Expert Systems in Tuberculosis Prevention Established in Certainty Factor

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***Abstract*—Tuberculosis remains a highly relevant public health concern, especially in contexts with limited access to medical services, highlighting the need for tools that support early diagnosis. In this study, a web-based expert system was developed to assist in tuberculosis detection, using Buchanan's methodology, which consists of five phases: identification, conceptualization, formalization, implementation, and validation. The system was designed with a knowledge rule-based approach and incorporated the Certainty Factor to quantify confidence in diagnostic conclusions. Validation was carried out through expert judgment using a 15-question survey. The results showed a high overall positive consensus, with question 13 standing out as it obtained the highest mean score (4.80) and the lowest dispersion (SD = 0.61), reflecting the most favorable perception and greatest agreement among the experts. Conversely, question 4 recorded the lowest mean score (4.00) and the highest dispersion (SD = 1.12), indicating aspects of the system that generated more divided opinions. Overall, these findings confirm that the system is effective, reliable, and usable, making it a relevant tool to support clinical decision-making in resource-limited settings. As an additional contribution, the integration of complementary technologies is suggested, such as (ML) algorithms, radiological image analysis, and mobile applications for symptom tracking, in order to optimize early detection and strengthen clinical care for tuberculosis.**

Keywords*—Buchanan's methodology; certainty factor; expert system; public health; tuberculosis; web application

I. Introduction

Tuberculosis (TB) is an infectious disease caused by Mycobacterium tuberculosis, which primarily affects the respiratory system, although it can also compromise other vital organs. Since ancient times, TB has represented a significant threat to global public health and, despite advances in research, diagnosis, and therapies, it continues to be one of the major challenges in the healthcare field. According to the World Health Organization (WHO), millions of new cases and hundreds of thousands of deaths are reported each year, keeping TB among the deadliest infectious diseases worldwide, especially in low-resource regions [1] [2]. Likewise, it is necessary to implement preventive measures that allow anticipating the onset of symptoms and, in this way, facilitate the administration of timely and appropriate treatment for each person.

The control of tuberculosis faces various structural and clinical obstacles. One of the most critical is the difficulty in achieving early and accurate diagnosis, since initial symptoms such as persistent cough, mild fever, or weight loss are often confused with other common respiratory diseases. This delay in detection not only prevents the timely administration of treatment but also facilitates community transmission of the disease. In addition, the lack of knowledge among the population about the modes of transmission, prevention, and treatment of TB intensifies its spread, particularly in environments where overcrowding, poverty, and limited healthcare coverage persist [3]. Added to this is the emergence of drug-resistant strains (MDR-TB and XDR-TB), which hinder therapeutic effectiveness, increase healthcare costs, and prolong treatment regimens. Finally, insufficient medical infrastructure and a lack of specialized personnel in many underdeveloped regions limit diagnostic, monitoring, and control processes, weakening eradication programs established by international organizations [4]. Altogether, these limitations make it evident that traditional approaches are insufficient to address the magnitude and complexity of the problem.

In light of this reality, there is a need to incorporate innovative technological tools to support healthcare systems in the identification, control, and treatment of tuberculosis. In this sense, expert systems and (AI)represent an alternative with great potential, as they allow clinical information to be processed under conditions of uncertainty, reduce the margin of error in medical decision-making, and generate faster and more reliable diagnoses [5]. Moreover, these tools have the capacity to optimize available resources, as they can be implemented in low-infrastructure environments and simultaneously serve a large number of users. Their usefulness lies not only in improving early diagnosis but also in supporting less-experienced physicians, standardizing clinical criteria, and providing support in high-demand healthcare contexts. The application of these technologies can significantly contribute to strengthening public health policies, improving the operational efficiency of health services, and ultimately reducing morbidity and mortality rates associated with tuberculosis [6] [7]. Thus, the development and implementation of expert systems is justified as a key strategy not only for individual clinical care but also for the global epidemiological control of this disease.

Therefore, this research focuses on developing an expert system (ES) for the early identification of tuberculosis, applying Buchanan's methodology for the construction of expert systems. The objective of the study is to diagnose tuberculosis based on symptoms reported by the patient and to provide a level of certainty through the use of the Certainty Factor (CF), with the purpose of supporting medical personnel in clinical decision-making and contributing to the prevention and control of tuberculosis.

II. Literature Review

This section presents the structure of the literature review, which is organized around two main axes. First, related works are addressed, where previous research by various authors who have applied expert systems in the medical field is analyzed. The purpose of this section is to contextualize the object of study, identifying advances and limitations in previous research in order to provide a broader and more well-founded perspective on the topic. Second, the theoretical foundations are developed, presenting the conceptual frameworks and theories related to the central variables of this research: Expert Systems and Tuberculosis.

A. Related Work

Various studies have contributed to advances in the detection of tuberculosis. In particular, the authors [8] [9] [10] highlight the importance of web-based expert systems to facilitate the diagnosis of respiratory diseases. Their proposal focuses on six pathologies: tuberculosis, bronchitis, pneumonia, pleurisy, tonsillitis, and asthma. To achieve more accurate results, the system uses 40 symptomatic indicators as a source of information. The reported results show that the application reaches a considerable level of effectiveness, offering reliable diagnoses for these diseases. In order to enrich previous studies, an ES was designed exclusively focused on tuberculosis diagnosis, especially aimed at people who do not have timely access to medical checkups. For this purpose, the Case-Based Reasoning (CBR) method was applied, which allows comparing the symptoms of a new patient with records of previous cases and thus estimating the most probable diagnosis. This approach, supported by expert knowledge, is presented as a practical and reliable alternative within the healthcare field. The results showed that pulmonary tuberculosis reached 85% similarity, while the extrapulmonary form obtained 62%, which allowed concluding that the analyzed case corresponded to pulmonary tuberculosis. In hospital settings, limitations persist in guaranteeing quality and truly personalized care for each patient. In response to this challenge, the developed ES is presented as a clinical support tool that follows a specialized assistance pattern in cases of pulmonary tuberculosis, even before confirmation through laboratory tests. Its architecture is based on a rule base and a patient knowledge base, which interact with an inference engine responsible for processing the data entered through the user interface. The usability evaluation yielded an average score of 5.6 out of 7, reflecting a performance above the expected standard. In this sense, the Tuberculosis Diagnosis ES, developed with Exsys Corvid, constitutes a robust and effective technological solution, rule-based, aimed at optimizing the diagnostic process and improving the quality of hospital services [11] [12]. Thus, a development based on expert systems and information technology aims to optimize TB diagnosis, overcoming existing limitations in timely access to healthcare services. For this purpose, an application supported by expert system architecture was implemented, applying the Forward Chaining method, which enables the processing of clinical data and symptoms to generate diagnostic inferences. The result of this work was an application capable of identifying TB accurately and providing users with structured information on symptoms, as well as recommendations and alternative solutions to the disease, consolidating itself as an efficient technological tool to support the diagnostic process and medical guidance [13] [14].

Tuberculosis is an infectious disease mainly of bacterial origin that critically affects the respiratory system and, in some cases, other organs, making it a highly relevant public health problem. In this context, various studies have proposed technological solutions aimed at improving its diagnosis and surveillance. For example, one study aimed to design an ES that replicated the clinical reasoning of a health professional to support the diagnosis of pulmonary tuberculosis based on the identification of symptoms in patients, considering economic limitations in access to healthcare services. This system, based on Bayes' Theorem formulated by Thomas Bayes and refined by Laplace, achieved a positive diagnostic rate of 87%, demonstrating its effectiveness in the early detection of the disease and its applicability in resource-limited settings [15] [16]. Complementarily, a web-based ES was developed that used the Dempster-Shafer inference method, integrating a PHP backend with MySQL and a frontend built with HTML, CSS, and JQuery. This project followed a structured methodology that included preliminary studies, literature review, symptom collection, knowledge rule design, modeling, implementation, and evaluation, achieving the generation of reliable probabilistic diagnoses for both healthcare professionals and general users. In a different line, another work proposed an online ES oriented to the epidemiological surveillance of tuberculosis, developed with web platforms and the Swi-Prolog programming language, following Buchanan's methodology composed of four phases. Validation, through a 15-item questionnaire distributed across three dimensions, reported an 85% acceptance rate among users, supporting its relevance and effectiveness as a support tool for tuberculosis prevention and awareness [17] [18]. In another instance, [19] [20] explored the application of ML techniques in the diagnosis of tuberculosis, evaluating the CAD4TB computer-assisted detection system, originally designed for adults, on pediatric radiographs of children under 13 years of age. The model, trained with pediatric radiological images and validated by specialists through a prospective observational methodology, showed a significant improvement in its performance after fine-tuning, increasing from an AUC of 0.58 to 0.72 ($p = 0.0016$), evidencing the potential of this tool to strengthen diagnosis in pediatric populations and highlighting the importance of continuing validation in larger and more diverse samples.

Likewise, the authors [21] [22] developed an expert API for the early detection of tuberculosis, implementing inference algorithms such as Forward Chaining and Certainty Factor in order to support preliminary diagnosis of the disease. The proposal materialized through an API-based architecture that processes symptoms and generates diagnostic inferences, while its validation was carried out through functionality tests and in-depth interviews with medical specialists. Satisfactory results were obtained, evidencing that the system is capable of providing reliable support in the early identification of tuberculosis, thus constituting a viable technological tool to strengthen prevention and diagnostic tasks in healthcare. In another study, a Bayesian inference-based ES was developed to facilitate and speed up tuberculosis diagnosis, reducing the time required by conventional procedures that include clinical interviews and sputum laboratory analysis. Microsoft

Visual Studio 2010 was used as the programming platform and Microsoft Access 2010 as the data management system for its construction. The methodology implemented included the creation of a medical knowledge base, the integration of a Bayes-based inference engine, and the validation of the system through tests with real clinical cases. The results showed that the tool is capable of analyzing patient symptoms and clinical data to calculate the probability of tuberculosis, constituting a reliable resource that optimizes diagnosis and supports medical decision-making, offering advantages over traditional methods in both efficiency and accuracy [23] [24] [25]. Thus, the development of a hybrid Clinical Decision Support System (CDSS) aimed at recommending individualized treatments for patients with drug-resistant tuberculosis facilitated the application of personalized therapies by less experienced physicians. A hybrid approach combining an expert knowledge base with ML was used to identify complex patterns in clinical data, evaluating its performance with metrics such as precision at 1, mean reciprocal rank, and mean average precision. Indeed, the methodology included the construction of the knowledge base, the iterative generation of training datasets, analysis through ML algorithms, and validation with independent data to detect overfitting. Finally, the results showed an accuracy of 95% in recommending the first treatment, although independent validation reduced accuracy to 78%, evidencing that this hybrid approach constitutes a promising step toward the automation of personalized treatment and can be applied to other pathologies [26] [27].

According to study [28], computers constitute a widely used tool in the medical field to support the diagnosis of respiratory diseases, including tuberculosis. In this context, the research focused on the development of an ES aimed at the early diagnosis of this pathology. This system estimates the probability level of a patient having the disease, expressed through a certainty value. This value is determined using the CF, a methodology that allows quantifying the degree of confidence in environments characterized by high uncertainty and that is also capable of representing absolute convictions within the diagnostic inference process. Taking the context into account, this research is complemented by the evaluation of an ES applied to ML techniques for the classification of TB bacteria through images. Additionally, algorithms such as Decision Trees, Random Forest (RF), and Adaptive Boosting (AdaBoost) were trained using a set of 126 images classified into two classes, as part of the methodology. As a result, it was observed that the Random Forest model was the most outstanding, reaching an accuracy of 85%, making it the most effective model for tuberculosis diagnosis through the ES [29] [30]. On the other hand, [31] [32] carried out a study focused on tuberculosis prevention through the implementation of a Bayes-based ES, with the aim of providing a more accurate diagnosis. The methodology included the identification of medical problems related to the treatment of the disease. It was observed that, in one patient, a high probability of tuberculosis could be determined, with a confidence value of 64%, evidencing that this approach enables medical personnel to diagnose and recognize symptoms quickly and efficiently. According to the authors [33] [34], the rapid spread of tuberculosis is favored by the lack of public knowledge about the disease. In this context, the implementation of an ES allows the application of early medical diagnostic techniques, with the aim of facilitating the prompt administration of treatment. Regarding the results obtained through system testing, together with validation using the black-box technique, it was demonstrated that each functionality operates correctly and that the information provided is reliable. Additionally, the system showed efficient performance in managing a high number of concurrent users, making it suitable for clinical environments with high demand for consultations.

In this sense, one of the deficiencies identified in previous studies is the lack of integration of web-based expert systems that combine rule-based inference, the certainty factor, and validation through expert judgment, which limits the applicability of findings in resource-limited contexts. Moreover, most studies focus on isolated methods, such as Bayesian inference or ML models, without combining multiple approaches, which reduces the generalization and robustness of the diagnostic support provided.

B. Theoretical Bases

1) Tuberculosis: TB is a chronic infectious disease primarily caused by Mycobacterium tuberculosis, an acid–alcohol-resistant bacillus with a high capacity for airborne transmission. Its most common form affects the respiratory system, although in extrapulmonary presentations it can involve various organs and tissues. Likewise, infection occurs after the inhalation of contaminated droplets that reach the pulmonary alveoli, where the microorganism establishes a complex interaction with the host's immune response. From a clinical and epidemiological perspective, TB represents a major global public health challenge due to its high impact in terms of prevalence and mortality, in addition to its close association with social determinants such as poverty, malnutrition, and overcrowding. Despite the availability of effective therapies, poor treatment adherence promotes the emergence of multidrug-resistant strains, which significantly complicates its control and eradication [35]. In summary, this disease causes severe pulmonary and respiratory complications that, over time, can significantly compromise both quality of life and life expectancy.

a) Pulmonary tuberculosis: It is the most common form of tuberculosis, characterized by infection of the lungs with Mycobacterium tuberculosis. It is transmitted primarily through respiratory droplets expelled when coughing, sneezing, or talking, making it the main source of infection in the community [36]. Clinical manifestations include chronic cough, hemoptysis, chest pain, fever, night sweats, weight loss, and fatigue.

b) Extrapulmonary tuberculosis: It refers to all forms of tuberculosis that affect organs and systems outside the respiratory system. It accounts for approximately 20% of cases and can involve lymph nodes, pleura, bones, meninges, kidneys, digestive system, skin, among others. Its symptoms depend on the affected site, and although it is not usually transmissible, it poses a clinical and diagnostic challenge due to the variety of presentations and associated complications [37].

Fig. 1 shows a horizontal bar graph representing the percentage of TB cases by age group during the years 2019, 2021, and 2022, highlighting that the 30 to 49 age groups concentrate the highest proportion of cases, while the age extremes have a lower incidence. On the other hand, Fig. 2 presents a map of Peru with the TB incidence rate per 100,000 inhabitants in 2022, where the red regions show the highest risk (≥ 76), the yellow ones intermediate risk (50 to 74), and the green ones lower risk (< 50). This figure is complemented by a table detailing the cases by department and year, showing that departments such as Callao, Lima, and Ucayali have had the highest rates in recent years. Together, these images allow us to visualize both the age distribution and the geographic distribution of TB in the country over time.

2) Expert systems: An ES is a type of computational system within the field of AI designed to emulate the reasoning process and decision-making ability of a human specialist in a specific domain. Its operation is based on a knowledge base, which contains facts and rules about the application area, and an inference engine, responsible for applying these logical rules to solve problems, provide diagnoses, or recommend solutions. On the other hand, these systems do not seek to replace the human expert but rather to assist in solving complex problems, especially in contexts where specialized expertise is limited or unavailable. Moreover, their main value lies in offering consistency in reasoning, speed in generating solutions, and the possibility of transferring expert knowledge to technological platforms [39] [40] [41]. Ultimately, expert systems aim to emulate the knowledge of a human specialist in a given field in order to solve complex problems, provide recommendations, and support decision-making in an efficient and reliable manner, even in the absence of a human expert. Consequently, Fig. 3 shows the architecture of Buchanan's methodology for an expert system, illustrating the flow of knowledge from a human expert to an end user.

III. METHODOLOGY

A. *Definition of the Buchanan Methodology*

Buchanan's methodology constitutes a systematic approach applied to the analysis and design of systems, aimed at solving complex problems through an orderly, structured, and progressive process. Its foundation lies in breaking down the problem into sequential phases that enable progress from an abstract understanding of the need to the achievement of an implemented and operational solution. These phases include: identification, where the problem and its boundaries are recognized; conceptualization, in which objectives are defined and a preliminary conceptual model is established; formalization, which specifies the technical and functional requirements of the solution; implementation, where the design is materialized into a functional system; and execution or operation, the stage in which the solution is integrated into the real environment with monitoring and feedback mechanisms. This framework is illustrated in Fig. 4, which presents the phases of Buchanan's methodology, visually showing each stage of the process [42]. Consequently, this methodology reduces ambiguity, optimizes decision-making, and ensures consistency across stages, making it a robust tool to guarantee the quality, relevance, and effectiveness of developed systems.

1) Identification: In accordance with the established framework, this stage marks the beginning of Buchanan's methodological process, starting with the identification phase. Table I presents the Identification phase corresponding to Buchanan's methodology, in which the main issue is recognized: the difficulty of diagnosing tuberculosis early and accurately due to the similarity of its symptoms with other respiratory diseases. Based on this, the need is established to develop an expert system that supports medical personnel in clinical decision-making. Likewise, the objective of this phase is defined as the clear delimitation of the problem and the initial scope of the system, which are oriented toward the collection and analysis of symptoms through the CF model to provide a level of confidence in the diagnosis. Consequently, the expected benefit is highlighted: to contribute to the prevention and control of tuberculosis through a reliable computational tool that supports clinical diagnosis. In this sense, Table II represents the main sources of knowledge integrated into the expert system. These include specialists such as pulmonologists and infectious disease experts, who contribute to the identification of symptoms and risk factors, as well as official WHO guidelines that serve as references in the formulation of rules [43]. It is important to emphasize that the beginning of this phase constitutes the starting point for the development of subsequent processes.

2) Conceptualization: In this phase, the functional objectives and the conceptual model of the expert system are defined. The purpose is to establish an overall vision of how the proposed solution will operate, identifying its main components and the relationships among them, without yet delving into the technical details of implementation. Consequently, Fig. 5 describes the system objectives, outlining what it does allowing the user to enter symptoms, calculate a certainty factor, and generate recommendations—and what it does not do such as replacing a physician or laboratory tests. In addition, the diagram illustrates the conceptual model, which includes the key symptoms, how knowledge is represented (through rules and a certainty factor), and the definition of conceptual rules with examples [44]. Finally, it shows the expected outcome: an expert system report that, based on the certainty level, identifies the type of tuberculosis (active, extrapulmonary, or latent) and suggests actions such as visiting a healthcare center for confirmatory tests.

Knowledge Representation

The expert system's knowledge is represented by production rules. The structure of these rules is shown below:

$$\boxed{\textbf{IF } (\textit{Condition}) \implies \textbf{THEN } (\textit{Conclusion}) \ [\textit{Certainty Factor}]}$$

This formalism allows the system to combine multiple pieces of evidence and generate diagnostic conclusions with associated degrees of certainty. The CF ranges from 0 (no confidence) to 1 (absolute confidence), providing a way to handle uncertainty in medical decision-making.

3) Formalization: The formalization stage consists of transforming the knowledge obtained from experts and structured documentary sources into a format that can be processed by the system. Accordingly, Table IIIc presents the formalization of the expert system rules for tuberculosis diagnosis, organized into three subtables. Subtable III presents the rules based on clinical symptoms, which consider

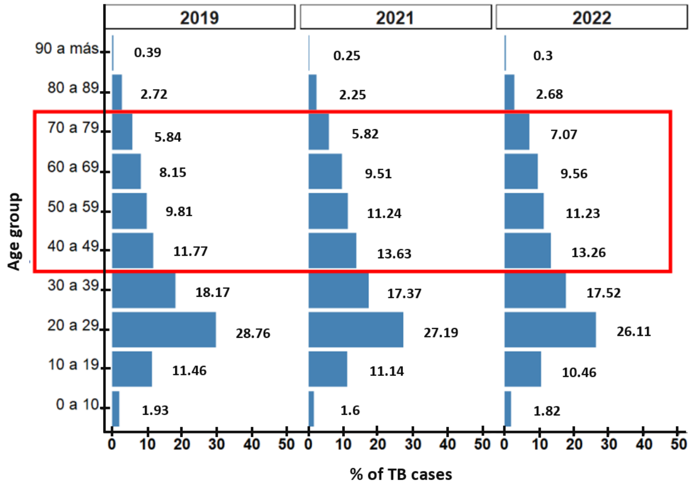
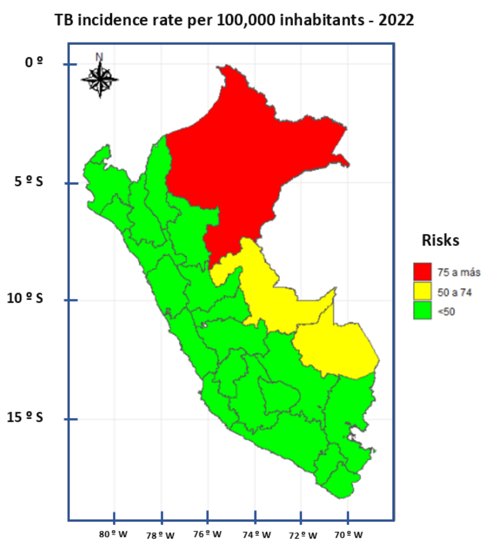


Fig. 1. Statistical graph of TB cases by age [38].



Departament	2019	2020	2021	2022
Peru	**105.14**	**78.06**	**82.25**	**34.32**
AMAZONAS	18.97	15.93	21.36	10.94
ANCASH	66.31	49.21	47.82	19.59
APURIMAC	20.35	12.77	16.38	9.77
AREQUIPA	60.71	44.81	46.00	17.24
AYACUCHO	31.87	23.50	36.23	10.72
CAJAMARCA	15.81	11.01	13.87	6.46
CALLAO	180.46	124.71	127.39	51.12
CUSCO	35.50	28.00	27.18	9.47
HUANCAVELICA	19.64	13.96	14.27	5.41
HUANUCO	60.96	48.80	54.83	27.80
ICA	161.25	113.72	112.13	44.90
JUNIN	59.50	42.67	45.93	19.86
LA LIBERTAD	85.36	59.75	64.93	29.99
LAMBAYEQUE	89.26	47.15	55.18	22.11
LIMA	131.09	109.57	115.28	53.86
LIMA CENTRO	264.66	173.99	181.92	76.62
LIMA ESTE	148.57	114.27	108.47	41.05
LIMA NORTE	125.11	94.53	97.39	41.81
LIMA SUR	104.96	81.66	81.62	29.47
LORETO	140.10	121.45	144.18	75.22
MADRE DE DIOS	191.10	129.45	152.93	52.29
MOQUEGUA	83.00	76.79	68.09	25.05
PASCO	12.15	11.40	9.89	4.83
PIURA	32.70	21.73	27.71	11.41
PUNO	28.88	23.83	31.93	9.78
SAN MARTIN	41.48	31.57	33.78	16.00
TACNA	131.17	111.33	99.05	42.67
TUMBES	54.65	55.66	37.23	23.50
UCAYALI	209.77	144.12	164.35	74.32

Fig. 2. TB cases by province per year [38].

combinations of manifestations such as persistent cough, fever, night sweats, or weight loss, each associated with a specific CF. Subtable IIIb includes the rules related to risk factors, such as recent exposure to the disease, HIV coinfection, or residence in endemic areas, which increase the diagnostic probability. In this regard, subtable IIIc contains the rules derived from diagnostic tests, such as chest X-rays, sputum smear microscopy, molecular tests, or cultures, which present the highest certainty values, highlighting their relevance in confirming the disease. On the other hand, Fig. 6 represents the database model, which is responsible for the flow and integrity of the data within the expert system [45]. In this sense, the TBExpertSystem database was implemented to comprehensively manage the information that feeds the expert system for tuberculosis diagnosis, in accordance with the business rules defined in the previous stages.

IV. Mathematical Formulas in Expert Systems

The following formulas are frequently used in expert systems for formalizing rules, handling uncertainty, and applying fuzzy logic. Therefore, mathematical expressions have been compiled that demonstrate the logic underlying the operation of these systems [46] [47].

1) Certainty Factor (CF): The CF is a mechanism that allows us to quantify the degree of confidence in a hypothesis when considering new evidence. This process adjusts the prior certainty of H based on the strength of the evidence E [see Eq. (1)].

$$CF_{H,E} = CF_H + CF_E \cdot (1 - CF_H) \quad (1)$$

Used to combine the certainty level of a hypothesis H with the evidence E.

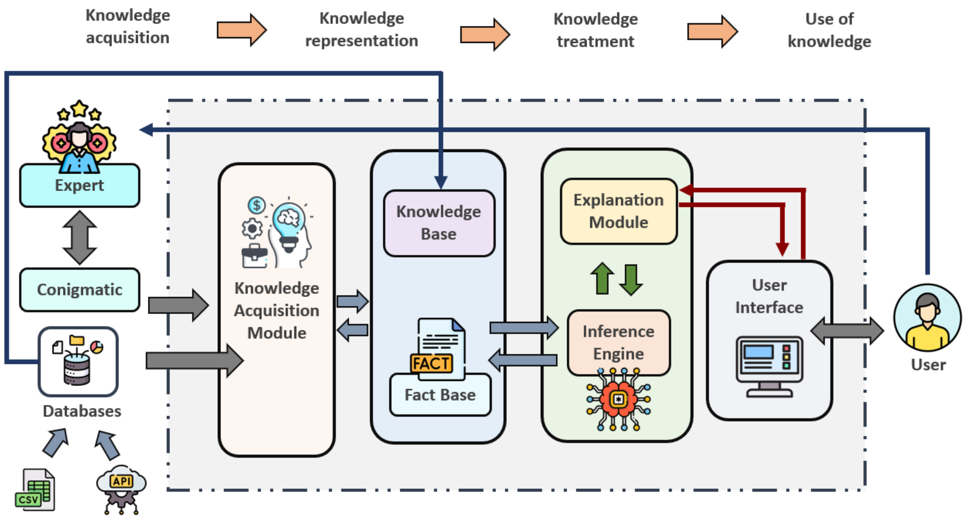


Fig. 3. Buchanan methodology architecture.

TABLE I. IDENTIFICATION PHASE: BUCHANAN METHODOLOGY

Element	Description
Identified problem	Difficulty in the early and accurate detection of tuberculosis because its symptoms can be confused with other respiratory diseases.
Need	Develop an expert system that supports medical personnel in clinical diagnosis, reducing ambiguity and improving decision-making.
Phase objective	Recognize and define the problem to be solved, establishing the initial scope of the system to be implemented.
Initial Scope	The system will be designed to collect patient-reported symptoms, process them using the CF model, and provide a level of certainty regarding the possible presence of tuberculosis.
Expected Benefit	Contribute to the prevention and control of tuberculosis by providing reliable computational support in the diagnostic process.

TABLE II. KNOWLEDGE SOURCES FOR THE EXPERT SYSTEM

Source	Description
Expert interviews	Consultations with pulmonologists and infectious disease specialists to determine the most relevant TB symptoms and risk factors.
WHO guidelines	Use of the Global Tuberculosis Report and official protocols as reference for rule formulation.
Clinical literature	Medical textbooks and peer-reviewed journals on internal medicine and infectious diseases.
Patient case data	Historical clinical cases used to validate CF and refine the knowledge base.

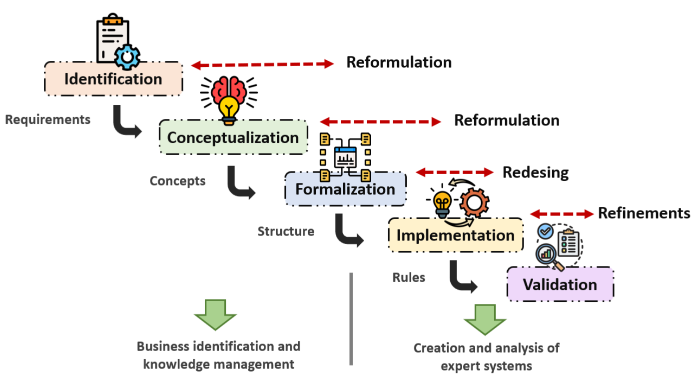


Fig. 4. Buchanan methodology.

2) Bayesian probability: Bayesian probability updates the degree of belief in a hypothesis H when new evidence E is observed. This process combines the prior probability with the likelihood of the evidence to obtain a more accurate estimation [see Eq. (2)].

$$P(H \mid E) = \frac{P(E \mid H) \cdot P(H)}{P(E)} \tag{2}$$

Fundamental formula for probabilistic expert systems. It calculates the probability of hypothesis H given that evidence E occurred.

3) Bayesian probability with multiple evidences: This extended Bayesian approach calculates the probability of a hypothesis H when multiple evidences are considered simultaneously. It combines prior knowledge with the likelihood of each evidence to refine the overall estimation [see Eq. (3)].

$$P(H \mid E_1, E_2, \ldots, E_n) = \frac{P(H) \cdot \prod_{i=1}^{n} P(E_i \mid H)}{P(E_1, E_2, \ldots, E_n)} \tag{3}$$

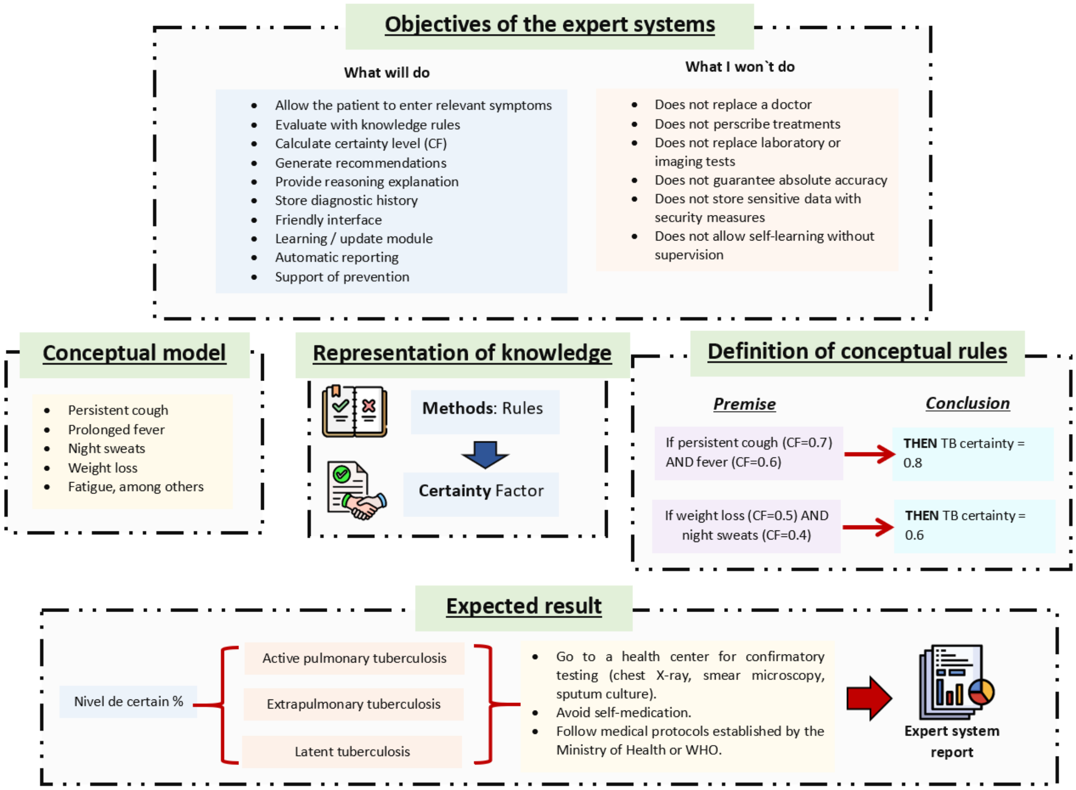


Fig. 5. Expert system process functionality.

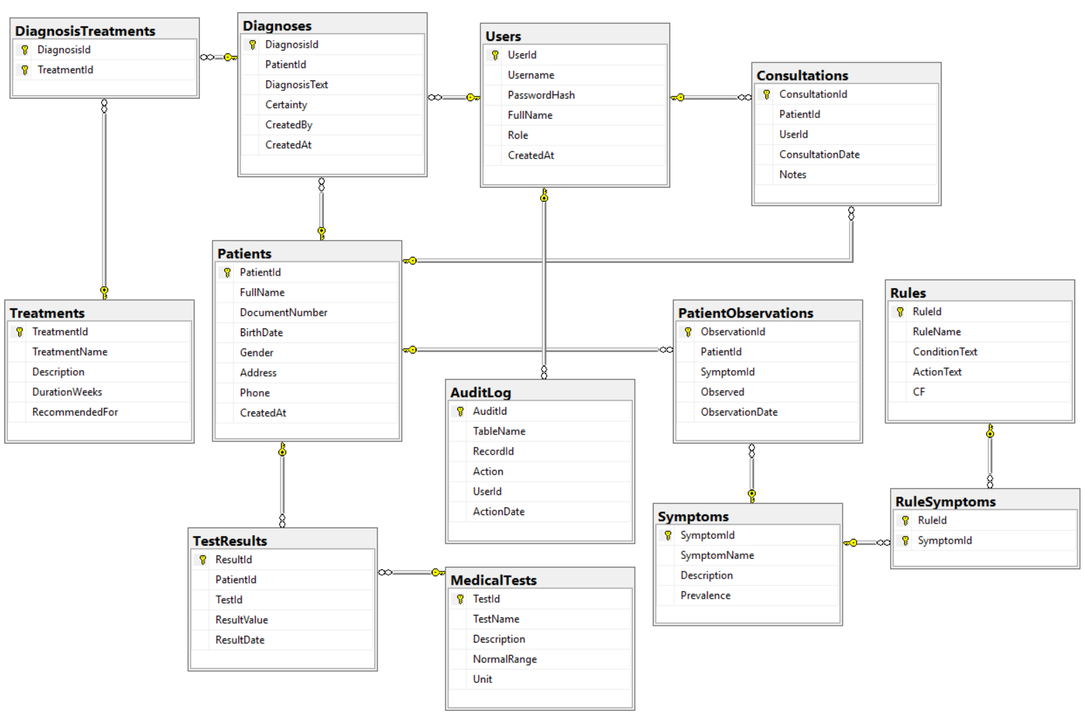


Fig. 6. Data flow for the expert system.

TABLE III. FORMALIZATION OF RULES FOR TUBERCULOSIS DIAGNOSIS

(A) RULES BASED ON CLINICAL SYMPTOMS

Rule	Condition	Certainty (CF)
R1	Persistent cough $\wedge$ Fever $\rightarrow$ TB	0.4
R2	Night sweats $\wedge$ Weight loss $\rightarrow$ TB	0.3
R3	Persistent cough $\wedge$ Hemoptysis $\rightarrow$ TB	0.5
R4	Chest pain $\wedge$ Breathing difficulty $\rightarrow$ TB	0.25
R5	Fatigue $\wedge$ Weakness $\rightarrow$ TB	0.2
R6	Fever $\wedge$ Night sweats $\rightarrow$ TB	0.35
R7	Persistent cough $\wedge$ Loss of appetite $\rightarrow$ TB	0.3
R8	Persistent cough $\wedge$ Weight loss $\rightarrow$ TB	0.45
R9	Chronic cough lasting $>$ 3 weeks $\rightarrow$ TB	0.55

(B) RULES BASED ON RISK FACTORS

Rule	Condition	Certainty (CF)
R10	Recent TB exposure $\wedge$ Persistent cough $\rightarrow$ TB	0.6
R11	HIV-positive patient $\wedge$ Fever $\wedge$ Night sweats $\rightarrow$ TB	0.65
R12	Living in high-risk area $\wedge$ Chronic cough $\rightarrow$ TB	0.5
R13	History of untreated TB contact $\rightarrow$ TB	0.55

(C) RULES BASED ON DIAGNOSTIC TESTS

Rule	Condition	Certainty (CF)
R14	Positive Mantoux test $\rightarrow$ TB	0.7
R15	Abnormal chest X-ray $\rightarrow$ TB	0.8
R16	Positive sputum smear microscopy $\rightarrow$ TB	0.85
R17	Positive GeneXpert test $\rightarrow$ TB	0.9
R18	Positive sputum culture test $\rightarrow$ TB	0.95

Extended version for multiple simultaneous pieces of evidence. It evaluates the probability of hypothesis H given evidences $E_1, E_2, \ldots, E_n$.

4) Fuzzy membership function (triangular): The triangular membership function represents how a value x belongs to a fuzzy set A with a gradual transition. It is widely used in fuzzy logic due to its simplicity and ability to approximate uncertainty smoothly [see Eq. (4)].

$$\mu_A(x) = \begin{cases} 0 & x \leq a, \\ \dfrac{x-a}{b-a} & a < x \leq b, \\ \dfrac{c-x}{c-b} & b < x < c, \\ 0 & x \geq c \end{cases} \tag{4}$$

Defines the membership of a value x to a fuzzy set A. The shape is triangular, which is commonly used in fuzzy logic.

5) Fuzzy inference (Mamdani rule): The Mamdani inference rule models the reasoning process in fuzzy systems by combining fuzzy sets through min–max operations. It determines the degree to which an output z belongs to set C given the inputs x and y [see Eq. (5)].

$$\mu_C(z) = \sup_{x,y} \left(\min \left(\mu_A(x), \mu_B(y) \right) \right) \tag{5}$$

Represents a fuzzy inference for a rule. If $x \in A$ and $y \in B$, then $z \in C$.

6) Defuzzification by centroid: The centroid defuzzification method transforms a fuzzy output set into a crisp numerical value. It is the most common technique in fuzzy control systems, as it provides a balanced representation of all possible outcomes [see Eq. (6)].

$$z^* = \frac{\int_Z z \cdot \mu_C(z)\, dz}{\int_Z \mu_C(z)\, dz} \tag{6}$$

Converts a fuzzy value into a numerical output. This method is widely used in fuzzy control systems.

7) Information entropy: Information entropy quantifies the level of uncertainty or randomness in a variable X. It measures how much information is gained or how unpredictable the outcomes are within a system [see Eq. (7)].

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i) \tag{7}$$

Measures the uncertainty associated with a random variable X. Entropy quantifies the amount of information or unpredictability.

a) Implementation: Finally, the implementation phase corresponds to the translation of the previous stages into a web-based expert system, in which the knowledge base, inference engine, and user interface are integrated into a functional platform. In this stage, the defined rules are materialized, the reasoning mechanisms are programmed, and the functionalities that enable interaction with the end user are designed [48]. Thus, Fig. 7 presents the user interface corresponding to the login module, which allows users to enter their credentials (username, password, and assigned role). In addition, it incorporates a search module that verifies whether the user belongs to the healthcare system, ensuring real-time data validation. Finally, a registration form is provided to enable the creation of new accounts, ensuring proper access management and traceability of user profiles within the web expert system.

In another instance, Fig. 8 presents three user interface panels of an information or expert system on tuberculosis (TB). The panel in Fig. 8a, labeled "Administrative panel," is designed for user management, displaying a list of records, search options, and buttons to register, update, or delete user codes. The panel in Fig. 8b is a "Rules Record," where detection rules for different types of TB are defined and managed, including details such as rule name, condition, action, and centrality. Finally, the panel in Fig. 8c is the "User panel," which shows the medical history of a patient (Juan Alvarez Perez) and a "Quick Symptom Form" that allows the user or physician to register symptoms and predict the type of TB, highlighting the latest medical result and the status of the disease.

V. Results

This section details the findings of the statistical analysis of the user perception scores assigned to the 15 interface prototypes, a fundamental process for validating the design and functionality of the web-based expert system by healthcare professionals. The evaluation was based on a 15-question questionnaire structured around five key dimensions (Usability, Technical Functioning, Knowledge Base, Inference Engine, and Expected Impact), as detailed in Table IV. Fig. 9 displays the distribution of responses (on a scale of 1 to 5) and showed a high overall positive consensus, with the majority of scores concentrated at levels 4 and 5. Additionally, the descriptive metrics presented in Table V confirm the consistency of the sample (N=20 per prototype). Prototype 13 (P-13) stood out with the highest mean (4.80) and the lowest dispersion (SD = 0.61), indicating the most favorable perception and the greatest agreement among experts. In contrast, Prototype 4 (P-4) recorded the lowest mean (4.00) and the greatest dispersion (SD = 1.12), indicating the area with the most divided opinions.

VI. Discussion

This section discusses the findings obtained from the evaluation of the web expert system prototypes for tuberculosis diagnosis, relating them to previous studies and evidence reported in the literature. It analyzes healthcare professionals' perceptions regarding the system's usability, technical performance, knowledge base, and inference engine, as well as its relevance as a clinical support tool. Furthermore, it examines how inference methods and knowledge structuring contribute to optimizing the early detection of tuberculosis. This discussion contextualizes the results, highlights the original contributions of the study, and establishes its relevance in the field of public health. The findings from the analysis of the 15 web expert system prototypes for tuberculosis diagnosis generally show a high level of positive consensus among healthcare professionals, with Prototype 13 standing out (mean = 4.80; SD = 0.61), indicating both favorable perceptions and a high level of agreement among experts. These results are consistent with previous studies that have demonstrated the effectiveness of rule-based expert systems and specialist knowledge in supporting clinical decision-making in respiratory diseases [11] [9] [10]. Likewise, the evaluation through a structured questionnaire covering five dimensions (Usability, Technical Performance, Knowledge Base, Inference Engine, and Expected Impact) made it possible to systematically identify strengths and areas for improvement, following strategies similar to those reported in the validation of web expert systems in other clinical contexts [17] [18]. It is worth noting that the integration of inference methods such as Forward Chaining and Certainty Factor, together with a knowledge base of previous cases, reflects successful approaches documented in the literature, which significantly contribute to improving the reliability of preliminary diagnoses [21] [22] [15] [16]. On the other hand, the greater dispersion observed in Prototype 4 (SD = 1.12) highlights the need to make adjustments in certain functionalities or in the interface, which aligns with the importance of proper symptom structuring and user interaction, as emphasized by [31] [32]. Nevertheless, the usability assessment and the concentration of high scores support the view that the application constitutes a practical and reliable tool, capable of optimizing early tuberculosis detection, improving patient guidance, and strengthening clinical support even before laboratory confirmation, consistent with the findings of previous expert systems [23] [24] [25] [26] [27]. Taken together, these results confirm that the system developed not only follows best practices identified in prior studies but also contributes a specialized, expert-validated approach for the early identification of tuberculosis, consolidating itself as a robust technological tool to support medical decision-making and improve timely care in settings with limited access to healthcare services.

VII. Conclusion

Tuberculosis continues to be a disease of great relevance to public health due to its high morbidity and the significant impact it generates on the population, especially in contexts with limited access to medical services. In this regard, the situation highlights the need to implement effective strategies for early detection and clinical management. Likewise, it is essential to have technological tools that facilitate medical decision-making, optimize diagnoses, and help reduce the spread of the disease in vulnerable communities. Therefore, the implementation of a web-based expert system is presented as a particularly pertinent and effective alternative. For this research, the Buchanan methodology proved to be an optimal choice, since its approach allows the entire expert system development process to be addressed in a structured manner, from the conceptualization of the problem posed to obtaining results based on the system's evaluation.

The Buchanan methodology consists of five clearly defined stages. In the first stage, identification, the problem analysis is carried out, based on the project's needs. Subsequently, the conceptualization phase focuses on outlining the internal functioning of the system, that is, how knowledge is managed and the rules it follows to generate predictions. During the

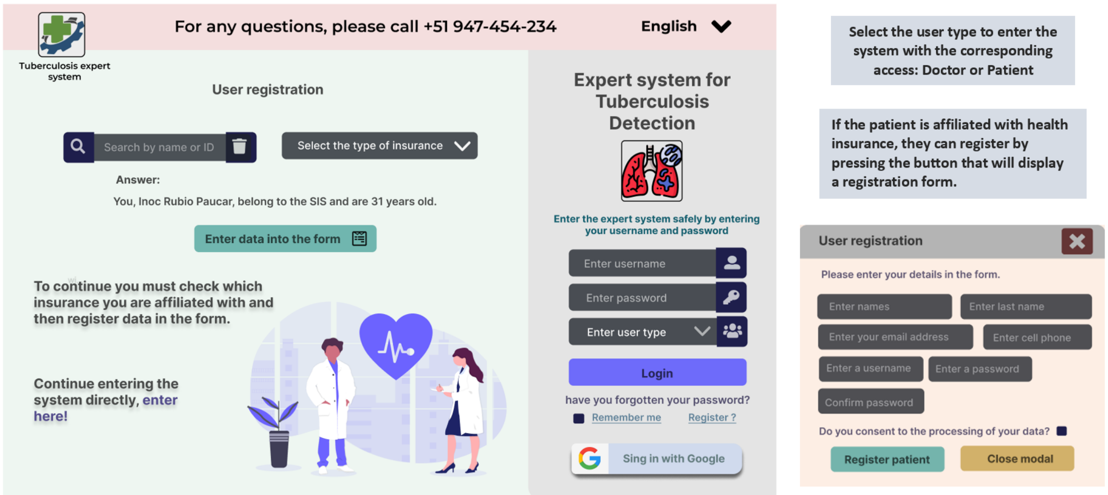
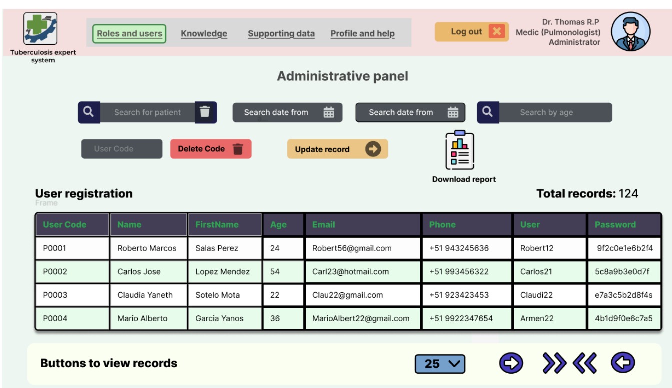
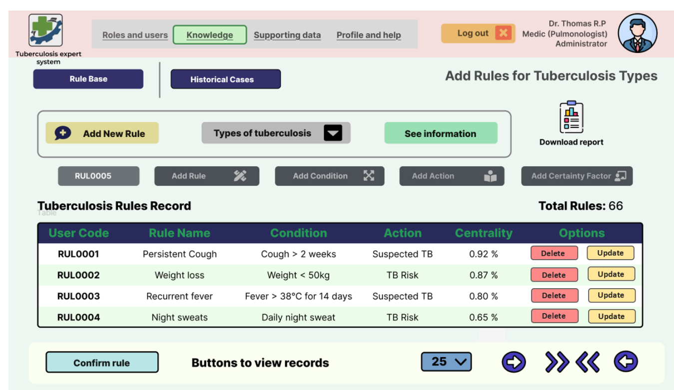


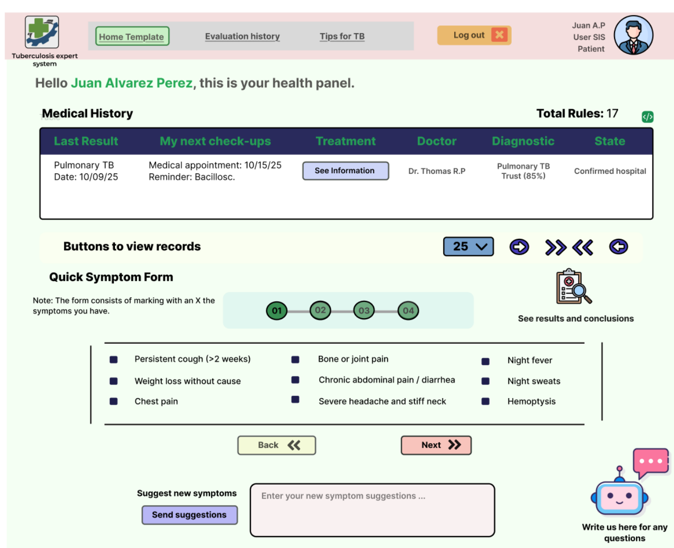
Fig. 7. Patient login and registration prototype.



(a) Administrative panel for user management.



(b) Managing rules to detect the type of TB.



(c) User panel to predict the type of TB.

Fig. 8. Prototypes of an expert web system for TB detection.

TABLE IV. EXPERT JUDGMENT QUESTIONNAIRE FOR PHYSICIANS

Dimension	Question
Usability	1. Do you consider the system interface clear and easy to use for a healthcare professional?
	2. Does the layout of menus, forms, and results facilitate quick access to clinical information?
	3. Does the system offer an intuitive design that minimizes the need for prior training?
Technical Functioning	4. Does the system respond quickly and remain stable during use in clinical practice?
	5. Do you consider the credential validation (user, role, access) secure and reliable?
	6. Does the system present technical errors or inconsistencies that may affect the user experience?
Knowledge Base	7. Is the information on symptoms, risk factors, and diagnostic criteria for tuberculosis accurate and scientifically valid?
	8. Do you consider that the rules implemented in the system adequately reflect current clinical practice?
	9. Should the knowledge base be updated more frequently to remain aligned with new clinical guidelines?
Inference Engine	10. Does the system provide diagnostic recommendations consistent with the usual clinical logic for tuberculosis detection?
	11. Do you consider the accuracy of the inferences adequate to support medical decision-making?
	12. Does the system avoid contradictions or ambiguities in the suggested results?
Expected Impact	13. Does the expert system have the potential to reduce diagnostic errors in the identification of tuberculosis cases?
	14. Do you consider it a useful tool in primary care settings or in resource-limited contexts?
	15. Do you think the expert system will contribute to improving efficiency and quality in the early diagnosis of tuberculosis?

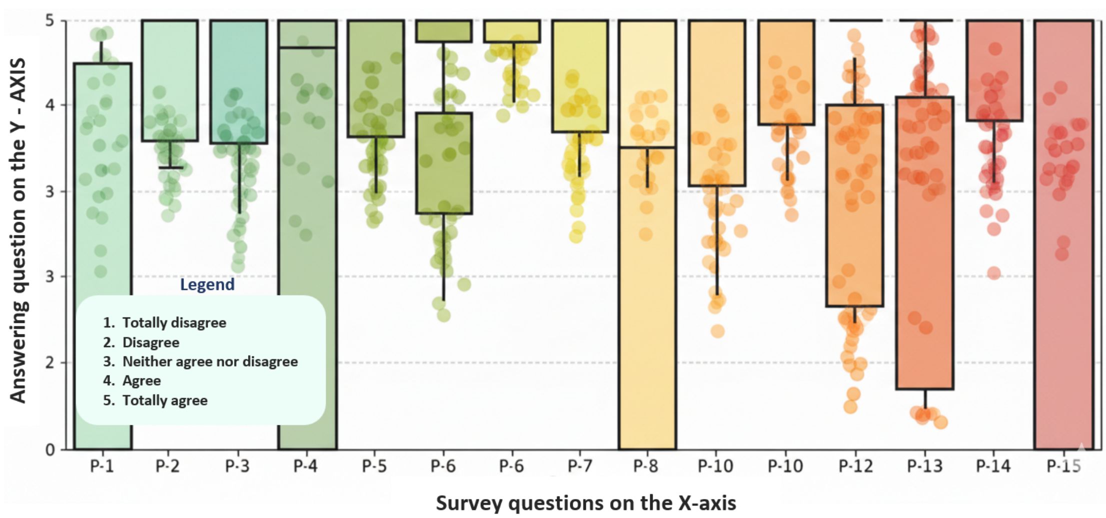


Fig. 9. Patient login and registration prototype.

TABLE V. DESCRIPTIVE METRICS OF PERCEPTION SCORES BY PROTOTYPE

Prototype	N	Mean	Standard Deviation (SD)	Median	Minimum	Maximum
P-1	20	4.35	0.93	4.5	2	5
P-2	20	4.15	0.93	4.0	1	5
P-3	20	4.35	0.99	5.0	1	5
P-4	20	4.00	1.12	4.5	2	5
P-5	20	4.60	0.68	5.0	3	5
P-6	20	4.45	0.94	5.0	2	5
P-7	20	4.65	0.75	5.0	2	5
P-8	20	4.60	0.68	5.0	3	5
P-9	20	4.60	0.68	5.0	3	5
P-10	20	4.40	0.82	4.5	3	5
P-11	20	4.65	0.67	5.0	2	5
P-12	20	4.60	0.68	5.0	3	5
P-13	20	4.80	0.61	5.0	2	5
P-14	20	4.70	0.73	5.0	3	5
P-15	20	4.55	0.69	5.0	3	5

formalization phase, the rules to be used as filters in the patient's test are precisely established, incorporating the use of the Certainty Factor to quantify the degree of confidence in the expert system's conclusions, as well as the data flow in the knowledge base. The implementation phase focuses on the development of the graphical user interface, reflecting and consolidating all the previous processes into a functional web-based expert system. Finally, the validation phase was carried out through expert judgment, using a 15-question questionnaire designed to assess the effectiveness, reliability, and usability of the system. The results showed a high overall positive consensus, with question 13 standing out for obtaining the highest mean (4.80) and the lowest dispersion (SD = 0.61), reflecting the most favorable perception and the greatest agreement among specialists. In contrast, question 4 recorded the lowest mean (4.00) and the highest dispersion (SD = 1.12), indicating aspects of the system that generated more divided opinions. Taken together, these results confirm that the web-based expert system constitutes a reliable and relevant tool to support the diagnosis of tuberculosis, backed by the direct evaluation of healthcare professionals.

Finally, understanding the complexity of early tuberculosis diagnosis is essential to strengthening healthcare delivery and improving clinical decision-making. Based on the findings obtained through the evaluation of the web-based expert system and expert judgment, it is suggested to develop complementary technological tools, such as the integration of ML algorithms, radiological image analysis, mobile applications for symptom tracking, and early warning platforms that can anticipate tuberculosis cases and facilitate timely interventions. Likewise, future studies could incorporate additional variables, explore other inference methods, and expand the knowledge base in order to optimize diagnostic accuracy and contribute to the design of more robust, accessible, and efficient clinical support systems in resource-limited settings.

ACKNOWLEDGMENT

Thanks to the University of Sciences and Humanities, which made this project a reality.

REFERENCES

[1] B. Seabra and R. Duarte, "Tuberculosis national registries and data on diagnosis delay – is there room for improvement?" *Pulmonology*, vol. 30, no. 2, pp. 130–136, 2024, doi:10.1016/j.pulmoe.2021.05.004.

[2] P. A. H. Organization, "Tuberculosis in the americas. regional report 2021," 2021, doi:10.37774/9789275126493.

[3] M. M. van der Zalm, V. W. Jongen, R. Swanepoel, K. Zimri, B. Allwood, M. Palmer, R. Dunbar, P. Goussard, H. S. Schaaf, A. C. Hesseling, and J. A. Seddon, "Impaired lung function in adolescents with pulmonary tuberculosis during treatment and following treatment completion," *eClinicalMedicine*, vol. 67, p. 102406, 2024, doi: 10.1016/j.eclinm.2023.102406.

[4] Y. Liu, Y. H. Wu, S. C. Zhang, L. Liu, M. Wu, and M. M. Cheng, "Revisiting computer-aided tuberculosis diagnosis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 46, no. 4, pp. 2316–2332, 2024, doi:10.1109/TPAMI.2023.3330825.

[5] S. Swain, A. Kumar, V. K. Vishwakarma, A. A. K, A. Mittal, and N. Wig, "Diagnosis and management of latent tuberculosis infection: Updates," *Infectious Disorders - Drug Targets*, vol. 24, no. 4, pp. 12–19, 2024, doi: 10.2174/0118715265275319231124053615.

[6] P. F. Pinto, C. S. Teixeira, M. Y. Ichihara, D. Rasella, J. S. Nery, S. O. Sena, E. B. Brickley, M. L. Barreto, M. N. Sanchez, and J. M. Pescarini, "Incidence and risk factors of tuberculosis among 420 854 household contacts of patients with tuberculosis in the 100 million brazilian cohort (2004–18): a cohort study," *The Lancet Infectious Diseases*, vol. 24, no. 1, pp. 26–46, 2024, doi:10.1016/S1473-3099(23)00371-7.

[7] W. Bai and E. K. Ameyaw, "Global, regional and national trends in tuberculosis incidence and main risk factors: a study using data from 2000 to 2021," *BMC Public Health*, vol. 24, no. 12, pp. 1–14, 2024, doi: 10.1186/s12889-023-17495-6.

[8] M. Furqan, A. H. Hasugian, and T. Elisa, "Expert system for diagnosing respiratory diseases in humans using forward chaining method," *Journal of Information System Application (Computer & Management)*, vol. 4, no. 1, pp. 80–89, 2023, doi:10.1234/jpsi.2023.0401.

[9] A. Wijayanti, F. N. Arifah, D. E. Putri, M. D. Satriyanto, and S. Sallu, "Expert system for diagnosing tuberculosis implementing case-based reasoning method," *Journal of Computer System and Informatics (JoSYC)*, vol. 4, no. 3, pp. 570–577, 2023, doi:10.47065/josyc.v4i3.3409.

[10] A. Sharma, E. Machado, K. V. B. Lima, P. N. Suffys, and E. C. Conceição, "Tuberculosis drug resistance profiling based on machine learning: A literature review," *Brazilian Journal of Infectious Diseases*, vol. 26, no. 1, p. 102332, 2022, doi:10.1016/j.bjid.2022.102332.

[11] N. Tang, M. Yuan, Z. Chen, J. Ma, R. Sun, Y. Yang, Q. He, X. Guo, S. Hu, and J. Zhou, "Machine learning prediction model of tuberculosis incidence based on meteorological factors and air pollutants," *International Journal of Environmental Research and Public Health*, vol. 20, no. 5, p. 3910, 2023, doi:10.3390/ijerph20053910.

[12] K. Godiyal and S. Pokhriyal, "Tuberculosis prediction by machine learning techniques," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 10, no. 1, pp. 92–98, 2022, doi:10.17762/ijritcc.v10i1s.5797.

[13] Z. Indra and M. R. P. Harahap, "Development of an expert system for diagnosing tuberculosis during the pandemic using forward chaining at medan johor health center," *Karismatika*, vol. 8, no. 3, 2022, doi:10.1234/karismatika.2022.0803.

[14] M. Singh, G. V. Pujar, S. A. Kumar, M. Bhagyalalitha, H. S. Akshatha, B. Abuhaija, A. R. Alsoud, L. Abualigah, N. M. Beeraka, and A. H. Gandomi, "Evolution of machine learning in tuberculosis diagnosis: A review of deep learning-based medical applications," *Electronics (Switzerland)*, vol. 11, no. 17, 2022, doi:10.3390/electronics11172634.

[15] G. W. N. Wibowo, S. Widiastuti, M. Muratno, E. Lolang, and S. Soraya, "Application of bayes' theorem method in diagnosing tuberculosis," *Building of Informatics, Technology and Science (BITS)*, vol. 4, no. 4, pp. 1782–1788, 2023, doi:10.47065/bits.v4i4.3035.

[16] J. Sapdana and Y. Henryanto, "Implementation of expert system for diagnosing tuberculosis using dempster-shafer method," *International Journal of Software Engineering and Computer Science (IJSECS)*, vol. 2, no. 1, pp. 26–32, 2022, doi:10.35870/ijsecs.v2i1.763.

[17] L. Andrade-Arenas, I. M. R. Paucar, and C. Yactayo-Arias, "Expert systems and epidemiological surveillance for tuberculosis: Innovative tools for disease prevention and control," *International Journal of Engineering Trends and Technology*, vol. 72, no. 3, pp. 72–90, 2024, doi:10.14445/22315381/IJETT-V72I3P108.

[18] Y. Luo, Y. Xue, W. Liu, H. Song, Y. Huang, G. Tang, F. Wang, Q. Wang, Y. Cai, and Z. Sun, "Development of diagnostic algorithm using machine learning for distinguishing between active tuberculosis and latent tuberculosis infection," *BMC Infectious Diseases*, vol. 22, no. 1, 2022, doi:10.1186/s12879-022-07954-7.

[19] M. Palmer, J. A. Seddon, M. M. van der Zalm, A. C. Hesseling, P. Goussard, H. S. Schaaf, J. Morrison, B. van Ginneken, J. Melendez, E. Walters, and K. Murphy, "Optimising computer-aided detection to identify intra-thoracic tuberculosis on chest x-ray in south african children," *PLOS Global Public Health*, vol. 3, no. 5, pp. 1–15, 2023, doi:10.1371/journal.pgph.0001799.

[20] R. Mehrrotraa, M. A. Ansari, R. Agrawal, P. Tripathi, M. B. B. Heyat, M. Al-Sarem, A. Y. M. Muaad, W. A. E. Nagmeldin, A. Abdelmaboud, and F. Saeed, "Ensembling of efficient deep convolutional networks and machine learning algorithms for resource effective detection of tuberculosis using thoracic (chest) radiography," *IEEE Access*, vol. 10, 2022, doi:10.1109/ACCESS.2022.3194152.

[21] N. D. Wirasbawa, C. T. P. Widjaja, C. I. Wenji, and S. Hansun, "Expert api for early detection of tb disease with forward chaining and certainty factor algorithms," *Informatica (Slovenia)*, vol. 46, no. 6, pp. 117–124, 2022, doi:10.31449/inf.v46i6.3947.

[22] X. Hu, J. Wang, Y. Ju, X. Zhang, W. Qimanguli, C. Li, L. Yue, B. Tuohetaerbaike, Y. Li, H. Wen, W. Zhang, C. Chen, Y. Yang, J. Wang, and F. Chen, "Combining metabolome and clinical indicators with machine learning provides some promising diagnostic markers to precisely detect smear-positive/negative pulmonary tuberculosis," *BMC Infectious Diseases*, vol. 22, no. 1, 2022, doi:10.1186/s12879-022-07694-8.

[23] M. R. Syahwana and R. M. Simanjorang, "Analysis of expert system using bayes method for diagnosing tuberculosis," *Jurnal Sistem Informasi, Teknik Informatika dan Teknologi Pendidikan*, vol. 1, no. 2, pp. 57–66, 2022, doi:10.55338/justikpen.v1i2.7.

[24] L. Wang, X. D. Zhang, J. W. Tang, Z. W. Ma, M. Usman, Q. H. Liu, C. Y. Wu, F. Li, Z. B. Zhu, and B. Gu, "Machine learning analysis of sers fingerprinting for the rapid determination of mycobacterium tuberculosis infection and drug resistance," *Computational and Structural Biotechnology Journal*, vol. 20, pp. 5364–5377, 2022, doi:10.1016/j.csbj.2022.09.031.

[25] T. R. Lane, F. Urbina, L. Rank, J. Gerlach, O. Riabova, A. Lepioshkin, E. Kazakova, A. Vocat, V. Tkachenko, S. Cole, V. Makarov, and S. Ekins, "Machine learning models for mycobacterium tuberculosis in vitro activity: Prediction and target visualization," *Molecular Pharmaceutics*, vol. 19, no. 2, pp. 674–689, 2022, doi:10.1021/acs.molpharmaceut.1c00791.

[26] L. Verboven, T. Calders, S. Callens, J. Black, G. Maartens, K. E. Dooley, S. Potgieter, R. M. Warren, K. Laukens, and A. V. Rie, "A treatment recommender clinical decision support system for personalized medicine: Method development and proof-of-concept for drug resistant tuberculosis," *BMC Medical Informatics and Decision Making*, vol. 22, no. 1, p. 56, 2022, doi:10.1186/s12911-022-01790-0.

[27] O. Hrizi, K. Gasmi, I. B. Ltaifa, H. Alshammari, H. Karamti, M. Krichen, L. B. Ammar, and M. A. Mahmood, "Tuberculosis disease diagnosis based on an optimized machine learning model," *Journal of Healthcare Engineering*, vol. 2022, p. 8950243, 2022, doi:10.1155/2022/8950243.

[28] B. M. B. Sembiring and P. M. Hasugian, "Tuberculosis disease diagnosis expert system using certainty factor method," *Journal Of Computer Networks, Architecture and High Performance Computing*, vol. 2, no. 1, pp. 129–134, 2020, doi:10.47709/cnapc.v2i1.373.

[29] A. Rachmad, N. Chamidah, and R. Rulaningtyas, "Mycobacterium tuberculosis identification based on color feature extraction using expert system," *Annals of Biology*, vol. 36, no. 2, pp. 196–202, 2020, doi:10.5555/20203239846.

[30] F. Yang, H. Yu, K. Kantipudi, M. Karki, Y. M. Kassim, A. Rosenthal, D. E. Hurt, Z. Yaniv, and S. Jaeger, "Differentiating between drug-sensitive and drug-resistant tuberculosis with machine learning for clinical and radiological features," *Quantitative Imaging in Medicine and Surgery*, vol. 12, no. 1, pp. 675–687, 2022, doi:10.21037/qims-21-290.

[31] N. Sari, V. Sihombing, and D. Irmayani, "Implementation of the bayes method for diagnosing tuberculosis," *SinkrOn*, vol. 5, no. 2, pp. 325–331, 2021, doi:10.33395/sinkron.v5i2.10903.

[32] S. P. Althomsons, K. Winglee, C. M. Heilig, S. Talarico, B. Silk, J. Wortham, A. N. Hill, and T. R. Navin, "Using machine learning techniques and national tuberculosis surveillance data to predict excess growth in genotyped tuberculosis clusters," *American Journal of Epidemiology*, vol. 191, no. 11, pp. 1936–1943, 2022, doi:10.1093/aje/kwac117.

[33] F. Weng, Y. Meng, F. Lu, Y. Wang, W. Wang, L. Xu, D. Cheng, and J. Zhu, "Differentiation of intestinal tuberculosis and crohn's disease through an explainable machine learning method," *Scientific Reports*, vol. 12, no. 1, p. 5551, 2022, doi:10.1038/s41598-022-05571-7.

[34] W. Deelder, G. Napier, S. Campino, L. Palla, J. Phelan, and T. G. Clark, "A modified decision tree approach to improve the prediction and mutation discovery for drug resistance in mycobacterium tuberculosis," *BMC Genomics*, vol. 23, no. 1, p. 46, 2022, doi:10.1186/s12864-022-08291-4.

[35] T. S. Brown, L. Tang, S. V. Omar, L. Joseph, G. Meintjes, G. Maartens, S. Wasserman, N. S. Shah, M. R. Farhat, N. R. Gandhi, N. Ismail, J. C. Brust, and B. Mathema, "Genotype–phenotype characterization of serial mycobacterium tuberculosis isolates in bedaquiline-resistant tuberculosis," *Clinical Infectious Diseases*, vol. 78, no. 2, p. 269–276, 2024, doi:10.1093/cid/ciad596.

[36] N. J. Day, P. Santucci, and M. G. Gutierrez, "Host cell environments and antibiotic efficacy in tuberculosis," *Trends in Microbiology*, vol. 32, no. 3, p. 1862–1870, 2024, doi:10.1016/j.tim.2023.08.009.

[37] J. H. Hyun, M. Lee, I. Jung, E. Kim, S. M. Hahn, Y. R. Kim, S. Lim, K. Ihn, M. Y. Kim, J. G. Ahn, J. S. Yeom, S. J. Jeong, and J. M. Kang, "Changes in tuberculosis risk after transplantation in the setting of decreased community tuberculosis incidence: a national population-based study, 2008–2020," *Annals of Clinical Microbiology and Antimicrobials*, vol. 23, no. 1, 2024, doi:10.1186/s12941-023-00661-4.

[38] P. C. Renjifo Ramos, "Situación epidemiológica de la tuberculosis en el perú," 2022, accessed: 2025-09-25. [Online]. Available: https://es.scribd.com/document/602251896/03

[39] M. M. Kumbure, A. Tarkiainen, J. Stoklasa, P. Luukka, and A. Jantunen, "Causal maps in the analysis and unsupervised assessment of the development of expert knowledge: Quantification of the learning effects for knowledge management purposes[formula presented]," *Expert Systems with Applications*, vol. 236, 2024, doi:10.1016/j.eswa.2023.121232.

[40] L. P. Wanti, O. Somantri, N. W. A. Prasetya, and L. Puspitasari, "Fuzzy expert system design for detecting stunting," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 34, no. 1, pp. 556–564, 2024, doi:10.11591/ijeecs.v34.i1.pp556-564.

[41] N. Marvi, S. Mollazadeh, F. E. Arghavanian, A. Atashi, and T. Khadivzadeh, "Designing, validation and evaluation of the expert system of "healthy menopause" and assessing its effect on the management of menopause symptoms: an exploratory mixed method study protocol," *Reproductive Health*, vol. 21, no. 1, p. 9, 2024, doi:10.1186/s12978-024-01740-1.

[42] D. P. Maison, "Tuberculosis pathophysiology and anti-vegf intervention," *Journal of Clinical Tuberculosis and Other Mycobacterial Diseases*, vol. 27, 2022, doi:10.1016/j.jctube.2022.100300.

[43] K. C. Rahlwes, B. R. Dias, P. C. Campos, S. Alvarez-Arguedas, and M. U. Shiloh, "Pathogenicity and virulence of mycobacterium tuberculosis," *Virulence*, vol. 14, no. 1, p. 1, 2023, doi:10.1080/21505594.2022.2150449.

[44] B. Zacharia and A. Roy, "Multi drug resistant tuberculosis," *European Journal of Clinical and Experimental Medicine*, vol. 17, no. 3, pp. 316–353, 2019, doi:10.15584/EJCEM.2019.3.11.

[45] J. Meghji, O. M. Kon, and A. Ainley, "Clinical tuberculosis," *Medicine (United Kingdom)*, vol. 51, no. 11, pp. 768–773, 2023, doi:10.1016/j.mpmed.2023.08.012.

[46] R. D. Kanabalan, L. J. Lee, T. Y. Lee, P. P. Chong, L. Hassan, R. Ismail, and V. K. Chin, "Human tuberculosis and mycobacterium tuberculosis complex: A review on genetic diversity, pathogenesis and omics approaches in host biomarkers discovery," *Microbiological Research*, vol. 246, 2021, doi:10.1016/j.micres.2020.126674.

[47] C. Lange, "Management of drug-resistant tuberculosis," *Deutsche Medizinische Wochenschrift*, vol. 148, no. 19, pp. 1236–1241, 2023, doi:10.1055/a-1939-0000.

[48] J. Espinosa-Pereiro, A. Sánchez-Montalvá, M. L. Aznar, and M. Espiau, "Mdr tuberculosis treatment," *Medicina (Lithuania)*, vol. 58, no. 2, p. 188, 2022, doi:10.3390/medicina58020188.