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From tradition to technology: artificial intelligence advancements in dental age estimation*

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Abstract

Conventional dental age (DA) estimation methods, relying on visual and clinical assessments, have significant limitations, especially in large-scale incidents like mass disasters. Recent advancements in artificial intelligence (AI) have revolutionized this field, offering enhanced accuracy, efficiency, and the ability to handle large datasets. AI techniques, including machine learning (ML) models like random forest (RF) and support vector machine (SVM) and deep learning models such as convolutional neural networks (CNNs), have demonstrated superior performance compared to conventional methods. This review explores the evolution of dental age estimation methods from traditional visual and radiographic techniques to modern AI-assisted approaches. It discusses the benefits and challenges of implementing AI in forensic odontology, including the need for high-quality training data, effective algorithm selection, and robust preprocessing techniques.

Keywords: artificial intelligence; dental age estimation; forensic odontology; legal identity

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Introduction

Forensic odontology holds a crucial position within the realm of forensic science, primarily concerning the identification of human remains. An integral component of this field involves the assessment of an individual's age through the examination of dental attributes, a procedure termed dental age estimation. This process assumes paramount importance in scenarios like disaster victim identification, where the expeditious and precise evaluation of age becomes imperative due to the presence of numerous unidentified remains. Traditionally, dental age estimation has heavily relied upon visual and clinical methods, often entailing meticulous manual scrutiny conducted by forensic experts (1). While these conventional approaches have contributed significantly to our understanding, they also present inherent challenges, notably when dealing with large-scale incidents, such as mass disasters (2).

Forensic odontology has recently undergone a significant transformation, driven by integrating state-of-the-art artificial intelligence (AI) technologies. The utilization of AI in dental age estimation signifies a remarkable leap forward, holding the promise of streamlining the age assessment process, heightening precision, and alleviating the challenges linked with manual evaluations. This innovative approach offers the potential to expedite the identification of victims in disaster-stricken scenarios. It raises prospects for enhancing age estimation's overall efficiency and accuracy in routine forensic cases and research (3). With the increasing global trends in immigration and the number of refugees, the demand for rapid age estimation is rising. Additionally, age group classification can facilitate robust yet quick judgments and has a wide range of applications in areas such as homeland security, passport services, statistical analysis of age group distributions, and forensic science. Machine learning-based age group estimation algorithms and human perception-based methods for age estimation have been actively explored in the literature, making this a dynamic research area (4).

In dentistry, a historical perspective reveals the development of various machine-learning tools. These tools primarily found applications in image diagnostics, with a limited focus on age estimation. In previous studies, age estimation was approached either by employing neural networks to infer the age directly or by estimating measures subsequently used in a complex regression model to predict the patient's age. However, it is worth noting that none of these studies proposed a two-stage deep learning model. This innovative approach involves age estimation through an initial image segmentation process followed by post-segmentation measurements. This unique methodology seeks to replicate the cognitive mechanisms employed by experts in calculating the I3M, marking a departure from the conventional approaches in the field (5).

This review aims to discuss the existing literature on the subject and provide insights into the current state of AI in dental age estimation. It will shed light on the benefits, challenges, and prospects of implementing AI technologies in forensic odontology. Through a comprehensive analysis of the available studies, this review aims to inform and guide researchers and practitioners in the field, paving the way for more efficient and precise age estimations in forensic contexts.

Visual and radiographic dental age estimation

Visual inspection is one of the oldest and most basic methods for dental age estimation. Forensic odontologists, often aided by dental charts and reference atlases, meticulously examine the morphological changes in teeth over time. It is based on evaluating the tooth eruption sequence in the oral cavity and the morphological changes in tooth structure due to functions such as attrition, abrasion, and wear patterns (6). Attrition analysis, for instance, examines wear on occlusal surfaces, with the extent of attrition linked to age. Wear patterns on tooth surfaces are examined for insights into age-related dietary and dental habit changes. At the same time, the pulp-tooth ratio method considers changes in the pulp chamber's size relative to the crown (7–9).

After tooth development, age determination is mainly done by visual examination. In dental age estimation, visual inspection is used to determine the stage of tooth development and the degree of wear and tear on the teeth (1). Visual inspection is an invaluable tool in the absence of advanced equipment and resources, and it has been instrumental in mass disaster scenarios where immediate identification is crucial. However, its accuracy and reliability often depend on the examiner's expertise, and it may not be as precise as more modern methods (10).

Dental radiography has revolutionized age estimation practices within forensic odontology. Techniques such as panoramic and periapical radiographs offer a detailed view of dental structures, including tooth roots, pulp chambers, and alveolar bone. These images are indispensable for assessing dental development and age-related changes. Dental radiography allows for accurate measurements and comparisons, enabling a quantitative approach to age estimation (11). However, it necessitates specialized equipment, skilled radiographers, and exposure to ionizing radiation, which are not always readily available in field settings.

The estimation of age from dental radiographic records is based on the evaluation of some characteristics such as the formation of jaw bones, the appearance of tooth germs, the degree of crown completion and its eruption, the degree of resorption of deciduous teeth, the measurement of open apices in teeth, the volume of the pulp chamber and root canals, the formation of physiological secondary dentin, the tooth-to-pulp ratio, or the development and topography of the third molar (12).

Dental age estimation through radiographic approaches encompasses several methods, each offering a distinct approach to assessing dental maturation. These methods include the staging/scoring method, exemplified by the Demirjian method, Nolla method, and Willems methods; the atlas method, featuring techniques like the AlQahtani, Blenkin-Taylor, Schour and Massler, and Ubelaker methods; and the examination of post-formation changes in teeth, including the Gustafson's, Kvaal, and Cameriere's methods. The Demirjian dental age estimation method is a procedure utilized to approximate the age of young individuals by assessing the level of dental maturation. The technique was initially outlined in 1973 by Demirjian et al. and relied on a cohort of French-Canadian children as the study population (13). The Demirjian approach has been verified in several demographics, encompassing Romanian, Belgian, Turkish, Indian, Chinese, and Brazilian. Previous studies' results have demonstrated varying accuracy levels, underscoring the need for adaptable dental maturity scores tailored to each specific population (14–18).

The Willems dental age estimation method is used to estimate an individual's age based on the degree of dental development of their teeth. The method measures the developmental stages of the seven left permanent mandibular teeth. A score is obtained for each tooth from sex-specific tables, and the scores are added to obtain the dental age (19). The Willems method is a modification of the Demirjian method and was first applied in a Belgian Caucasian population in 2002. Several recent studies have found the Willems method more accurate than the original Demirjian method (12,20,21).

The Nolla dental age estimation method evaluates the degree of dental development in the mandibular and maxillary teeth on the left side, excluding the third molar. It accomplishes this by categorizing the development into ten distinct degrees. A score is assigned to each of the teeth, which is converted to an average score, according to sex, in a calculation developed by Nolla. These individual scores are subsequently summed to determine the dental age (22). The method can be used as a complementary tool for estimating the age of children of Spanish origin (23). However, some studies have found that the Nolla method underestimated the chronological age (CA) of individuals, and the underestimation of age increased as the age of the individual increased (21). Despite this, some studies found the Nolla method more accurate than Demirjian (24,25).

The London Atlas of Human Tooth Development and Eruption, formulated by AlQahtani et al., is a valuable tool for estimating an individual's age by assessing both tooth development and alveolar eruption (26). This method has demonstrated impressive accuracy in determining dental age, particularly in children and adolescents with systemic diseases (27). An insightful study in Surabaya, Indonesia, shed light on the applicability of the AlQahtani and the Willems methods in estimating dental age within the Surabaya population (11). The method has also been used in forensic dentistry for age estimation for legal purposes (28).

The Kvaal dental age estimation method is used to estimate an individual's age based on the pulp size using periapical dental radiographs. The method was developed by Kvaal et al. in 1995 and has been used in forensic dentistry for age estimation for legal purposes (29). A study conducted in Côte d'Ivoire found that the Kvaal method, when used with a cone beam, could determine a local formula for the age estimation of adult African melanoderma subjects. The study found that the Kvaal method was reliable for age estimation in adult African melanoderma subjects (30).

Histological examination for dental age estimation

Tooth histology and microscopy provide a unique perspective on age estimation by examining the microscopic features of dental tissues. Analysis of dentin microstructure, cementum apposition, and enamel prism patterns can offer valuable insights into age-related changes. While highly precise, these techniques require access to dental samples, specialized laboratory equipment, and extensive training in histological analysis (31,32). Histological examination is a method used in dental age estimation that involves the examination of tooth structure at a microscopic level (33). This method is based on observing changes in tooth structure due to aging, such as the formation of secondary dentin, changes in the pulp chamber, and changes in the cementum (34).

Dental age estimation methods based on histological examination involve the microscopic analysis of dental tissues to assess an individual's age. These methods rely on examining various structural features within teeth, such as dentin, cementum, and enamel. One such method, Molar Cementum Annulation (MCA), assesses the periodicity of cementum annulation, with each annulation representing a year of growth. MCA is often utilized in forensic cases where well-preserved dental remains are available, making it particularly valuable for age estimation (35). Another method, Tooth Cementum Lines (TCL), similarly relies on cementum layers, counting incremental growth lines to estimate age, and is suitable for various age groups. Incremental Lines in Dentin (ImDS) assesses incremental lines within the dentin, providing age estimates through line counting in living individuals and forensic contexts. Microwear analysis examines microscopic features on tooth surfaces, utilizing wear patterns to estimate age, primarily applied in archaeological and paleontological studies. Finally, enamel histology, which examines enamel prism patterns, offers insights into age and dietary habits, typically used in paleoanthropological and bioarchaeological contexts to estimate the age of ancient populations. These histological methods offer precise age estimates, particularly valuable in forensic investigations, but require specialized equipment, histological expertise, and suitable dental samples, making them less practical for living individuals due to their invasive nature (31).

AI-assisted Dental Age Estimation

In recent times, the utilization of AI has significantly advanced the dental age (DA) evaluation, benefiting from the remarkable progress in computational technology and algorithmic development (36). AI, a domain of computer science dedicated to creating systems that can execute tasks typically associated with human intelligence, encompasses various subfields, such as machine learning, probabilistic reasoning, robotics, computer vision, and natural language processing. The term "AI" denotes the emulation of human intelligence by machines. In contrast, machine learning, a subset of AI based on algorithms trained on data, excels at recognizing patterns and making predictions by processing information and experiences rather than relying on explicit programming. It is crucial to note that machine learning models adapt and improve their efficacy over time by incorporating new data and experiences, and deep learning, a subset of machine learning, employs neural networks to tackle complex problems (37). The studies reviewed in this article highlight the significant role of AI in enhancing dental age estimation, as summarized in Table 1.

Machine learning (ML), a key component of AI, offers a more accurate and efficient method for predicting DA compared to traditional radiological techniques. A study by Shen et al. (2021) demonstrated that ML models, including random forest (RF), support vector machine (SVM), and linear regression (LR), outperformed the traditional Cameriere formula in accuracy. Specifically, the SVM and RF models had lower mean error (ME), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) compared to the European and Chinese Cameriere formulas, indicating superior precision. The SVM model (ME = 0.004 years) and RF model (ME = -0.004 years) exhibited the best ME performance. The SVM model also had the lowest MAE of 0.489 years, making its DA estimates closest to the CA. Additionally, the RF model had the lowest MSE of 0.389 years. Overall, the SVM and RF models were the most accurate among the models evaluated. In contrast, the European Cameriere formula had ME, MAE, MSE, and RMSE values of 0.592, 0.846, 0.755, and 0.869 years, respectively. The Chinese Cameriere formula had corresponding values of 0.748 (ME), 0.812 (MAE), 0.890 (MSE), and 0.943 (RMSE) years (38).

Bunyarit et al. (2021) evaluated the effectiveness of the 8-tooth method, initially introduced by Chaillet and Demirjian, for Malaysian Malays aged 5.00–17.99 years. Their study aimed to develop more accurate teeth maturity scores for age estimation using artificial neural networks (ANN).

Table 1. The summary of the reviewed literature focused on the implementation of AI in dental age estimation.

Title	Authors	Year	Sample size	Age range (years)	Parameters	Algorithm architecture	Findings
Machine learning assisted Cameriere method for dental age estimation	Shen S et al.	2021	748 OPGs	5.0 – 13.0	Mandibular tooth development	RF SVM LR	The study indicates that the Support Vector Machine (SVM), Logistic Regression (LR), and Random Forest (RF) models exhibit higher accuracy compared to the European and Chinese Cameriere formulas. Notably, the SVM and RF models demonstrate lower Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) values, underscoring their enhanced precision. These findings advocate adopting machine learning algorithms over traditional Cameriere formulas in forensic dental age estimation.
Dental age estimation of Malay children and adolescents: Chaillet and Demirjian's data improved using artificial multilayer perceptron neural network	Bunyarit SS, et al.	2021	1569 OPGs	5.0 – 17.9	Mandibular tooth development	ANN-MLP	Comparisons between known chronological age (CA) and estimated dental age (DA) using Chaillet and Demirjian's dental maturity scores showed that DA was consistently underestimated by 2.09 ± 0.90 years for Malay boys and 2.79 ± 0.99 years for Malay girls across all age groups (*p* <0.05). Artificial neural networks (ANN) were employed to create new dental maturity scores (NDA) specifically for Malay subjects to enhance age estimation accuracy. This method significantly improved accuracy, with the NDA underestimating DA by only 0.035 ± 0.84 years for boys and 0.048 ± 0.928 years for girls (*p*>0.05).
Comparison of different machine learning approaches to predict dental age using Demirjian's staging approach	Galibourg A, et al.	2021	3605 OPGs	2.0 – 24.0	Mandibular tooth development	RF SVM DT BRR KNN ADAB POLYREG MLP STACK VOTE	This study aims to evaluate the accuracy of ten machine learning algorithms in predicting dental age in children using the seven left permanent mandibular teeth and from childhood to young adulthood using these teeth along with the four third molars. The traditional Demirjian method significantly overestimated dental age compared to the Willems method (−0.71 ± 0.07 and −0.22 ± 0.08, respectively). Across all metrics, the Willems method demonstrated greater accuracy than the Demirjian method. Furthermore, all machine learning algorithms tested showed significantly higher accuracy than the reference methods for all metrics. Among the machine learning models, ADAB and BRR had the lowest performance in terms of MAE.
The Application of Artificial-Intelligence-Assisted Dental Age Assessment in Children with Growth Delay	Wu TJ, et al.	2022	2431 OPGs	3.0 – 18.0	Mandibular tooth development	CNN	AI-assisted methods can predict chronological age (CA) with much greater accuracy, showing mean errors of less than 0.05 years, compared to traditional methods that overestimate age for both sexes. For children with growth delays (GD), convolutional neural networks (CNN) detected delayed dental age (DA) in both boys and girls, whereas machine learning models identified this delay only in boys.
Artificial Intelligence as a Decision-Making Tool in Forensic Dentistry: A Pilot Study with I3M	Bui R et al.	2023	456 OPGs	≤18 (57%) >18 (43%)	Third molar maturity index	Mask R-CNN U-Net	The findings indicated that the U-Net model was the most effective in generating accurate masks of the mandibular third molar. The two topological approaches also demonstrated comparable performance in accurately inferring parameters a, b, and c, thereby determining the I3M score. The proposed method successfully emulated forensic expertise with an accuracy of 94.7%. Nonetheless, several methodological, technical, and ethical considerations require further discussion.
Predictive Artificial Intelligence Model for Detecting Dental Age Using Panoramic Radiograph Images	Aljameel SS, et al.	2023	529 OPGs	10.0 – 19.0	Mandibular tooth development	Xception VGG16 DenseNet121 ResNet50	Five experiments were conducted to evaluate the models. In the first experiment, the entire dataset was tested using cropping and renaming techniques, with ResNet50 achieving an MAE of 1.5633, which is unsatisfactory. The second and third experiments focused on age ranges of 6–12 years and 6–11 years, respectively. ResNet50 achieved an MAE of 1.4429 in the second experiment, while the Xception model improved to an MAE of 1.4173 in the third experiment, indicating better performance with a narrower age range. The fourth experiment used images of seven-year-old patients, with VGG16 achieving an MAE of 0.6915. In the fifth experiment, using images of nine-year-old patients, the MAE was 0.9499. These results suggest that narrowing the age range enhances model accuracy.

Age-group determination of living individuals using first molar images based on artificial intelligence	Kim S, et al.	2023	1586 OPGs	0.0 – >60.0	Four first molar	CNN	The accuracy of tooth-wise estimation ranged from 89.05% to 90.27%. Performance was primarily assessed using a majority voting system and area under the curve (AUC) scores, which varied between 0.94 and 0.98 across all age groups, indicating excellent capability. CNNs' learned features were visualized as heatmaps, showing that the networks focused on different anatomical parameters, such as tooth pulp, alveolar bone level, and interdental space, depending on the age and tooth location. This analysis provided insights into the most informative regions for different age groups. The high prediction accuracy and detailed heatmap analyses demonstrate the effectiveness and utility of this AI-based age determination model.
Dental age estimation: A comparative study of convolutional neural network and Demirjian's method	Sivri MB, et al.	2024	5898 OPGs	4.0 – 17.0	Mandibular tooth development	Alexnet VGG16 ResNet152 DenseNet201 InceptionV3 Xception NASNetLarge InceptionResNetV2 MobieNetV2	DenseNet201 achieved the lowest MAE of 0.73 years, demonstrating its superior accuracy in age estimation compared to other architectures. For most age categories, the predicted age closely matched the actual age, with the most inconsistencies observed at ages 12 and 13. The results also showed a strong correlation between the ages predicted by the CNN and those estimated using Demirjian's method. In conclusion, the CNN approach is a viable alternative to Demirjian's age estimation method.
Notes: Artificial Neural Networks (ANN); Bayesian Ridge Regression (BRR); Boosting Method AdaBoost (ADAB); Convolutional Neural Network (CNN); Decision Tree (DT); K-Nearest Neighbors (KNN); Logistic Regression (LR); Multi-layer Perceptron (MLP); Polynomial Regression (POLYREG); Random Forest (RF); Stacking (STACK); Support Vector Machine (SVM); Voting (VOTE)							

The research analyzed 1569 dental panoramic tomographs of Malaysian individuals, applying a scoring system adapted from Demirjian's eight developmental stages to record tooth development. These maturity scores were then converted to dental age (DA). The study calculated the mean and standard deviation of CA, DA, and the difference between CA and DA. New dental maturity scores (NDA) were developed using ANN, and their accuracy was assessed. The ANN-based method demonstrated improved precision in estimating dental age, with an average difference of 0.035 ± 0.84 years for boys and 0.048 ± 0.928 years for girls ($p > 0.05$) (39).

Galibourg et al. (2021) compared ten machine learning (ML) methods to predict dental age using the Demirjian and Willems methods. The study analyzed 3605 panoramic radiographs of healthy French patients aged 2 to 24, focusing on seven left permanent mandibular teeth and four third molars. The ML algorithms tested included random forest (RF), support vector machine (SVM), decision tree (DT), Bayesian ridge regression (BRR), k-nearest neighbors (KNN), AdaBoost (ADAB), polynomial regression (POLYREG), multi-layer perceptron (MLP), and combinations of these techniques using stacking (STACK) and voting (VOTE). Accuracy was assessed using five indicators: coefficient of determination (R^2), mean error (ME; chronological age minus predicted age), root mean square error (RMSE), mean square error (MSE), and mean absolute error (MAE). The Demirjian method significantly overestimated dental age compared to the Willems method (-0.71 ± 0.07 vs. -0.22 ± 0.08). The Willems method showed greater accuracy across all metrics. All ML algorithms outperformed the traditional methods in all metrics, with ADAB and BRR showing the lowest performance in terms of MAE (40).

Wu et al. (2022) conducted a study using AI to evaluate dental age in children with growth delays, comparing the performance of AI-assisted machine evaluations with conventional methods. The study revealed significantly higher accuracy in predicting CA using AI, with the CNN-assisted model exhibiting the most effective performance in assessing dental age delays for both male and female children with growth delays. This research highlights the potential of AI to improve age estimation in clinical and forensic contexts (41).

The third molar maturity index (I3M) assessment is a common approach for dental age estimation. Bui et al. (2023) compared two deep learning methods, Mask R-CNN and U-Net, on mandibular radiographs. Their study resulted in a two-part instance segmentation, including apical and coronal segments. The study found that U-Net outperformed Mask R-CNN with a mean intersection over union metric (mIoU) score of 91.2% compared to 83.8%. Combining U-Net with topological data analysis (TDA) or TDA without deep learning (TDA-DL) for I3M computation yielded accurate results compared to dental forensic experts. The average absolute

error was 0.04 ± 0.03 years for TDA and 0.06 ± 0.04 years for TDA-DL. This study showcases the potential feasibility of automating the I3M process by combining deep learning and topological approaches, achieving a 95% accuracy rate compared to expert assessments (5).
Similarly, Aljameel et al. (2023) aimed to develop a deep learning-based regression model using panoramic radiograph images to predict dental age. Their dataset consisted of 529 panoramic radiographs collected from a dental hospital in Saudi Arabia. Various deep learning methods, including Xception, VGG16, DenseNet121, and ResNet50, were employed to implement the model. The Xception model exhibited the most favorable performance, with an error rate of 1.417 for the 6-11 age group, suggesting the potential of this model to assist dentists in planning treatments based on DA rather than CA (42).
Kim et al. (2023) conducted a study on age-group determination based on first molar analysis. The study aimed to develop an accurate and robust AI-based system for age estimation using a CNN with dental X-ray images of the first molars extracted from panoramic radiographs. The dataset included four first molar images—two from the maxilla and two from the mandible—of 1586 individuals across various age groups. The tooth-wise estimation accuracy ranged from 89.05% to 90.27%. Performance was primarily evaluated using a majority voting system and area under the curve (AUC) scores, which ranged from 0.94 to 0.98 across all age groups, indicating excellent capability. Heatmap visualizations of the CNNs' learned features showed that the networks focused on various anatomical parameters, such as tooth pulp, alveolar bone level, and interdental space, depending on the age and location of the tooth (4).
A recent study by Sivri et al. (2024) compared the accuracy of the CNN technique to the conventional Demirjian dental age estimation method. The study analyzed 5898 panoramic radiographs of patients aged 4 to 17. Two researchers performed tooth staging using the Demirjian method, while another two applied the CNN technique. Several CNN architectures were evaluated, including AlexNet, VGG16, ResNet152, DenseNet201, InceptionV3, Xception, NASNetLarge, InceptionResNetV2, and MobileNetV2. DenseNet201 achieved the lowest MAE of 0.73 years, indicating higher accuracy, with most predicted ages closely matching the actual ages. The most significant discrepancies were observed in the 12 and 13-year age groups (43).
Several critical factors influence the accuracy of dental age estimation using AI. Firstly, the quality and representativeness of the training data are paramount, as diverse and well-labeled data ensure the model's applicability to the target population. Secondly, the choice of AI algorithm significantly impacts performance, with convolutional neural networks (CNNs) often proving effective due to their ability to discern complex patterns in dental images. Additionally, the quality of the dental images and the preprocessing techniques employed, such as image filtering and normalization, are essential for accurate feature extraction. Variability in dental development, influenced by genetics, nutrition, and environmental conditions, also poses a challenge, affecting the precision of AI predictions.
Moreover, AI models can suffer from bias and overfitting, necessitating cross-validation and regularization techniques to maintain accuracy. The interpretability and explainability of AI results are crucial for building trust in the technology, achievable through feature importance analysis and visualizations. Finally, continuous updates and refinements of AI models with new data are necessary to ensure their ongoing accuracy and effectiveness. These factors highlight the complexities and considerations in developing reliable AI-based dental age estimation methods (42,44,45).

Conclusion

Recent advancements in AI technology have greatly enhanced the accuracy and efficiency of dental age estimation. Research has shown that ML models, such as RF and SVM, outperform traditional methods like the Cameriere and Demirjian methods. These AI models benefit from high-quality, diverse training data, effective algorithm selection, and robust preprocessing methods. Although challenges such as variability in dental development and potential biases exist, AI models have demonstrated impressive accuracy in estimating dental age across various populations. Regular updates and improvements with new data are essential to maintain their effectiveness. Overall, AI-based methods are promising to improve dental age estimation in clinical and forensic settings, offering more reliable and interpretable results than traditional techniques.

Declaration of Interest

None

Author Contributions

AK and AM contributed to the study conceptualization and supervision. AK, ST, IR, TLR, ML, WASP and MH contributed to data collection and analysis. AK, TLR and WASP contributed to writing the draft of the manuscript. All authors have contributed and approved the final draft of the manuscript.

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