimed to define the precise epidemiological characteristics of tuberculosis patients who experienced relapse, and to evaluate treatment outcomes in this group in Khémisset province, Morocco. The collected data will form the basis for the development of future predictive models. The study also draws on specialist literature concerning recent applications of tuberculosis. The study presents a vision for the future of tackling this serious public health problem.

2 Method

This is a retrospective review of the medical records of TB patients who relapsed during the period of 2014-2020 and who were being treated at the TB diagnostic center in Khémisset, Morocco. Patients are observed at this center during treatment.

Inclusion and exclusion criteria and analysis

We included all cases of tuberculosis relapse that were documented and observed during the study period. We excluded cases with incomplete medical records or an undetermined outcome.

Data collection and analysis

All data were collected in accordance with anonymity requirements from medical records. We collected data on patients' age, gender, origin, form and location of tuberculosis, as well as their weight during treatment and the outcome of treatment.

Data analysis was performed using Jamovi 2.3.26 software package. Data were analyzed using descriptive statistics were calculated for all variables and presented as frequencies and percentages. The results are presented in the form of frequency distribution tables. A binary logistic regression was then used to determine which variables were associated with treatment failure. These are presented as odds ratios (OR) with a 95% confidence interval. Variables with a p-Value of less than 0.05 are considered significant.

The aim of this research is to highlight the value and significance of AI in TB clinical analysis and its role in public health, based on research conducted in various countries, in order to inform future tuberculosis control programmes. The study also identifies current research and treatment needs and challenges and describes the potential applications of AI in biology and public health in relation to tuberculosis.

3 Results

During the study period, 274 cases of tuberculosis relapse were recorded, of which 179 (65.3%) were male and 95 (34.7%) were female. The male-to-female sex ratio was 1.9. The average age was 44.7 ± 18.1 years, with a minimum age of 16 and a maximum age of 96. Apart from children under 15 years of age, all age groups in the study population were susceptible to developing tuberculosis relapses, with the highest incidence in the 25-34 age group at 24%, and other age groups at around 16.1% ± 0.8.
In terms of origin, more than half of the cases came from urban areas, i.e., 184 cases (67.2%), compared to 90 cases (32.8%) from rural areas. (Table 1).

Table 1. Sociodemographic characteristics of patients with tuberculosis relapse

	Number	Percentage
Gender (N=274)		
Male	179	65.3
Female	95	34.7
Age groups (N=274)		
Under 15	0	0
15–24	34	12.6
25 – 34	67	24
35–44	41	15.2
45–54	46	17.1
55–64	44	16.4
≥ 65	42	15.6
Marital status (n= 274)		
Single	58	21.2
Married	142	51.8
Widowed	44	16.1
Divorced	30	10.9
Middle class (N=274)		
Urban	184	67.2
Rural	90	32.8%

The cases of tuberculosis relapse studied were mainly pulmonary, with 214 cases (78.1%) and 60 cases (21.9%) extrapulmonary.
The diagnosis can be made by bacteriological examination to identify the germ responsible for the disease, Mycobacterium tuberculosis, by histological examination in some extrapulmonary forms, by radiology, and by clinical examination. Analysis of the data

revealed that 205 cases (74.8%) were confirmed bacteriologically, 26 cases (9.5%) were confirmed histologically, and 43 cases (15.7%) were examined by radiology and clinical examination. Among extrapulmonary forms, lymph node tuberculosis accounted for 8.7% of all cases, followed by pleural tuberculosis with 6.9%. Other forms of tuberculosis, such as bone, peritoneal, breast, skin, neuro-meningeal, intestinal, and urogenital tuberculosis, each accounted for less than 2% of all cases. (Table 2)

Table 2. Distribution of tuberculosis relapse cases by form, location, and diagnosis

	Number	Percentage
Type (n= 274)		
Pulmonary tuberculosis	214	78.1
Extrapulmonary tuberculosis	60	21.9
Bacteriological confirmation (n= 274)		
Bacteriologically confirmed	205	74.8
Histologically confirmed	26	9.5
Clinically	43	15.7%
Location (n= 274)		
Pulmonary	214	78.1
Ganglionic	24	8.7
Pleural	19	6.9%
Bone	4	1.5
Peritoneal	4	1.5
Breast	3	1
Skin	2	0.7%
Neuro-meningeal	1	0.4
Bone+neuro-meningeal	1	0.4
Intestinal	1	0.4%
Urogenital	1	0.4%

The therapeutic results showed a therapeutic success rate of 74.3%, divided into 39.2% (105 cases) cured and 35.1% (94 cases) having completed treatment. The failure rate was 4% (11 cases), the mortality rate was 7.8% (21 cases), the rate of vision loss was 9.8% (24 cases), the rate of resistance to anti-tuberculosis drugs was 3.4% (9 cases), and 1.5% (4 cases) of cases were not evaluated. (Table 3)

Table 3. Treatment outcomes for patients with tuberculosis relapse

	Number (268)	Percentage
Cure	105	39.2%

Treatment completed	94	35.1
Failure	11	4.1
Death	21	7.8
Lost to follow-up	24	9.0
Transfer to resistant form	9	3.4
Outgoing transfer	4	1.5

Several studies have shown that AI can predict the risk of relapse in patients after treatment, taking into account factors such as age, initial bacterial load, the presence of co-infections (such as HIV), and certain immunological markers. It can be used for the early detection of resistance to anti-tuberculosis drugs. Automated analysis of Mycobacterium tuberculosis genome sequences now makes it possible to rapidly detect mutations associated with resistance to major molecules such as rifampicin and isoniazid. These approaches are an alternative to conventional phenotypic methods, which are time-consuming and costly. By allowing the duration and combination of treatment to be adjusted according to the patient's biological profile, AI paves the way for more personalized medicine and is a valuable asset in the fight against resistant forms of tuberculosis.

Table 4. Analysis of factors associated with treatment failure : univriate and multiviate regression models

Predictor	P-value	Unadjusted OR (95% CI)	P-value	Adjusted OR (95% CI)
Age	0.570	1.005 (0.9868–1.024)	0.302	0.988 (0.965–1.011)
Sex M – F	0.611	1.206 (0.585–2.484)	0.780	1.118 (0.509–2.458)
Residential setting Urban – Rural	0.066	0.524 (0.263–1.043)	0.065	0.510 (0.249–1.044)
Form of tuberculosis Pulmonary – Extrapulmonary	0.412	1.446 (0.5997–3.485)	0.465	1.430 (0.548–3.733)
Non-adherence to treatment Bad Servance – Good Serve	0.166	1.678 (0.8061–3.495)	0.311	1.587 (0.649–3.877)
Weight change	0.013	0.388 (0.183–0.821)		0.373 (0.166–0.841)

In univariate analysis, weight gain was significantly associated with failure of anti-tuberculosis treatment (unadjusted OR of 0.388; 95% CI: 0.183 to 0.821; P = 0.013). The variable place of residence showed an association close to the significance threshold, with an unadjusted OR of 0.524 (0.263–1.043; p = 0.066). No other variable was significantly associated with treatment failure. In multivariate analysis, after adjusting for all variables, only weight gain remained significantly associated with treatment failure (adjusted OR 0.373; 95% CI: 0.166 to 0.841; p= 0.017). The variable of place of residence remained

insignificant but close to the threshold (adjusted OR of 0.510; 95% CI: 0.249–1.044; p= 0.065). The other variables remained statistically insignificant (Table 3).
AI is now a powerful tool for analyzing complex data. Machine learning and deep learning methods make it possible to use large clinical, microbiological, and genetic datasets to predict the course of disease.

Figure 1. Applications of AI to the analysis of public health and biological data

AI is a powerful tool not only for individuals but also for public health and TB epidemiology. Predictive algorithms can model disease transmission between region while taking into account demographic variables such as population mobility, urban density, vaccination rates, and accessibility to healthcare. They also help identify high-risk areas by simultaneously analyzing health, socio-economic, and environmental data. This multi-dimensional approach allows us to create dynamic and predictive maps for public health interventions, identify at risk groups, and optimize the allocation of our resources (Figure 1).

4 Discussion

Tuberculosis relapse occurs when an individual who has already undergone effective treatment for tuberculosis and has been declared cured or has completed treatment sees the disease reappear. Our research has shown that various age groups, ranging from 25 to 60 years old, are at risk. A variety of studies have highlighted this phenomenon, however, with variations: some studies have observed a risk of relapse in tuberculosis patients aged 19 to 44 , while others have identified this risk in those aged 30 to 59 [8]. Furthermore, another study has shown that this risk of relapse is only present in individuals over the age of 65 [9]. In our research, being male is associated with an increased risk of relapse [9,10]. The ratio compared to females is 5:1. Factors such as toxicity and employment status are significant in men, while women are less frequently studied. With regard to geographic origin, in our study, it was observed that urban residents are more exposed to the risk of relapse than rural residents, contrary to other studies that indicate a higher exposure to the risk of relapse in rural or resource-limited areas compared to urban areas [9]. Tuberculosis relapses mainly

manifest as pulmonary tuberculosis. Most research indicates that the majority of relapse cases occur after pulmonary tuberculosis, particularly cavitary forms [11]. Relapses are less common following extrapulmonary tuberculosis, but they can occur, particularly in urogenital or generalized cases. Patients with resistant tuberculosis are at significantly higher risk of relapse, changing the initial site of infection [11,12] . Other risk factors for relapse include poor compliance and the presence of comorbidities such as alcoholism, HIV, or diabetes [9,10].
The treatment success rate observed in our study is approximately 75%. Other research has indicated that this rate can vary between 65% and 75%, depending on the populations and contexts studied. 32% of patients who relapse may experience treatment failure, loss to follow-up, or death. However, in our study, this rate is slightly lower, at around 21%. Treatment resistance leads to a significant decrease in success rates, with cure rates falling to 20-34% in patients with resistant tuberculosis. Relapses are associated with a higher risk of mortality, treatment failure, and subsequent recurrence, particularly in the presence of comorbidities such as diabetes or HIV, or in cases of meso-compliance [13].
Weight change, whether stable or decreasing during the treatment period, was the only variable that showed significant regression in cases of treatment failure, making it a useful prognostic indicator. This weight changes throughout the treatment period is a very important factor to monitor, as it can indicate therapeutic progress. Stable weight or weight loss during the treatment period can be a factor in relapse, even after successful treatment. To help patients control their weight and improve their health, their eating habits and level of physical activity must be taken into account [14].
Ai has the potential to monitor health status, whether therapeutic or nutritional, ensuring therapeutic or nutritional therapeutic success without recurrence, both clinically and epidemiologically. It can predict relapse and drug resistance, enabling patients care to be adapted accordingly. AI uses multidimensional modelling to identify high-risk areas and mode of can also facilitate collaboration between clinicians and simplify decision-making based on large clinical data sets at each stage of the treatment period. Notably, it can detect potential medical errors [15].

5 Conclusion

This study highlights the low rate of therapeutic success and tuberculosis relapse, emphasizing the need for an appropriate action plan to be implemented. In addition to ensuring patients adhere to their treatment, nutritional management is essential to improving their quality of life and preventing relapses and resistance to anti-tuberculosis drugs. It is also imperative to offer patients psychological and social support, as well as adequate health education and awareness about tuberculosis.
Thanks to technological advances, integrating AI through predictive models based on the machine and deep learning could facilitate the early detection of tuberculosis relapse cases at high risk of recurrence during or after treatment. This would enable the protocol to be adapted to each individual case. In the long term, this could enhance the management of this patient group.

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