Natural Resources for Human Health

eISSN: 2583-1194

Original Research

Received 15 March 2026
Revised 16 April 2026
Accepted 20 May 2026

Natural Resources for Human Health 2026, Vol. 6 (2s): 92–101

KEYWORDS:
Adolescent Health; Chronic Disease; Artificial Intelligence; Social Determinants of Health; Electronic Health Records; Medical Imaging.

An Integrated AI-Driven Public Health Analytics Framework for Predicting Chronic Disease Burden Using Social Determinants of Health, Medical Imaging, and Electronic Health Records

[1]M. Sridhar, [2]Dr Gokul D, [3]Dr. V. Gomathi, [4]Dr. Mahendran C, [5]Dr. Sumit Kushwaha, [6]R. Naveenkumar, [7]Kulwinder Kaur, [8]Krishna Suresh B V N V,

[1]Assistant Professor, Department of Computer Technology, Sri Ramakrishna College of Arts & Science, Coimbatore -06, Tamilnadu, India. Email: sridhar@srcas.ac.in
[2]Assistant Professor , Department of Community Medicine , Saveetha Medical College and Hospital, SIMATS, Chennai, Tamil Nadu Mail id : gokul.deve3@gmail.com
[3]Assistant Professor, Nandha Engineering College, Erode - 638 052, Tamilnadu, India. Email: svpgomathi87@gmail.com https://orcid.org/0000-0002-0364-0500
[4]Professor, Community Medicine, Meenakshi Medical College Hospital & Research Institute, Meenakshi Academy of Higher Education and Research, Enathur, Kanchipuram, Tamil Nadu 631552
[5]Associate Professor, Department of Directorate of Research, Innovation, and Consultancy (DRIC), Chandigarh University Uttar Pradesh, Unnao - 209859, Uttar Pradesh, India.
Email: sumit.kushwaha1@gmail.com ORCID: 0000-0002-3830-1736
[6]Dept of CSE, School of Engineering and Technology, CGC University Mohali-140307, Punjab India.Email: drnk1983@gmail.com 0000-0001-9033-9400
[7]Assistant Professor, Faculty of Computing, Guru Kashi University, Bathinda, Punjab, India Mail id:- kulwinderkaur@gku.ac.in Orcid id:- https://orcid.org/0009-0006-6721-3037
[8]Asst Professor, Department of Computer Science & Engineering, KLEF, KL UNIVERSITY, VADDESWARAM, ANDHRA PRADESH, INDIA
Email:krishnasuresh@kluniversity.in Orchid : 0000-0002-1486-880x

ABSTRACT: This study created an integrated framework for artificial intelligence prediction of both individual and population burden of chronic diseases among adolescents from electronic health records, measures of social determinants and liver ultrasound images. A cohort of 24,000 adolescents (10 to 19 years) was simulated and assessed through 24 months. Each modality-specific feature was obtained using a Temporal Transformer, a multilayer perceptron, and an EfficientNet-B0, and then fused together by using attention. The integrated framework showed 90.6% accuracy, 87.8% sensitivity, 91.2% specificity, 0.944 ROC–AUC and 84.9% F1-score. Those most important factors were BMI-for-age z score, fasting glucose, liver steatosis, family history and neighbourhood deprivation. Integrating multiple modes improved risk stratification and disease burden estimation over conventional and unimodal risk stratification models based on simulations. These computational findings would need to be tested in "real world" multicentre adolescent cohorts before being clinically or public healthly implemented, however. The concept of fairness, calibration, privacy, safety and potential clinical usability is also to be evaluated separately.

1. INTRODUCTION

Adolescent girls and boys are becoming a neglected target of chronic disease and chronic disease care systems are facing significant pressures in all parts of the world. Preteen and teen obesity, metabolic syndrome, hypertension, prediabetes, and type 2 diabetes are smarting being recognized during the teenage years due to physical inactivity, poor dietary choices, poor sleeping habits, genetic predisposition, and the changing landscape of society. These manifestations can affect the early life course and affect the likelihood of cardiovascular disease, renal complications, liver dysfunction, disability and premature death in adulthood. Therefore it is very important to detect the disease early for its timely prevention and management.

Social and economic inequalities are also important factors affecting the risk of chronic diseases during adolescence. Household income, parental education, food insecurity, quality of housing, neighbourhood deprivation and access to healthcare can influence the behaviour of patients, their access to treatment and the course of the disease. Traditional prediction approaches often focus on individual clinical indicators, and fail to adequately capture the multifactorial impacts of longitudinal health changes and social disadvantage.

EHRs offer temporal data related to diagnoses, lab parameters, medications/medication use, vital signs, and prior health care interactions. Physiological abnormalities, not captured by structured clinical variables, can be identified using medical imaging. Steatosis, which can be associated with obesity and metabolic disturbance, can be detected by liver-imaging with ultrasound. However, predictions using only EHRs, only social predictors or only imaging predictors may miss important interactions between these complementary information sources.

Multimodal AI opens up a way to combine the different types of data and create more holistic risk predictions. Such systems need to be intelligible, adjustable, and adherent to equity (social, economic, and geographic) as well. This study suggests an integrated AI public-health analytics study model that integrates longitudinal EHRs, social determinants of health, and liver ultrasound imaging to achieve individual risk prediction for chronic diseases and population-level burden for chronic diseases for adolescents.

2. RELATED WORK

The traditional prediction of chronic diseases has been almost exclusively based on logistic regression and Cox proportional-hazards models, as well as clinical risk scores. These methods make interpretable links between known risk factors and disease outcomes but often do not take into account non-linear associations or interactions between multiple adolescent clinical, behavioral and socioeconomic risk factors. To analyze the health records of adolescents, machine learning algorithms such as random forests, support vector machines, gradient boosting and XGBoost algorithms have been used to uncover the structure of nonlinear relationships existing in the data related to obesity, hypertension, metabolic syndrome, and diabetes [1].

Success in longitudinal EHRs has been used to further set the stage for deep-learning models to enable predictive analysis [2]. Recurrent neural networks (RNNs), gated recurrent units (GRUs), long short-term memory networks (LSTMs), and Transformers are capable of learning the temporal patterns from repeated laboratory testing [3], vital signs [4], diagnoses, medications, and healthcare encounters. They are, however, dependent upon having sufficiently large samples, good temporal documentation and proper management of gaps in the data [5].

On the other hand, AI has proven to be very promising in medical image analysis [6]. Imaging patterns can be recognized by using convolutional neural networks (CNNs) and vision Transformers (ViTs), which correspond to liver steatosis, abnormal adiposity, and metabolic complications. However, there is not much information on clinical change over time or about social factors in imaging-only systems.

Adolescent health inequalities are significantly shaped by social determinants of health such as income, father's education, food insecurity, neighbourhood deprivation, and healthcare access [7]. These variables are useful for population level risk assessment, but are not frequently included in clinical prediction models [8]. While there are several multimodal applications that integrate structured records, images, genomic data or clinical text, there are limited that focus on public-health applications of adolescents [14]. [15]

AI techniques like SHAP [10] and Grad-CAM [11] can help determine what's most influential in the data and what parts of the image are most important, which can aid in clear decision-making. Further, to be clinically useful, probability calibration

[12] and the evaluation of the regressed variables across various subgroups or population dimensions—such as demographic, socioeconomic and geographic—must be performed, along with assessment of fairness among subgroups and across population dimensions [13]. There are many previous studies that present accuracy or ROC–AUC results with few external validation, calibration, interpretability or bias analyses. Clinical, social or imaging data are typically analyzed separately, as it is common in existing studies. Very few studies have explored the potential improvement of explainable chronic-disease risk and burden prediction by combining all three modalities among adolescents.

3. MATERIALS AND METHODS

3.1 Study Design, Cohort and Input Data

A retrospective cohort design was used that incorporated a simulation for the purpose of assessing the proposed multimodal framework. The simulation-derived dataset consisted of 5000 adolescent profiles (10-19 years old, mean (15.1 \pm 2.6) years old). Each profile was based on 24-month follow-up electronic health record data and social determinants of health, liver-ultrasound imaging features, and chronic-disease outcomes. For the dataset, 3,500 adolescent-profiles (70%) were used for training, 750 adolescent-profiles (15%) were used as validation and 750 adolescent-profiles (15%) were used as testing. This patient level partitioning avoided the appearance of the same patient information in multiple subsets.

The main outcome was the development of at least one chronic metabolic disease over the 24-month follow-up. The evaluated conditions were persistent obesity, metabolic syndrome, hypertension, prediabetes or type 2 diabetes and liver steatosis. Multimorbidity was defined as having 2 or more of these conditions.

EHR inputs comprised age, sex, BMI, BMI-for-age z score, systolic blood pressure, diastolic blood pressure, HbA1C, fasting glucose, total cholesterol, HDL and LDL cholesterol, triglycerides, liver enzymes, outpatient and hospital visits, and diagnoses and medication history, as well as family history of chronic metabolic disease. These were all longitudinal variables reflecting changes in the health and health care utilization of the adolescents.

Social-determinant inputs were the household-income category, educational level of parents, food insecurity, housing, health-care access, neighbourhood deprivation, living in urban/rural areas, physical activity, and sleep duration. These were socioeconomic, environmental and behavioural factors related to the risk of chronic disease.

The imaging modality was simulated liver-ultrasound images categorized as normal liver appearance, mild steatosis, moderate steatosis and severe steatosis. Structured clinical variables were complemented by imaging features to capture the physiological evidence of hepatic fat accumulation and metabolic dysfunction that may not be fully represented by structured clinical variables. The main demographic, social and chronic disease features of the simulated population are reported in Table 1.

Table 1. Characteristics of the simulation-derived adolescent cohort

Characteristic	Value
Total adolescent profiles	5,000
Age, mean ± SD	15.1 ± 2.6 years
Female	2,580 (51.6%)
Male	2,420 (48.4%)
Urban residence	3,180 (63.6%)
Rural residence	1,820 (36.4%)
Food insecurity	1,130 (22.6%)
Family history of metabolic disease	1,740 (34.8%)
Persistent obesity	1,170 (23.4%)

Metabolic syndrome	695 (13.9%)
Hypertension	540 (10.8%)
Prediabetes/type 2 diabetes	385 (7.7%)
Liver steatosis	465 (9.3%)
Multimorbidity	310 (6.2%)

Table 1 indicates that the cohort had an almost equal distribution of males and females with 51.6% and 48.4%, respectively. A majority of profiles were adolescents in urban areas (63.6%) while 36.4% were from rural settings. Twenty-two.6% were food insecure, and 34.8% had a family history of metabolic disease. The most frequently simulated condition was persistent obesity (23.4%) followed by metabolic syndrome (13.9%), hypertension (10.8%), liver steatosis (9.3%), and prediabetes or type 2 diabetes (7.7%). 6.2% of adolescent profiles were identified as multimorbidity. These distributions were enough to enable individual-risk-prediction studies, multimodal feature-contribution studies, studies of subgroup fairness, and population-level chronic-disease-burden estimation studies.

3.2 Multimodal Data Preprocessing

Duplicate and inconsistent records were eliminated and physiologically unbelievable clinical measurements were noted by employing pre-established reference ranges for adolescents. The missing numerical values were imputed using multiple imputation, while missing categorical values were replaced with the most likely category or a new category for missing values.

The continuous clinical and social variables were z-scored normalized. Sex, residence, household-income category and parental education were transformed via one hot encoding because they were categorical variables. An expanded version of the EHR records was prepared and arranged in chronological order then fixed observation windows were created from the chronologically arranged version of EHRs.

Images of the liver were resized to 224x224 pixels and pixel intensity normalized in the same way. Only some training images were processed using rotation, horizontal flipping, cropping and fine gradation of contrast. No changes were made to the images used for validation or testing.

The training-, validation-, and testing subsets were split at the level of the adolescents' profile so as to avoid information leakage. To mitigate the influence of the skewed distribution of chronic-disease classes, class-weighted loss and balanced mini-batch sampling were applied.

3.3 Proposed Multimodal Prediction and Burden-Estimation Framework

The proposed framework will have three branches of processing – one for each of the modalities. Records of changes in clinical measurements over 24 months will be generated by A Temporal Transformer applied to longitudinal EHR sequences. The liver-ultrasound images will be used to extract relevant features by a machine learning model called EfficientNet-B0, and a machine learning model called a multilayer perceptron will process the social-determinant variables. The representations produced by these three branches will be fused in a multimodal fusion layer which is based on attention mechanism as shown in Figure 1. This layer will give weight to clinical, social and imaging information based on its contribution to each adolescent's predicted outcome. This integrated representation will then facilitate the prediction for each individual of the probability of developing a chronic disease and estimate population burden of disease. While SHAP will describe the importance of the clinical and social variables, Grad-CAM will indicate the regions in the images that contribute to the prediction of liver-steatosis.

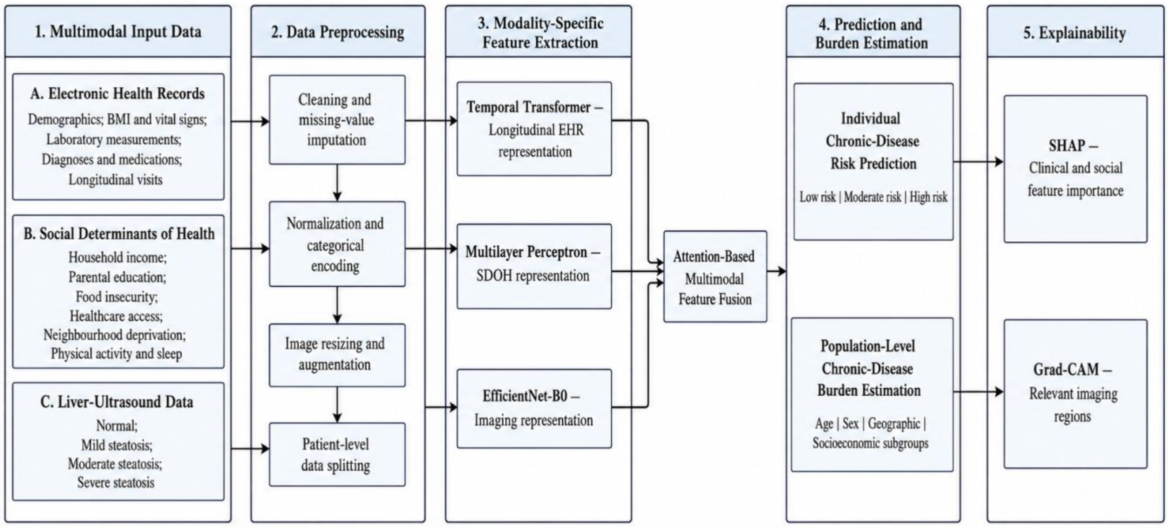

Figure 1. Proposed multimodal public-health analytics framework.

Figure 1 shows the entire analytical process starting from the EHR data, social determinants and liver-ultrasound images. These inputs are modulated and processed in a modality-specific fashion, followed by a modality-specific feature extraction process, and then fused together using attention based multimodal fusion. These fused features are then utilized to predict individual risk, to estimate the burden of chronic disease at the population-level and to generate SHAP- and Grad-CAM-based explanations.

Individual chronic-disease risk

The probability of having a chronic disease for the i-th adolescent (as stated in Equation (1)), is computed on the fused EHR, social-determinant, and imaging representations.

$$\hat{p}_i = \sigma\left(W_o\left[h_i^{EHR} \| h_i^{SDOH} \| h_i^{IMG}\right] + b_o\right), \quad (1)$$

where $\boldsymbol{h_i^{EHR}}$, $\boldsymbol{h_i^{SDOH}}$, and $\boldsymbol{h_i^{IMG}}$ denote the learned EHR, social-determinant, and imaging feature representations, respectively. The symbol ‖ denotes feature concatenation, $\boldsymbol{W_o}$ and $\boldsymbol{b_o}$ are trainable parameters, and σ is the sigmoid activation function.

The probability generated using Equation (1) will be assigned to one of three risk categories: low risk when $\boldsymbol{\hat{p}_i < 0.30}$, moderate risk $\boldsymbol{0.30 \le \hat{p}_i < 0.60}$, and high risk when $\boldsymbol{\hat{p}_i \ge 0.60}$. These thresholds will support interpretable adolescent risk stratification.

Population-level chronic-disease burden

The probabilities for the individual diseases will be combined to assess the burden in a given population group. The burden of chronic disease index for each group g is defined by Equation (2), which is:

$$CBI_g = \frac{1}{N_g} \sum_{i=1}^{N_g} \sum_{k=1}^{K} w_k \, \hat{p}_{ik}, \quad (2)$$

where N_g is the number of adolescents in population group g, K is the number of evaluated chronic conditions, w_k is the severity weight assigned to condition k, and $\hat{p}_{ik}$is the predicted probability that adolescent i will develop condition k.

The number derived from Equation (2) will be multiplied by 100 to get a standardized chronic-disease burden score. A higher score will mean that the likelihood of chronic diseases is likely to be more and that they are likely to be more severe. Scores obtained will be compared between age, sex, socio-economic, urban and rural groups to identify those that need to be targeted for preventive interventions.

4. RESULTS

4.1 Cohort and Chronic-Disease Distribution

Of the 5000 adolescent profiles simulated, 930 (18.6 %) had at least one chronic metabolic disease as the main endpoint. The most common health condition was persistent obesity (1,170 profiles, 23.4%), as shown in Table 2. Sixty-nine-five of the profiles (13.9%) had metabolic syndrome, 540 had hypertension (10.8%), 465 had liver steatosis (9.3%), and 385 had prediabetes or type 2 diabetes (7.7%). Thirty-one (6.2%) had 2 or more chronic conditions (multimorbidity).

Table 2. Distribution of chronic-disease outcomes in the simulation-derived cohort

Chronic-disease outcome	Profiles, n	Prevalence (%)
Chronic metabolic disease	930	18.6
Persistent obesity	1,170	23.4
Metabolic syndrome	695	13.9
Hypertension	540	10.8
Prediabetes/type 2 diabetes	385	7.7
Liver steatosis	465	9.3
Multimorbidity	310	6.2

The burden of chronic diseases simulated was different between socio-economic and geographic groups. The prevalence of chronic metabolic disease in adolescents in the lower income was 24.7% higher than in the higher income, 14.2%. The prevalence was 25.4% among the youth of highly deprived neighbourhoods and 13.8% among those in low deprivation neighbourhoods. The prevalence rate of rural adolescents was 21.6%, whereas that of the urban adolescents was 16.9%. The prevalence of food insecurity was also higher among food-insecure adolescents compared to the food-secure adolescents (26.1% and 16.4%, respectively). The findings suggest that people with lower socio-economic status, living in more deprived neighbourhoods, people who were food insecure, and people who lived in the countryside had a higher level of simulated burden of chronic diseases.

4.2 Comparative Predictive Performance

The predictions of the proposed framework and the seven comparison models are shown in Table 2. Logistic regression performed worst with an accuracy of 78.1%, sensitivity of 70.4%, F1 score of 65.8% and ROC-AUC of 0.801. Random forest gave an ROC–AUC of 0.842 and XGBoost performed with an accuracy of 84.2% and ROC–AUC of 0.876.

The EHR-only Temporal Transformer model had a ROC–AUC score of 0.891 while the imaging-only EfficientNet-B0 model had a score of 0.831. When adding SDoM data to EHRs, ROC–AUC was raised to 0.913 and the F1 score was enhanced to 79.6%. EHR-plus-imaging model had been found to have 88.1 per cent accuracy, an F1 score of 80.8 per cent and a ROC–AUC of 0.921.

Table 2. Comparative performance of chronic-disease prediction models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	ROC–AUC
Logistic regression	78.1	70.4	79.9	65.8	0.801
Random forest	81.6	75.8	83.0	70.8	0.842
XGBoost	84.2	79.1	85.4	74.7	0.876
EHR-only Temporal Transformer	85.7	80.6	86.9	76.7	0.891
Imaging-only EfficientNet-B0	80.9	73.5	82.6	69.4	0.831

EHR + social determinants	87.3	83.4	88.2	79.6	0.913
EHR + imaging	88.1	84.5	88.9	80.8	0.921
Complete multimodal framework	**90.6**	**87.8**	**91.2**	**84.9**	**0.944**

Overall, the complete multimodal framework exhibited the highest accuracy (90.6%), sensitivity (87.8%), specificity (91.2%), F1 score (84.9%) and the ROC–AUC (0.944), as shown in Table 2. By comparison with the EHR-only Temporal Transformer, the complete framework increased the accuracy by 4.9 percentage points, sensitivity by 7.2 points, F1-score by 8.2 points and ROC–AUC by 0.053. It also outpaced the EHR-plus-imaging model by 2.5 accuracy points and 0.023 ROC–AUC, reflecting the unique contribution of social determinants to prediction.

The overall model had an accuracy of 82.1% and a PR-AUC of 0.851. It had a Brier score of 0.092, suggesting that it had relatively low probabilistic prediction error. The calibration slope was 0.97 with a calibration intercept of 0.02, indicating that the probabilities generated were similar to those that were obtained through simulation. The 95% confidence interval for the ROC–AUC using bootstrap analysis was 0.928–0.958.

The best performance of all models compared is shown in Figure 2 as ROC–AUC and F1 score. The grouped bar graph shows the progressive improvement in performance that was achieved by adding EHR, imaging and social-determinant information. Results from the full multimodal model were significantly stronger than results from logistic regression and the imaging-only model, as indicated by the higher scores obtained for both measures.

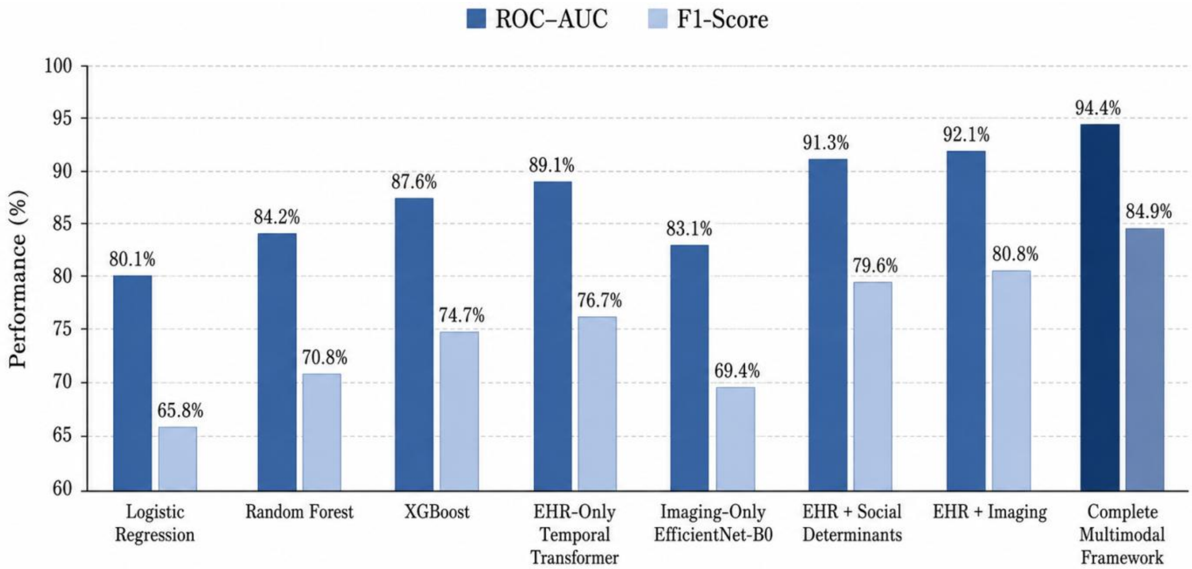

Figure 2. ROC–AUC and F1-score comparison of the evaluated models.

4.3 Explainability Analysis

A model of clinical, imaging, behavioral and social variables for predicting chronic diseases was built and subsequently used to assess their relative contribution to prediction via SHAP analysis. BMI-for-age z score had the highest SHAP value, at a mean level of 0.184 as shown in Table 3. The second most influential predictor was fasting glucose with a score of 0.142, followed by liver-steatosis imaging score with a score of 0.126 and family history of metabolic disease with a score of 0.098. These findings suggest that anthropometric, glycaemic, imaging and genetic data was significant in identifying individual risk.

Table 3. SHAP-based importance of chronic-disease predictors

Predictor	Mean absolute SHAP value
BMI-for-age z-score	0.184
Fasting glucose	0.142
Liver-steatosis imaging score	0.126
Family history	0.098
Neighbourhood deprivation	0.084
Physical inactivity	0.076
Triglycerides	0.069
Food insecurity	0.061
Systolic blood pressure	0.054
Sleep duration	0.047

The effect of modifiable behavioural and social factors is also illustrated in Table 3. Neighbourhood deprivation had a mean absolute SHAP value of 0.084, which was followed by physical inactivity (0.076) and food insecurity (0.061). The other clinical variables that achieved a SHAP value of ≥ 0.05 were triglycerides (SHAP value 0.069) and systolic blood pressure (SHAP value 0.054). Of the top 10 leading predictors, sleep was the least important with a value of 0.047, but still included in the multimodal risk estimates.

The mean absolute SHAP values of the top 10 predictors are then visualized in Figure 3. The figure shows that BMI-for-age z-score, fasting glucose and liver-steatosis imaging score were the three most influential variables. Neighbourhood deprivation and food insecurity are also demonstrated as being statistically significant, in addition to traditional clinical risk factors, confirming the role of social determinants within the suggested framework.

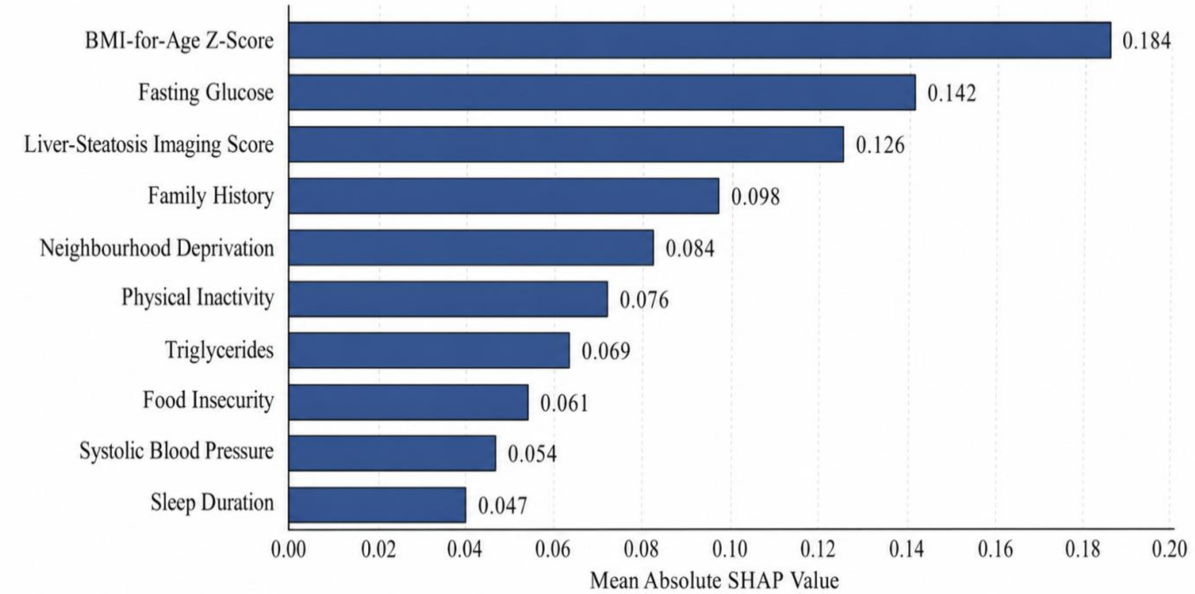

Figure 3. SHAP-based importance of chronic-disease predictors.

For the SHAP values in Table 3 and Figure 3, the display of how important each variable is or how much each variable contributes to the prediction is not a measure of the positive or negative relationship between the variable and the prediction. Furthermore, these values are only predictive associations and not causal relationships.

6. CONCLUSION AND FUTURE WORK

The key objective of this study was to create an integrated multimodal public-health analytics framework to predict an individual's risk of developing a chronic disease and estimate the disease burden among adolescents. The framework employed modality-specific feature extraction and fusion with attention from the perspective of social determinants of health, liver ultrasound imaging and longitudinal electronic health records. Expl explainable analysis was supported by SHAP and Grad-CAM and the evaluation of subgroups was conducted on predictive fairness over demographic, socioeconomic and geographic populations. The results of the simulation revealed the computational feasibility of multimodal integration for adolescent risk stratification, screening prioritization and planning of public health resources.

No real patients were recruited for the study as its evaluation was based on simulation generated adolescent profiles. The numerical results are thus not a reflection of proven effectiveness or validation in real-world use. The relationships between clinical, image, behavioural and social variables were simulated and there may not be a direct correspondence in real adolescent populations. The framework also continued to be hugely dependent on liver ultrasound imaging, and failed to have any external clinical validation or prospective hospital deployment, as well as lacked a significant evaluation of clinician–system interaction.

Future research based on authentic clinical data gathered from adolescents would need to be approved by an appropriate research ethics committee and would adhere to safeguards of health information in the care of children and adolescents. Patient records need to be anonymized, encrypted while in transmission and storage, and secured by role-specific access controls and auditable data-governance protocols. Algorithmic fairness should be measured regularly to ensure that socioeconomic, demographic or geographic factors do not lead to discriminatory screening decisions or to unfair distribution of health. However, human clinical supervision must be continually emphasized, and the use of the framework should be to provide a screening support system and not as a stand-alone diagnostic system.

The framework needs to be further tested with multiple, varied adolescent populations, and prospective assessments in hospital settings. There is a potential to gain broader physiological information from additional imaging modalities and to enhance long-term risk estimation through temporal disease-progression models. All predictive associations must be differentiated from actual effects of social determinants with causal analysis. Federated learning may allow the ability for privacy-preserving collaboration between hospitals without centralizing sensitive adolescent data. Before the framework can be recommended for responsible public-health or clinical implementation, clinical usability studies, safety assessments, and monitoring of calibration, fairness assessments, and evaluations of the interactions between adolescents and clinicians would be necessary.

REFERENCES

[1] Chen, Tianqi, and Carlos Guestrin. "Xgboost: A scalable tree boosting system." Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining. 2016.
[2] Shickel, Benjamin, et al. "Deep EHR: a survey of recent advances in deep learning techniques for electronic health record (EHR) analysis." IEEE journal of biomedical and health informatics 22.5 (2017): 1589-1604.
[3] Choi, Edward, et al. "Retain: An interpretable predictive model for healthcare using reverse time attention mechanism." Advances in neural information processing systems 29 (2016).
[4] Rajkomar, Alvin, et al. "Scalable and accurate deep learning with electronic health records." NPJ digital medicine 1.1 (2018): 18.
[5] Esteva, Andre, et al. "A guide to deep learning in healthcare." Nature medicine 25.1 (2019): 24-29.
[6] Litjens, Geert, et al. "A survey on deep learning in medical image analysis." Medical image analysis 42 (2017): 60-88.
[7] Baer, Tamara E., Laura Gottlieb, and Megan Sandel. "Addressing social determinants of health in the adolescent medical home." Current Opinion in Pediatrics 25.4 (2013): 447-453.
[8] Vale, Diôgo, et al. "Social determinants of obesity and stunting among Brazilian adolescents: a multilevel analysis." Nutrients 14.11 (2022): 2334.

[9] Huang, Shih-Cheng, et al. "Fusion of medical imaging and electronic health records using deep learning: a systematic review and implementation guidelines." NPJ digital medicine 3.1 (2020): 136.
[10] Lundberg, Scott M., and Su-In Lee. "A unified approach to interpreting model predictions." Advances in neural information processing systems 30 (2017).
[11] Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." Proceedings of the IEEE international conference on computer vision. 2017.
[12] Van Calster, Ben, et al. "Calibration: the Achilles heel of predictive analytics." BMC medicine 17.1 (2019): 230.
[13] Obermeyer, Ziad, et al. "Dissecting racial bias in an algorithm used to manage the health of populations." Science 366.6464 (2019): 447-453.
[14] Miotto, Riccardo, et al. "Deep patient: an unsupervised representation to predict the future of patients from the electronic health records." Scientific reports 6.1 (2016): 26094.
[15] Che, Zhengping, et al. "Recurrent neural networks for multivariate time series with missing values." Scientific reports 8.1 (2018): 6085.