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AN EXPLAINABLE EXPERT SYSTEM FOR TUBERCULOSIS RISK SCREENING BASED ON SOCIODEMOGRAPHIC FACTORS AND COMORBIDITIES USING A HYBRID FORWARD CHAINING AND CERTAINTY FACTOR APPROACH

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ABSTRACT

Tuberculosis (TB) remains a significant public health challenge, particularly in terms of early detection and identification of high-risk populations at the community level. Existing screening approaches predominantly rely on clinical symptoms or radiological imaging and have not optimally incorporated sociodemographic factors and comorbidities based on local epidemiological evidence. This study aimed to develop and evaluate an explainable expert system for early TB risk screening using a hybrid Forward Chaining and Certainty Factor approach based on sociodemographic and comorbidity-related risk factors in Central Lampung Regency. The research was conducted in two stages: first, an analytical quantitative case-control study was performed to identify significant risk factors through bivariate and multivariate analyses; second, a system development phase was conducted using Extreme Programming within a Software Development Life Cycle (SDLC) framework. The findings indicate that low income, undernutrition (BMI < 18.5), and a history of close contact are significant determinants integrated into the system's knowledge base and consistently influence classification into low-, moderate-, and high-risk categories. The system produces transparent and traceable inferences, supporting its function as a decision-support tool, rather than as a diagnostic instrument. This study contributes to the development of an evidence-based, rule-driven, and explainable TB risk screening model that is contextually appropriate for primary health care and community-level prevention efforts.

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1. INTRODUCTION

Tuberculosis (TB) remains one of the leading causes of morbidity and mortality from infectious diseases worldwide, particularly in low- and middle-income countries, making early detection and risk-based screening essential components of disease control strategies (Kontsevaya et al., 2023). A major challenge in TB control is delayed diagnosis and insufficient case detection coverage, which contribute to sustained community transmission (Triyono et al., 2023). Current screening approaches continue to rely heavily on symptom-based assessments and radiological examinations; however, limitations in human resources and infrastructure in many regions restrict their effectiveness (Cao et al., 2021). The World Health Organization has recommended the use of artificial intelligence in TB screening to enhance the sensitivity of detecting high-risk populations, particularly in resource-constrained settings (Creswell et al., 2023). In Indonesia, digital self-screening applications have demonstrated potential for improving case detection through community participation; however, these systems predominantly focus on clinical symptom identification (Triyono et al., 2023).

Despite technological advancements, most TB screening systems remain centered on symptom-based or imaging-based diagnostics without comprehensively integrating sociodemographic determinants and comorbidities as population-level risk indicators (MacLean & Yapa 2024). Machine learning–based predictive models have demonstrated high accuracy in TB detection; however, they often lack explainability, limiting their adoption in primary healthcare settings (Suresh, 2025). Similarly, deep learning approaches have been criticized for their insufficient transparency in clinical decision-making processes (Özkurt, 2024). Screening interventions that overlook social determinants of health risk failing to reach vulnerable populations, even though intersectoral and socioeconomic factors play a substantial role in TB control efforts (da Silva et al., 2025). These limitations highlight the academic and practical need for an evidence-based, explainable risk screening system capable of handling uncertainty in public health decision making.

From a conceptual standpoint, TB risk is inseparable from the interaction among the host, agent, and environment, as articulated in classical epidemiological theory, which posits that disease occurrence arises from the complex interplay between individual susceptibility, infectious exposure, and environmental conditions (Marambire et al., 2022). Environmental conditions, including air quality, have been associated with an increased risk of TB, underscoring the importance of contextual risk assessment (Munandar et al., 2025). Social determinants, such as poverty and marginalization, further intensify TB incidence within specific populations (Ovesná et al., 2025). In decision-support contexts, rule-based reasoning and decision tree models have been employed to improve screening accuracy when they are integrated with clinically relevant parameters (Hong et al., 2025). Therefore, the integration of epidemiological frameworks with transparent computational models represents a crucial conceptual foundation for developing an explainable risk-based expert system.

Based on these considerations, this study aimed to develop and evaluate an explainable expert system for early TB risk screening using a hybrid Forward Chaining and Certainty Factor approach grounded in sociodemographic and comorbidity-related risk factors in Central Lampung Regency. The central research question addressed how a hybrid artificial intelligence model can be developed and implemented to conduct TB risk screening assessments based on statistically significant epidemiological estimates. The proposed system positions TB risk screening as a decision-support mechanism rather than a definitive diagnostic tool, consistent with the principles of public health screening that emphasize the early identification and triage of high-risk individuals (MacLean & Yapa, 2024).

The scientific contribution of this study lies in the development of an evidence-based knowledge base derived from a local multivariate epidemiological analysis, the transformation of significant Odds Ratios into certainty factor values through a monotonic mapping strategy, and the implementation of a transparent Forward Chaining inference mechanism. Unlike deep learning systems that function as black-box models, this approach prioritizes interpretability and accountability, which are essential for the adoption of artificial intelligence in primary healthcare services (Özkurt 2024). By integrating social determinants, comorbidities, and public health screening principles within a rule-based expert system, this study proposes a hybrid reasoning framework that is context-sensitive and operationally applicable for strengthening TB prevention and community health education initiatives.

2. LITERATURE REVIEW

Tuberculosis, as an infectious disease, is classically explained through the **host–agent–environment** epidemiological framework, which posits that disease occurrence results from the interaction between individual susceptibility (host), characteristics of *Mycobacterium tuberculosis* (agent), and physical and social environmental conditions (environment) that facilitate transmission and disease progression (Marambire et al., 2022). This perspective is further expanded by the social determinants of health approach, which emphasizes that poverty, overcrowded housing, and limited access to healthcare significantly contribute to TB risk of TB among vulnerable populations (da Silva et al., 2025). In the context of screening, the World Health Organization promotes systematic approaches that integrate symptom detection, radiological examination, and targeted strategies for high-risk populations to accelerate TB elimination efforts (MacLean & Yapa 2024). Recent advances in TB diagnostics have also reflected a shift toward integrating biomarkers, imaging technologies, and predictive algorithms to enhance screening sensitivity and clinical utility (Kontsevaya et al., 2023). Accordingly, the conceptual foundation of this study is grounded in the integration of classical epidemiological theory with risk-based decision support systems that incorporate social and clinical determinants.

Several prior studies have demonstrated that the digitalization of TB screening can enhance case detection through web-based applications and community participation, although these systems predominantly rely on subjective symptom identification (Triyono et al., 2023). Evaluations of application-based screening methods have shown improvements in *case detection rates* compared to manual questionnaires, particularly in primary healthcare settings (Pratikto & Peristiowati 2022). In parallel, artificial intelligence applications in radiological interpretation have demonstrated high sensitivity and specificity in chest X-ray-based TB screening, particularly when integrated with computer-aided detection systems (Cao et al., 2021). More recent deep learning models have achieved very high predictive performance for TB classification using clinical or imaging data (Suresh, 2025). Additionally, the use of ultraportable radiological facilities integrated with computerized technologies has proven effective in reaching vulnerable populations and accelerating active case detection (Nalivaico et al., 2024).

However, most of these approaches focus primarily on diagnosis or symptom- and imaging-based detection rather than risk assessment grounded in sociodemographic and comorbidity factors suitable for early community-level screening. Research in *explainable artificial intelligence* (XAI) underscores the importance of algorithmic transparency to ensure that clinical decisions can be understood and trusted by healthcare professionals (Özkurt, 2024). Studies on RNA biomarker–based screening further indicate that high diagnostic accuracy does not necessarily guarantee clinical utility if contextual implementation and subsequent diagnostic pathways are not considered (MacLean & Yapa, 2024). Moreover, decision tree–based classification models in specific populations have improved sensitivity but remain limited to selected clinical parameters and do not comprehensively integrate social determinants of health (Hong et al., 2025). These findings reveal a research gap in the development of evidence-based, explainable expert systems for TB risk screening that systematically incorporate epidemiological risk estimates into their design.

This study addresses this gap by integrating statistically significant Odds Ratios derived from local epidemiological analysis into a hybrid expert system using Forward Chaining and Certainty Factor reasoning. Unlike purely machine learning–based models, this approach emphasizes rule transparency and the explainability of risk classification outcomes. Global trends in AI adoption for TB screening demonstrate that successful implementation requires not only technical validation but also user acceptance and alignment with healthcare workflows (Creswell et al., 2023). Community-based health education interventions have also been shown to enhance participation in early TB detection, suggesting that screening systems should incorporate an educational function, alongside risk classification (Putra et al., 2021). Therefore, this study aims to synthesize epidemiological evidence, social determinant theory, and explainable AI principles within a unified decision-support framework.

Methodologically, prior studies have been dominated by quantitative experimental designs and predictive modeling based on secondary datasets or medical imaging (Suresh 2025). Longitudinal cohort research among household contacts highlights the importance of early risk identification to predict disease progression more comprehensively (Marambire et al., 2022). Furthermore, intersectoral approaches to TB control emphasize the integration of social, economic, and environmental factors into prevention strategies (da Silva et al., 2025). Consequently, a hybrid rule-based reasoning framework incorporating Certainty Factor mechanisms is methodologically appropriate for accommodating uncertainty while reflecting the multifactorial nature of TB risk in community settings.

The conceptual synthesis of the literature indicates that effective TB risk screening systems require the integration of epidemiological theory, quantitative risk evidence, and transparent inference mechanisms that are adaptable to local contexts. The existing literature supports the use of digital technologies and artificial intelligence to expand screening coverage but stresses the necessity of validation, explainability, and adherence to public health principles (Kontsevaya et al., 2023). Accordingly, this study positions the forward chaining CF-based expert system as a bridge between quantitative epidemiological analysis and practical, accountable decision-support implementation in community-based TB risk screening.

3. METHODS

This study employed a two-stage quantitative research design that integrated epidemiological analysis and expert system development. The first stage consisted of an analytical observational study with a case-control design to identify significant risk factors for tuberculosis (TB). The case-control approach was selected because of its methodological suitability for examining the associations between exposure variables and disease outcomes in infectious disease research (Marambire et al., 2022). This design enables the estimation of Odds Ratios (ORs) to quantify the strength of associations between risk factors and TB occurrence, thereby providing an empirical basis for risk modeling (MacLean & Yapa, 2024). The second stage involved the development of a web-based expert system using the Extreme Programming (XP) methodology within the Software Development Life Cycle (SDLC) framework, emphasizing iterative refinement and user-centered validation (Creswell et al. 2023).

Data Sources and Study Population

The first-stage data comprised primary and secondary sources. Primary data were collected through structured interviews using standardized questionnaires administered to 278 participants in Central Lampung Regency, comprising 139 confirmed TB cases and 139 non-TB controls. Secondary data were obtained from medical records and relevant epidemiological documentation to verify the risk factors. The variables examined included age, sex, education level, employment status, income level, nutritional status (Body Mass Index), history of close contact with patients with TB, diabetes mellitus, and HIV status. Data collection instruments were developed in accordance with the national TB screening guidelines, recognizing the importance of systematic risk-based screening in public health contexts (Kontsevaya et al., 2023).

The inclusion criteria for the cases were individuals diagnosed with TB based on clinical and/or laboratory confirmation, residing in Central Lampung Regency, and providing informed consent. Controls were individuals without a history of TB, residing in the same geographic area, and matching the general population characteristics of the patients. The exclusion criteria were incomplete data and severe comorbidities that could interfere with data collection. The unit of analysis in the epidemiological stage was an individual respondent.

3.1. Statistical Analysis

Data analysis in the first stage was conducted using bivariate analysis with the chi-square test to assess the associations between independent variables and TB status. Variables meeting the statistical threshold were subsequently entered into multivariate logistic regression analysis to estimate adjusted Odds Ratios (ORs) with 95% confidence intervals. Logistic regression is widely utilized in TB risk factor studies because of its capacity to control for confounding variables and estimate adjusted risk measures (Hong et al., 2025). Statistical analyses were performed using the SPSS software, with a significance level set at $p < 0.05$. Only statistically significant OR values from the multivariate model were incorporated into the expert-system knowledge base.

Knowledge Base Development and Risk Transformation

The second stage involved constructing an expert system knowledge base from statistically significant epidemiological findings. Significant Odds Ratios were transformed into Certainty Factor (CF) values using a monotonic transformation strategy to preserve the proportionality between risk magnitude and certainty weight. The Certainty Factor method was selected because it enables the representation of uncertainty within rule-based systems and expresses degrees of belief within a 0–1 scale, making it suitable for probabilistic screening contexts (Özkurt, 2024). Risk factors with statistically significant ORs were encoded as production rules using IF–THEN statements.

3.2. Inference Mechanism

The system employs a Forward Chaining inference mechanism, which initiates reasoning from user-inputted facts and progresses toward conclusions through rule activation within the working memory. This data-driven reasoning model supports transparent decision pathways and aligns with the principles of explainable AI in healthcare decision-support systems (Suresh, 2025). When multiple rules were activated, the Certainty Factor aggregation was computed using the standard CF combination formula to generate a final risk score. Risk classifications were defined as low, moderate, or high, based on predefined CF threshold values, consistent with the public health screening logic.

3.3. System Development and Validation

The system was developed following Extreme Programming practices, including iterative prototyping, continuous testing, and stakeholder feedback. XP was selected because of its adaptability to health technology projects that require incremental validation and rapid refinement (Nalivaico et al., 2024). Functional validation was conducted through black box testing of the input modules, inference processes, and output generation. Performance evaluation included accuracy, sensitivity, and specificity analyses to ensure that the system met the standards of a screening tool rather than a diagnostic instrument, consistent with public health screening principles (MacLean & Yapa, 2024). Expert reviews by public health professionals and information systems specialists were also conducted to assess logical consistency, usability, and practical relevance.

Through this integrated methodological framework, the study systematically combined quantitative epidemiological analysis with the development of an explainable, rule-based expert system tailored for TB risk screening in a community health setting.

4. RESULTS

4.1. System Functionality and Rule Execution

The web-based expert system successfully processed sociodemographic and comorbidity data according to a predefined input–process–output architecture. All statistically significant risk variables identified in the multivariate analysis—namely, low income (OR = 1.9), undernutrition (BMI < 18.5; OR = 2.0), and history of close contact (OR = 2.3)—were transformed into Certainty Factor (CF) values using a monotonic proportional mapping approach. Rule activation occurred when user inputs satisfied the premises encoded in the knowledge base, triggering the Forward Chaining inference mechanism until a risk classification was generated. The pattern of rule activation demonstrated that the presence of multiple significant risk factors increased the number of activated rules within working memory, thereby influencing the final aggregated CF score. Consistency testing through repeated simulations with identical input combinations produced stable CF outputs without computational deviations. This deterministic reasoning behavior aligns with the logic of rule-based screening systems and the emphasis on high sensitivity in public health triage tools (Hong et al., 2025); (MacLean & Yapa, 2024).

4.2. Tuberculosis Risk Assessment Outcomes

The system generated three primary risk categories: low, moderate, and high, based on the aggregated CF value ranging from 0 to 1. Respondents with a single statistically significant risk factor were generally classified as moderate risk, whereas those with two or more significant factors were classified as high risk, with CF values approaching 1. The high-risk category was predominantly characterized by a history of close contact and undernutrition. Comorbidities such as diabetes mellitus and HIV did not demonstrate statistical significance in the multivariate model and, therefore, did not substantially elevate the classification to the high-risk category within the system. Variations in CF values correspond proportionally to the number and strength of activated risk factors, reflecting the probabilistic nature of screening tools rather than definitive diagnostic systems (Kontsevaya et al., 2023). These results indicate that the system prioritizes locally derived epidemiological risk factors instead of relying solely on symptom-based approaches commonly used in digital TB screening applications (Triyono et al., 2023).

4.3. Explainability Outcomes

The system's explanation module displays the activated rules along with their corresponding CF values, enabling users to trace the inference pathway from the input variables to the final risk classification. Transparency in rule activation was demonstrated through a structured presentation of the contributing risk factors and their respective CF contributions to the aggregated result. For example, the combined presence of low income and a history of close contact generated a cumulative increase in the final risk. This traceability mechanism aligns with the principles of explainable artificial intelligence in healthcare decision-support systems (Özkurt, 2024). User feedback indicated that rule-based explanations were easier to interpret than black-box deep learning models that do not provide explicit reasoning pathways (Suresh, 2025).

4.4. System Validation Results

Functional testing using black box methods confirmed that all input modules, inference processes, and output classifications operated without logical or computational errors. The classification results generated by the system were consistent with the outcomes of the statistical epidemiological analysis. Performance metrics, including accuracy, sensitivity, and specificity, were calculated to evaluate the system's appropriateness as a screening instrument rather than a diagnostic tool, in accordance with public health screening principles (MacLean & Yapa, 2024). Expert evaluation by public health practitioners and information systems specialists indicated that the system was practically useful for early identification and community-based TB risk education, with logical structures aligned with inter-sectoral TB control strategies (da Silva et al., 2025). The system's capacity to incorporate contact history and socioeconomic determinants reflects the principles emphasized in longitudinal contact-based TB risk assessment studies (Marambire et al., 2022). Furthermore, its web-based implementation supports accessibility comparable to other digital screening innovations that enhance community participation in early TB detection (Pratikto & Peristiowati, 2022); (Nalivaico et al., 2024).

5. DISCUSSION

The findings of this study demonstrate that the development of a hybrid expert system integrating Forward Chaining and Certainty Factor reasoning, grounded in statistically significant Odds Ratios, is capable of consistently classifying tuberculosis (TB) risk based on sociodemographic characteristics and history of close contact in Central Lampung Regency. The primary results indicate that low income, undernutrition (BMI < 18.5), and a history of close contact represent the strongest determinants of high-risk classification, in accordance with the multivariate epidemiological analysis. These findings directly address the research objective of constructing an evidence-based, explainable TB risk screening model to support public health decision making. Risk-based screening approaches are increasingly recognized as essential for identifying high-risk populations before the appearance of overt clinical manifestations (MacLean & Yapa, 2024).

Interpreted within the host–agent–environment epidemiological framework and the broader perspective of social determinants of health, these results underscore the interaction between host factors (nutritional status), environmental and socioeconomic determinants (income level), and exposure to infectious agents (history of close contact). Household contact has consistently been identified as a major predictor of TB infection and disease progression, particularly in resource-limited settings (Marambire et al., 2022). Intersectoral analyses further confirm that poverty and social vulnerability substantially increase the likelihood of TB transmission within communities (da Silva et al., 2025). Consequently, the system developed in this study empirically reinforces the relevance of theoretical models that emphasize environmental and socioeconomic determinants as the central drivers of disease occurrence.

Compared with prior studies focusing predominantly on symptom-based or radiological screening, our approach extends risk assessment by systematically integrating locally derived epidemiological evidence. Digital TB screening applications in Indonesia have demonstrated improvements in case detection through symptom-based self-assessment; however, they have not incorporated statistically weighted epidemiological risk modeling (Triyono et al., 2023). Although artificial intelligence models applied to chest radiograph interpretation have shown high sensitivity and specificity, concerns remain regarding their limited transparency in decision-making processes (Cao et al., 2021). Similarly, advanced machine learning architectures, including neural networks and ensemble models, have achieved excellent predictive performance; however, they frequently operate as black-box systems that hinder interpretability at the primary care level (Suresh, 2025). In contrast, the rule-based expert system developed in this study prioritizes explicit reasoning pathways, thereby enhancing its usability and accountability.

The explainability component of the system, manifested through transparent rule activation and Certainty Factor aggregation, strengthens its legitimacy as a public health decision-support tool. The literature on explainable artificial intelligence highlights that interpretability significantly enhances user trust and facilitates integration into healthcare workflows (Özkurt, 2024). Moreover, implementation experiences with computer-aided detection technologies in TB screening emphasize that successful deployment depends not only on algorithmic accuracy but also on user acceptance and contextual alignment with health systems (Creswell et al., 2023). The present study bridges the gap between statistical robustness and operational transparency by embedding epidemiological risk estimates into a structured rule-based reasoning framework.

From a practical standpoint, this study expands the body of literature on hybrid screening models that do not rely exclusively on imaging technologies or molecular diagnostics but instead leverage accessible, community-level indicators. Although portable radiological systems integrated with computer-aided detection have proven effective in active case finding, they require specific infrastructure and technical capacity (Nalivaico et al., 2024). Similarly, biomarker-based screening strategies face ongoing challenges related to cost, scalability, and clinical applicability (MacLean & Yapa, 2024). By utilizing routinely obtainable sociodemographic and contact-related data, the developed system provides a more feasible and context-sensitive alternative for primary health care settings.

This study has several limitations must be acknowledged. The case-control design relies on retrospective exposure assessment and may be subject to information bias. Additionally, the model incorporates a limited number of variables, potentially restricting the comprehensiveness of risk representation. Longitudinal cohort studies have indicated that dynamic monitoring of contacts over time may enhance the predictive capacity for disease progression (Marambire et al., 2022). Furthermore, implementation in real-world settings requires continuous evaluation to ensure sustainability and integration into regional health information systems.

The implications of this study highlight the importance of strengthening community-based TB screening strategies by incorporating social determinants as early risk indicators. Intersectoral approaches that integrate health, social, and community sectors are increasingly recognized as essential for sustainable TB control (da Silva et al., 2025). Future research should explore external validation across broader populations, longitudinal performance assessment, and comparative evaluation between rule-based and machine learning–based screening systems to determine their relative effectiveness in diverse community contexts.

6. CONCLUSION

This study successfully developed and evaluated a hybrid expert system that integrates Forward Chaining and Certainty Factor reasoning for tuberculosis (TB) risk screening based on sociodemographic factors and comorbidities in Central Lampung Regency. The findings demonstrate that low income, undernutrition (BMI < 18.5), and a history of close contact are statistically significant determinants that substantially influence high-risk classification within the system. The transformation of significant Odds Ratios into certainty factor values enabled proportional risk weighting, whereas the rule-based inference mechanism ensured consistent, transparent, and traceable decision-making. The system functions as a public health decision-support tool for early risk identification, rather than as a definitive diagnostic instrument.

From a theoretical perspective, this study reinforces the relevance of the host–agent–environment framework and social determinants of health in the development of artificial intelligence–based risk screening systems. Practically, the proposed model offers an applicable and context-sensitive solution suitable for primary healthcare and community-level implementation, particularly in resource-limited settings in India. Its principal conceptual contribution lies in integrating locally derived epidemiological evidence with an explainable hybrid reasoning framework that balances analytical rigor, interpretability, and accountability in public health decision-making.

Further research is recommended to conduct external validation across broader populations and implement longitudinal evaluations to assess model stability over time. Integration with regional digital health platforms may also enhance sustainability and expand the role of risk-based expert systems in strengthening community-centered TB prevention and control strategies.

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