Discover Medicine

Research

A novel recommender framework with chatbot to stratify heart attack risk

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Abstract
Cardiovascular diseases are a major cause of mortality and morbidity. Fast detection of life-threatening emergency events and an earlier start of the therapy would save many lives and reduce successive disabilities. Understanding the specific risk factors associated with heart attack and the degree of association is crucial in the clinical diagnosis. Considering the potential benefits of intelligent models in healthcare, many researchers have developed a variety of machine learning (ML)-based models to identify patients at risk of a heart attack. However, the common problem of previous works that used ML concepts was the lack of transparency in black-box models, which makes it difficult to understand how the model made the prediction. In this study, an automated smart recommender system (Explainable Artificial Intelligence) for heart attack prediction and risk stratification was developed. For the purpose, the CatBoost classifier was applied as the initial step. Then, the SHAP (SHapley Additive exPlanation) explainable algorithm was employed to determine reasons behind high or low risk classification. The recommender system can provide insights into the reasoning behind the predictions, including group-based and patient-specific explanations. In the final step, we integrated a Large Language Model (LLM) called BioMistral for chatting functionally to talk to users based on the model output as a digital doctor for consultation. Our smart recommender system achieved high accuracy in predicting a patient risk level with an average AUC of 0.88 and can explain the results transparently. Moreover, a Django-based online application that uses patient data to update medical information about an individual's heart attack risk was created. The LLM chatbot component would answer user questions about heart attacks and serve as a virtual companion on the route to heart health, our system also can locate nearby hospitals by applying Google Maps API and alert the users. The recommender system could improve patient management and lower heart attack risk while timely therapy aids in avoiding subsequent disabilities.

1 Introduction

Annually, 17.9 million deaths are caused by cardiovascular diseases (CVD). Four out of five of those cases happen due to heart attacks and strokes [1]. There are several contributing factors to CVD, including smoking, diabetes, hypertension, age, and genetic predisposition [2]. There exist significant indicators of a heart attack including shortness of breath, cold sweating, pain in the different parts of the body, headache, etc. [3]. The World Health Organization (WHO) anticipates that CVD will persist as a leading cause of death, representing a notable risk to human life in the future, potentially extending after the year 2030. CVD emerges as a worldwide health problem, expecting the essential requirement for the advancement of efficient detection techniques [4].

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Gathering, processing, and evaluating health parameters measured in patients enhance to prediction of risk factors and the early-stage management of illnesses [5, 6]. Machine learning (ML) techniques play a significant role in predicting diseases by utilizing a large amount of data produced by the healthcare field. The Artificial Intelligence (AI) can strengthen machine learning's precision and speed, providing the approach for multiple healthcare challenges including the screening of cardiovascular diseases [4, 7]. Furthermore, clinical models incorporating polygenic risk scores have shown potential in improving the detection and management of cardiovascular diseases [8].

Recommender systems encompass software tools and techniques that offer recommendation of items likely to benefit a user [9]. The incorporation of recommender systems in the fields of electronic medicine and health has not yet been thoroughly explored in academic research [10]. The integration of recommender systems into healthcare services has the potential to impact preventive healthcare by improving health outcomes, cost-effectiveness, and enhanced experiences for both patients and healthcare providers. The exploration of recommender systems in preventive healthcare holds advancements in precision medicine [11]. Automated tools developed using ML models showed promises in detecting underdiagnosed conditions like peripheral artery disease (PAD), and improving cardiovascular health outcomes [12]. It was stated that there are still very few AI-based recommender systems being used in the clinical field [13–16].

The technical evolution of Large Language Models (LLM) plays a crucial role in the AI community, and LLM would change the way of development and application of AI algorithms [17]. In the future, the early cardiac diagnostics pattern will be focused on heart attack preventive medicine. The support of AI techniques for non-invasive medical imaging and different machine learning models has been studied in recent years [18, 19]. It is important to find out an increased risk of a heart attack early and treat it with preventive drugs before the need to use more complicate forms of therapy [20]. In recent years, LLMs have been applied in healthcare and demonstrated their significant roles [21], for example, using them for diagnosis or serving as prognostic tools [22, 23], notably in clinical settings by predicting heart attack risk [24, 25].

However, it is necessary to develop the predictive models and fill out the research gaps in the current detection approaches, such as the lack of transparency in black-box models, which makes it difficult to understand the prediction process [26]. Most of the LLMs are formulated as chatbots intended for general use, current scholarly investigations have been concentrated on the creation of specialized variations suitable to the medical field, for example, Meditron or BioMistral. These Chatbots are achieved through the augmentation of the training dataset of LLMs with medical expertise [21, 27]. Despite the attention surrounding the widespread adoption of ChatGPT, fine-tuning is the most effective approach for enhancing performance in two essential biomedical tasks of natural language processing and optimal outcomes achieved through fine-tuning BioBERT, which yielded superior results in both reasoning (F1: 0.80–0.902) and classification (F1: 0.85) tasks [28]. In a recent publication, an IoT-based heart disease monitoring system has been studied by researchers in the predictive healthcare field. That system monitors the patients' physical features, and also related environmental indicators. Four different data transmission modes were produced as the results of that study, and the models were able to balance conditional healthcare, support communication, and computing resources [29].

In this study, the capabilities of recommender systems were improved and empowered with an AI model, CatBoost, that specializes in medical interactions by incorporating an LLM, BioMistral. The user can interact with the model holistically and manage their stroke risks in real-time. The risk factors that can be measured using smart monitoring wearable devices are called dynamic, while other risk factors obtained from users directly are static. This system collects both types to predict a heart attack risk and explains the results transparently, which will be accessible on a website for patients and clinicians.

2 Methods

2.1 Overview

The smart health recommendation system in this study identifies and prioritizes factors that are most significant in predicting the risk of a heart attack. Specifically, a method was introduced for predicting the risk of heart attack by collecting dynamic and static data from the patient using a website and wearable device. In the first step, using the collected dataset, a CatBoost classifier [30] was applied to build a stroke classification model. Then, utilize the SHAP method [31, 32] to identify the key factors that significantly impacted the risk assessment. Finally, the results of the patients are presented on the website. The system would receive a warning notification when any risk factors were out of the normal range of values. The recommender system can also generate a patient-specific PDF report along with the closest hospitals on the map to provide comprehensive guidance to the users. Figure 1 shows the schematic flowchart of the steps for the proposed recommender system.

1. The user information is obtained from the web application and smartwatch.
2. In the data processing step, static data can be manually entered, and dynamic data can be retrieved from wearable devices.
3. The Django framework saves patient data securely based on an individual user account.
4. Creates a model from the training dataset for classification and performs heart disease prediction using the test dataset.
5. Builds CatBoost classifier. Then, the effect of each parameter on prediction is ranked and visualized using the SHAP explanation.
6. The Django Web framework produces a patient-specific report and bar charts describing each parameter's effect on prediction and risk outcome. The map with the nearest hospitals is generated by taking the patient's location.
7. A fine-tuned LLM called BioMistral, specifically trained by biomedical data (PubMed data), acts as a heart risk chatbot to communicate with each user and answer user-specific questions based on user information and CatBoost classifier output.

2.2 Patient dataset and data preparation

The heart attack dataset from the IEEE Dataport [33] was used in this study, which contains 1,190 patient information and 11 risk factors with a heart attack risk outcome. The output response is the heart attack risk presented by 1 or 0 to show if there is a risk or no risk, respectively. The 11 risk factors used for predicting the risk of heart attack are as follows: age, sex, chest pain type (cp), resting blood pressure (trestbps), cholesterol (chol), fasting blood sugar (fbs), resting electrocardiographic result (restecg), maximum heart rate achieved (thalach), exercise-induced angina (exng), ST depression induced by exercise relative to rest (oldpeak), lope of peak exercise (slope). Following data collection, the data preparation steps included data cleaning, risk factor selection, data transformation, balancing, and splitting. To address the significant gender imbalance in the dataset (consisting of 901 males and 289 females), we applied an undersampling technique to the male population to equalize the number of male and female patients. After cleaning the data by removing missing values (one case of zero resting blood pressure, one case of zero ST slope value and 172 cases of zero cholesterol value), the final dataset contains 542 patient information, consisting of 270 female and 272 male patient information. The dataset was divided into two independent subsets: the training set (80%): 433/542, and the testing set (20%): 109/542. Moreover, the Spearman correlation was applied to examine the correlation between risk factors (Table 1).

2.3 Heart attack risk classification model

To construct a classification model, the CatBoost classifier was opted [30]. This ML algorithm possesses the unique capability to handle categorical features directly, eliminating the need for additional preprocessing procedures. Our selection of CatBoost was motivated by its user-friendly nature, efficiency, and exceptional suitability for handling categorical data. The number of iterations and learning rate for model training were set to 1000 and 0.2, respectively.

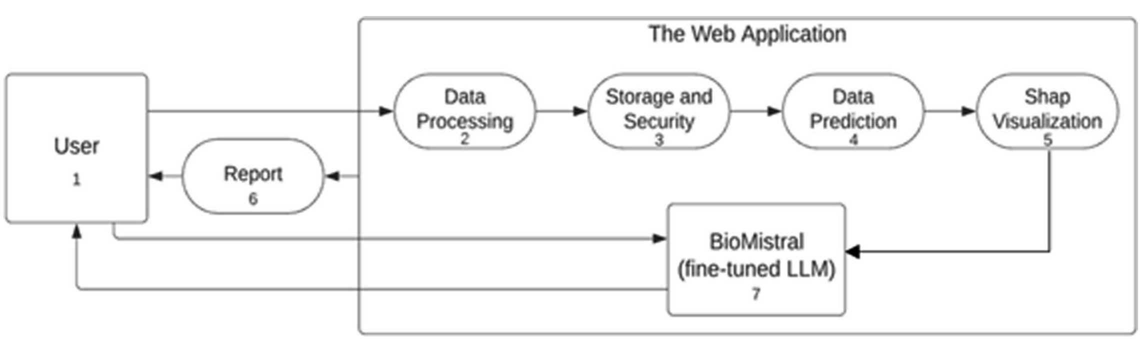


Fig. 1 A diagram showing the steps of the proposed method

Table 1 Spearman correlation shows the correlation between risk factors

	Age	Sex	cp	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	Output
Age	1.0	−0.17	0.19	0.27	0.20	0.18	0.15	−0.32	0.17	0.37	0.20	0.28
Sex	−0.17	1.0	−0.03	−0.15	−0.18	0.01	−0.09	0.09	−0.04	−0.28	−0.53	−0.01
cp	0.19	−0.03	1.0	0.05	0.11	0.01	0.21	−0.15	0.34	0.198	0.25	0.45
trtbps	0.27	−0.15	0.05	1.0	0.17	0.08	0.1	−0.03	0.2	0.21	0.20	0.14
chol	0.20	−0.18	0.11	0.17	1.0	0.11	0.17	−0.01	0.14	0.12	0.1	0.18
fbs	0.18	0.01	0.01	0.08	0.11	1.0	0.13	−0.08	0.1	0.03	−0.01	0.11
restecg	0.15	−0.09	0.21	0.1	0.17	0.13	1.0	0.01	0.09	0.13	0.13	0.19
thalachh	−0.32	0.09	−0.15	−0.03	−0.01	−0.08	0.01	1.0	−0.15	−0.23	−0.22	−0.12
exng	0.17	−0.04	0.34	0.22	0.14	0.10	0.09	−0.15	1.0	0.26	0.25	0.42
oldpeak	0.37	−0.28	0.2	0.21	0.12	0.03	0.13	−0.23	0.26	1.0	0.52	0.35
slp	0.2	−0.53	0.25	0.20	0.1	−0.01	0.13	−0.22	0.25	0.52	1.0	0.31
Output	0.28	−0.01	0.45	0.14	0.18	0.11	0.19	−0.12	0.42	0.35	0.31	1.0

2.4 SHapley Additive exPlanations (SHAP)

To explain the output of our ML model, the SHAP technique was conducted. It calculates the values for each feature, stating the contribution to the classification model's decision, which are called SHAP values [31, 32]. The SHAP technique can produce the SHAP values for each feature output without depending on the relation between the feature and the label.

2.5 Global-based explanation

The SHAP method can generate group-based model explanations, enabling the assessment of feature importance for the whole dataset. Analysis of the mean and variance of the SHAP values of the features allows us to understand how the model predicts outcomes for that particular group. Utilizing the complete dataset, we assigned SHAP values to each risk factor and ranked them based on global importance.

2.6 Local-based explanation

In SHAP, local explanations are used to provide insights into predicting a specific instance, such as different age groups, going beyond general global explanations of the model. The results give an understanding of risk factors, including their ranking with SHAP values. Using this explanation, we can identify the main contributed risk factors for the specific patient or one instance in the dataset.

2.7 Model evaluation methods

This study used various ML evaluation methods. Accuracy, precision, F1 score, recall, and the Cohen Kappa score [34] were calculated to observe the results of the CatBoost classifier model. These evaluation techniques were observed to improve our model's performance by setting different iterations and learning rates.

2.8 Django-based web framework

Django was utilized for our heart attack prediction model, an open-source framework that employs the Model Template View (MTV) architecture and has robust security features. Integrating Python with HTML, CSS, and JavaScript, the system serves as an interface for patients and clinicians, providing access to a machine-learning model for heart attack prediction and enhancing stroke risk management.

2.9 Data security

Besides patient risk prediction, the system includes a practical feature to display nearby hospitals on a map for quick access utilizing a Google Maps API. Another feature called real-time health alerts notifies users of deviations from normal metrics, urging immediate medical consultation. With a user-friendly interface, the system can encourage proactive health management, reducing heart-stroke risks. Moreover, data security is ensured through a PostgreSQL database, employing SHA256 encryption for patient data integrity and privacy. This setup allows for secure data storage and retrieval, which is essential for maintaining accurate patient records and analysis.

2.10 Data collection from smartwatch-based wearable device

To enhance the data collection process, the web application incorporates a wearable Smartwatch (GalaxyWatch 5) allowing them to acquire their heartbeat data, measured live through the smartwatch. ECG and BPM measurements in the Samsung Galaxy Watch 5 were approved by Health Canada, this was the reason behind the selection of this model. Users can directly transmit their heartbeat and blood pressure data to the system via Smartwatch through the use of our native application that integrates the user's current heartbeat and measured user blood pressure from the smartwatch. The Galaxy Watch 5-based Smartwatch (Health Canada approved) running on the Google Wear operating system was employed to integrate it into our Django framework. The development process took place within the Android Studio framework. The data collected from the smart wearable device is converted into a JSON file and then transmitted to the web application using a socket API. Subsequently, the web application processes the received data.

2.11 LLM—BioMistral + LangChain

Integrating the LLMs into healthcare applications marks a critical evolution in the domain. To create a conversational LLM model that will accurately answer users' questions and give up-to-date scientific information, the BioMistral 7B was employed in our heart attack risk recommender system. In detail, this model, trained (fine-tuned) on biomedical data such as PubMed, was employed to function as a heart risk chatbot, delivering patient-specific explanations and responses. To achieve this, we used initial prompts to configure the LLM to behave like a heart expert, followed by patient-specific input (clinical data) as context, allowing the model to generate personalized responses. The benchmarks for assessing the LLM's performance in this specific application, there is a lack of a dedicated dataset for stroke-specific question-answering, so we relied on both human evaluation and existing benchmarks to assess our LLM's performance in the biomedical domain. The established benchmark evaluations of BioMistral 7B had shown superior performance across several medical evaluation datasets, including [35, 36]. In addition, a dedicated endpoint from Hugging Face and implemented Langchain with a conversational chain were integrated to enhance its functionality as a conversational agent. The prompt template from Langchain is populated dynamically with user-specific data to enhance context awareness. This role-specific and prompt strategies approach enables BioMistral to provide targeted assistance, reflecting a significant step forward in minimizing errors and enhancing the utility of LLMs in healthcare settings.

3 Results

3.1 Evaluation of the proposed recommender system

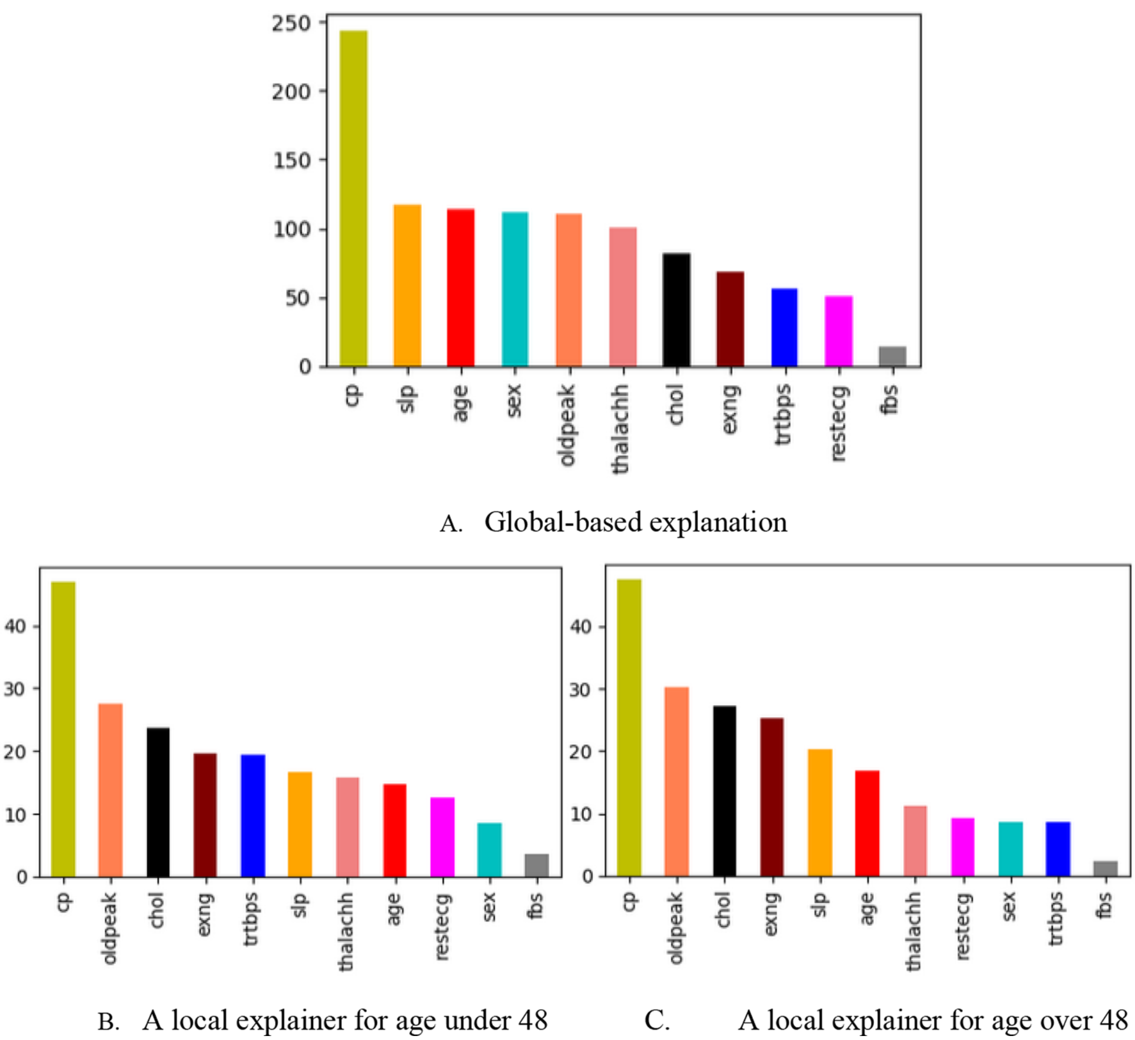
The developed Django-based smart recommender system effectively enabled user operations such as account creation and data storage (Fig. 1). This system collected user data, including static inputs from the website and dynamic inputs from a smartwatch, transmitted via a socket API and converted to JSON files (Steps 2 and 3). The prediction model then processed these risk factors to generate heart attack predictions (Step 4), with results displayed on the website, including model predictions and a patient-specific SHAP explanation (Fig. 3).

3.2 Model evaluation

In this study, we created a CatBoost classifier model using a dataset of 433 patients (80% of the original dataset) for training and 109 for testing. The evaluation results showed that the model achieved an average AUC (Area Under the Curve) of 0.88; the Cohen Kappa score, which measures inter-rater agreement, was 0.76. Additionally, the weighted average f1 score, a measure of precision and recall, was calculated as 0.92.

3.3 Global-based explanation

The SHAP method was used to understand individualized predictions and to identify key risk factors associated with it. SHAP works by affecting a SHAP value to each feature, which reflects its contribution to the outcome. The risk factors were ranked according to their SHAP value. The highest-ranked risk factors are considered the most crucial heart attack risk-related variables. The result (not shown) displayed the top 5 factors that exert the most significant influence on the final prediction, indicating that the number of major vessels chest pain (cp), slp, age, sex and oldpeak were the most influential features on the prediction outcome respectively. Figure 2 represents the SHAP explanation results.



A. Global-based explanation

B. A local explainer for age under 48 C. A local explainer for age over 48

Fig. 2 Global-based explanation and Local-based explanation. Group-based explanations were derived based on age (under 48 and over 48)

3.4 Local-based explanation

Local explanations in Fig. 2B, C provide the contribution and weight of each risk factor for different age groups with a cutoff age of 48. The results give risk factors associated with different age groups based on their ranking with SHAP values.

3.5 Patient-based explanation

User information and individualized recommendation output contribute to the prediction of individual patients. For example, a selected 62-year-old man with the following characteristics: chest pain—4, resting blood pressure—138, cholesterol—294, fasting blood sugar—1, resting electrocardiographic result—0, maximum heart rate achieved—106, exercise-induced angina—0, ST depression induced by exercise relative to rest—1.9 and lope of peak exercise—2. The model's prediction was accurate as it matched the actual class from the dataset, indicating that the individual has a risk of a heart attack (Fig. 3).

3.6 User-centric role-based system access

Clinicians can securely access patient data, review predictions and risk factors, and make better decisions based on SHAP results through the login function of this smart recommender system. This system supports two unique user roles: the physician, who serves as the system administrator, and the patient, who uses the system for personal health management. The clinician has complete control, including access to patient records, issue alerts, and receive messages about increased heart attack risks. Whereas patients can securely store their information, input risk factors, and receive personalized analysis. Overall, the login functionality enhances usability and security for both clinicians and patients. It provides seamless and personalized access, fosters collaboration, and improves the effectiveness of cardiovascular risk assessment and management. The program runs on a remote web server in the cloud and is easily accessible from a variety of locations. To maintain the confidentiality of patient data, strong encryption (namely SHA256) is used. Access to this sensitive information is limited to registered users and clinicians with administrative access.

3.7 Integration of BioMistral 7B as an AI healthcare assistant

BioMistral 7B distinguishes itself from generic LLM by using a customized approach to medical tasks, which leads to better dependability and a lower occurrence of hallucinations.

Based on previously created reports, it allows patients to participate in interactive discussions regarding the state of their cardiovascular health. Utilizing the refined BioMistral model, the AI assistant offers customized responses based on data unique to each patient. The created chatbot can respond to questions about heart attack and cardiovascular health

Risk Factors	Value
Patient ID	Rating
age	62
sex	0
cp	4
trtbps	138
chol	294
fbs	1
restecg	0
thalachh	106
exng	0
oldpeak	1.9
Slp	2

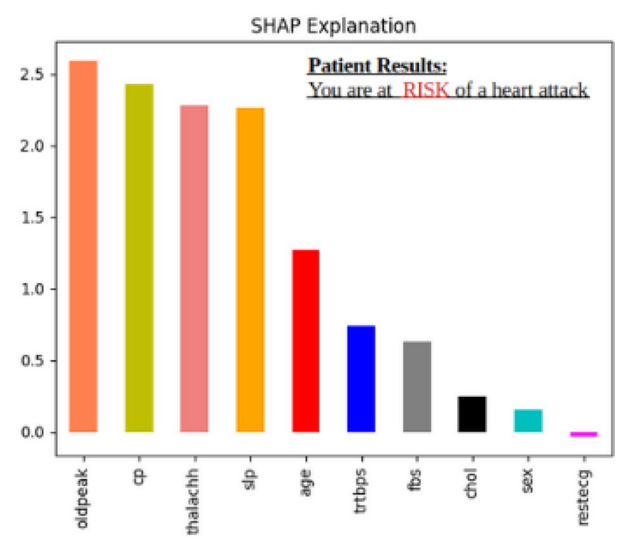


Fig. 3 Patient-specific risk factor ranking, generated by the automated online recommender system for John Doe (an anonymous user) using the SHAP method

and associate its answers with specific patient features and stroke risk factors. Moreover, when queries are asked without context, it can pull data from the Internet and wrap its answers with the patient's specific health recommendations.

4 Discussion

The emergence of LLMs has marked a significant breakthrough in natural language processing (NLP), leading to remarkable advancements in text understanding and generation [37]. This study proposed an online recommender system to predict heart attack-associated risk and rank patient-specific risk factors that matters clinicians and ordinary users. To make the user experience more personal and interactive, a fine-tuned LLM, BioMistral, was added, specifically created for biomedical data processing. Explainable recommendation refers to personalized recommendation algorithms that not only provide users with recommendations but also provide an explanation for why a specific item has been recommended [38, 39]. According to statistics, approximately one-third of Americans go online to research their health problems, and they also use social networks to reach out to others with similar health conditions [40].

We integrated a framework that collects data from the user, and Smartwatch and then displays the heart attack risk results with the user's data. The CatBoost classifier model accurately predicted heart attack risk, relying on the dataset of 542 patients' data. The model produced an average AUC of 0.88 and a Cohen Kappa score of 0.76 for the test dataset. The results showed that model produced a high level of accuracy in predicting the risk of a heart attack for individual patients. AI strategy highlights the key risk factors that have a significant impact on the final prediction, with taller bars representing higher SHAP values and indicating a greater influence (Fig. 2).

Notably, the addition of the LLM model to our system improved the process of patients understanding their stroke risk since the LLM is trained on vast clinical data and biomedical scientific papers. The chatbot component would answer user questions about heart attacks and other relevant problems will also serve as a virtual companion on the route to heart health, explaining medical terminology, providing lifestyle advice, and clearing up common misconceptions. For the convenience of users, our system can locate nearby hospitals by applying Google Maps API and implementing a real-time alert functionality when there is a case of abnormal blood pressure or heart attack signs. Current proprietary LLMs are promising. Nevertheless, the potential threats to privacy linked with the collection and manipulation of personal information are frequently not valued or ignored. Numerous users lack sufficient awareness regarding the extent to which their data is gathered, whether this data is transmitted to third parties, or the level of security and duration of storage [41]. Some researchers have surveyed the state-of-the-art security and privacy challenges in big data as applied to the healthcare industry and assessed how security and privacy issues occur in the case of big healthcare data [42].

Nonetheless, our Django website can be accessed through the link below: https://www.mamatjanlab.com/heart/, where users can create an account by entering their username, email, and password. To log in, users need to write their username and password. The user data is secured and encrypted in the database. Considerably, our online recommender system ensures the security and privacy of the patient's data through encrypted storage through the PostgreSQL database, following the best practices of data management. For dynamic data retrieval, we used the Samsung Galaxy Watch 5, where we built a watch application with the Android Studio framework. With this application, individuals can measure their heart rate and blood pressure along with sending the collected data to the web application using the socket API to perform the prediction and explain the results.

There is a limitation with the current smartwatches as they are not as precise as a medical-grade device. However, with this Health Canada approved smartwatch, users can dynamically measure their heart attack risk and receive early warning as a pre-assessment tool that guides users in taking preventative measures. The smart recommender system can be used by patients to predict heart attack risk and identify patient-specific risk factors. Clinicians can use this system to predict the heart attack risk of the patient along with viewing the most influential risk factors. Thus, it may guide them to understand underlying risks and further take the right steps to prevent heart disease from occurring in the first place.

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Author contributions Dr. Tursun Wali, Dr. Dilbar Salman and Almat Bolatbekov were responsible for content organizing, and manuscript writing. Almat Bolatbekov and Dr. Tursun Wali were responsible for collecting data and performing analysis. Ehesan Maimaitijiang created the website, AI model integration, online system and manuscript revision. Dr. Tursun Wali was responsible for testing the chatbot and analysis. Dr. Yasin Mamatjan designed and guided the project and provided the funding. All Authors reviewed and revised the manuscript and provided suggestions for manuscript writing.

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Declarations

Ethics approval and consent to participate Not applicable.

Competing interests The authors declare no competing interests.

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References

1. Mattingly Q. Cardiovascular diseases. World Health Organization (WHO). https://www.who.int/health-topics/cardiovascular-diseases#tab=tab_1. Accessed 14 Dec 2024.
2. Heart Disease and Stroke — CDC. Centers for Disease Control and Prevention. 2024. https://www.cdc.gov/heart-disease/risk-factors/index.html. Accessed 14 Dec 2024.
3. Kundu J, Kundu S. Cardiovascular disease (CVD) and its associated risk factors among older adults in India: evidence from LASI wave 1. Clin Epidemiol Glob Health. 2022;13:100937.
4. Ogunpola A, et al. Machine learning-based predictive models for detection of cardiovascular diseases. Diagnostics. 2024;14:144.
5. Das S, et al. Internet of things with machine learning based smart cardiovascular disease classifier for healthcare in secure platform. In: Bhattacharya A, Roy B, Sur SN, Mallik S, Dasgupta S, editors., et al., Internet of things and data mining for modern engineering and healthcare applications. Boca Raton: Chapman and Hall/CRC; 2022. p. 45–64.
6. Chauhan U et al. Cardiac arrest prediction using machine learning algorithms, 2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies, Kannur, India. 2019; 886–890, https://doi.org/10.1109/ICICICT46008.2019.8993296.
7. Ho V, Johnson CB, Ghanzouri I, Amal S, Asch S, Ross E. Physician-and patient-elicited barriers and facilitators to implementation of a machine learning-based screening tool for peripheral arterial disease: preimplementation study with physician and patient stakeholders. JMIR cardio. 2023;7(1):e44732.
8. Omiye JA, Ghanzouri I, Lopez I, Wang F, Cabot J, Amal S, Ross EG. Clinical use of polygenic risk scores for detection of peripheral artery disease and cardiovascular events. Plos ONE. 2024;19(5):e0303610.
9. Ricci F, Rokach L, Shapira B. Introduction to recommender systems handbook. In: Ricci F, Rokach L, Shapira B, Kantor PB, editors. Recommender systems handbook. Boston, MA: Springer; 2011. p. 1–35. https://doi.org/10.1007/978-0-387-85820-3_1.
10. Hors-Fraile S, et al. Analyzing recommender systems for health promotion using a multidisciplinary taxonomy: a scoping review. Int J Med Inform. 2018;114:143–55.
11. Howell P, Aryal A, Wu C. Web-based patient recommender systems for preventive care: protocol for empirical research propositions. JMIR Res Protoc. 2023;12:e43316.
12. Ghanzouri I, Amal S, Ho V, Safarnejad L, Cabot J, Brown-Johnson CG, Ross EG. Performance and usability testing of an automated tool for detection of peripheral artery disease using electronic health records. Sci Rep. 2022;12(1):13364.
13. Savić M et al. Analysis of machine learning models predicting quality of life for cancer patients, Proceedings of the 13th International Conference on Management of Digital EcoSystems. 2021; 35–42.
14. Kourou K, et al. A machine learning-based pipeline for modeling medical, socio-demographic, lifestyle and self-reported psychological traits as predictors of mental health outcomes after breast cancer diagnosis: an initial effort to define resilience effects. Comput Biol Med. 2021. https://doi.org/10.1016/J.COMPBIOMED.2021.104266.
15. Hollon T, et al. Near real-time intraoperative brain tumor diagnosis using stimulated Raman histology and deep neural networks. Nat Med. 2020;26(1):52–8.
16. McCarroll R, et al. Retrospective validation and clinical implementation of automated contouring of organs at risk in the head and neck: a step toward automated radiation treatment planning for low-and middle-income countries. J Glob Oncol. 2018. https://doi.org/10.1200/JGO.18.00055.
17. Zhao W et al. A survey of large language models. arXiv. 2023;2303.18223v13.
18. Alom A, et al. Early stage detection of heart failure using machine learning techniques, in: Proceedings of the International Conference on Big Data, IoT, and Machine Learning: BIM 2021. Springer. 2022; 75–88.

19. Sekar J, et al. An efficient clinical support system for heart disease prediction using TANFIS classifier. Comput Intell. 2022;38(2):610–40. https://doi.org/10.1111/coin.12487.
20. Rojek I, et al. Development of AI-based prediction of heart attack risk as an element of preventive medicine. Electronics. 2024;13:272.
21. Labrak Y et al. BioMistral: A collection of open-source pretrained large language models for medical domains. arXiv. 2024;2402.10373.
22. McDuff D et al. Towards accurate differential diagnosis with large language models. arXiv 2023;2312.00164.
23. Jiang L, et al. Health system-scale language models are all-purpose prediction engines. Nature. 2023;619:357–62.
24. Yazici Y, Mamatjan Y. A novel approach for efficient and accurate detection of myocardial infarction. Antalya: ICAT; 2014.
25. Abu-Alru S, et al. Smartwatch electrodiagrams for automated and manual diagnosis of atrial fibrillation: a comparative analysis of three models. Front Cardiovasc Med. 2022. https://doi.org/10.3389/fcvm.2022.836375.
26. ElShawi R, et al. Interpretability in healthcare: a comparative study of local machine learning interpretability techniques. Comput Intell. 2020. https://doi.org/10.1111/coin.12410.
27. Chen Z et al. Meditron-70b: Scaling medical pre-training for large language models. arXiv 2023;2311.16079.
28. Chen S, et al. Evaluating the ChatGPT family of models for biomedical reasoning and classification. J Am Med Inform Assoc. 2024;22:256.
29. Li C, Hua X, Zhang L. The IoT-based heart disease monitoring system for pervasive the IoT-based heart disease monitoring system for pervasive healthcare service healthcare service. Proc Comput Sci. 2017;112:2328–34.
30. Dorogush AV et al. CatBoost: a gradient boosting with categorical features support. CoRR. 2018; https://arxiv.org/abs/1810.11363.
31. Gohel P et al. Explainable AI: current status and future directions. arXiv preprint arXiv. 2021;2107.07045.
32. Lundberg S, Lee A. Unified Approach to Interpreting Model Predictions. Advances in Neural Information Processing Systems 30. NIPS. 2017.
33. Siddhartha M. November 5, 2020, "Heart Disease Dataset (Comprehensive)", IEEE Dataport, https://doi.org/10.21227/dz4t-cm36. https://ieee-dataport.org/open-access/heart-disease-dataset-comprehensive.
34. Mchugh ML. Interrater reliability: the kappa statistic Importance of measuring interrater reliability. Biochem Med. 2012;22(3):276–82.
35. Tran H et al. BioInstruct: instruction tuning of large language models for biomedical natural language processing. arXiv. 2023;2310.19975v2.
36. Wu C et al. PMC-LLaMA: further finetuning LLaMA on medical papers. arXiv. 2023;2304.14454v1.
37. Huang L et al. A survey on hallucination in large language models: principles, taxonomy, challenges, and open questions. arXiv. 2023;2311.05232.
38. Tintarev N, Masthoff J. A survey of explanations in recommender systems. In 2007 IEEE 23rd international conference on data engineering workshop. 2007;IEEE, 801–810.
39. Friedrich G, Zanker M. A taxonomy for generating explanations in recommender systems. AI Mag. 2011;32(3):90–8.
40. Ayers SL, Kronenfeld JJ. Chronic illness and health-seeking information on the internet. Health. 2016;11:327–47.
41. Jeckmans A, Beye M, Erkin Z, Hartel P, Lagendijk R, Tang Q. Privacy in recommender systems. In: Ramzan N, Zwol R, Lee JS, Clüver K, Hua XS, editors. Social media retrieval. London: Springer; 2012.
42. Abouelmehdi K, et al. Big healthcare data: preserving security and privacy. J Big Data. 2018. https://doi.org/10.1186/s40537-017-0110-7.

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