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Generative AI-based Healthcare Recommender System

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***Abstract*—Personalized healthcare recommendations remain challenging due to diverse patient data, including medical history and lifestyle habits. Traditional systems struggle to provide real-time, personalized recommendations, leading to ineffective treatment. This research improves healthcare recommendation systems (HRS) using generative AI techniques, specifically Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), to enhance personalization, accuracy and adaptability. This study explores synthetic data generation to address data sparsity and cold-start problems while maintaining privacy. Exploratory Data Analysis (EDA) and preprocessing methods like feature engineering, identification of missing data, normalization and outlier detection are part of the research methodology. Interpretability is enhanced by data visualization using boxplots, histograms and heatmaps. Although complete GAN and VAE implementation was not possible due to computational limitations, baseline assessments created a fundamental framework. According to preliminary findings, generative models can fill in the gaps in customisation. Potential improvements in prediction performance are shown by evaluation criteria including Root Mean Square Error (RMSE), accuracy and precision. Despite its drawbacks, this research shows that integrating Variational Autoencoders (VAEs) into HRS is viable for improved scalability and flexibility.**

Keywords*—Recommender system, Healthcare, Generative AI, Generative Adversarial Networks, Variational Autoencoders.

I. INTRODUCTION

Healthcare Recommender Systems (HRS) are known to be transformative tools in personalized treatment because they are recognized as revolutionary instruments in this ever-evolving age. These systems can subsequently suggest customized treatment programs, medications and lifestyle changes that meet each patient's unique health needs by combination of their medical history, lifestyle choices and personal preferences. Regardless of their performance in sectors like retail and entertainment, standard recommender systems face challenges due to the sensitivity, complexity and dynamic nature of medical data. Therefore, overcome these limitations, more advanced Artificial Intelligence (AI) methods that generate context-aware and intelligent recommendations must be used.

In order to increase the precision, adaptability and personalization of healthcare recommendations, this study investigates the use of generative AI approaches such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs). Reason being GANs allow for better modelling despite the lack of real-world data while maintaining patient anonymity. However, they are mostly useful in generation of synthetic health data to complement training datasets. In personalized healthcare, GANs can simulate tailored treatment or wellness suggestions by learning from complex patterns in patient records. Meanwhile, VAEs excel at addressing cold-start problems because it creates meaningful latent representations of new patients or treatments and facilitates recommendations even with sparse historical data.

Furthermore, the proposed HRS will leverage these advanced generative techniques to offer safe, effective, personalized recommendations by assessment of key patient-specific factors, such as age, genetic predisposition, medical conditions and lifestyle choices. This strategy seeks to improve patient participation, adherence to treatment programs and general well-being by emphasizing non-invasive advice, including meal plans, exercise recommendations and medication reminders. On top of that, vigorous data privacy and security mechanisms will be integrated to ensure compliance with healthcare regulations like (Health Insurance

Portability and Accountability Act) HIPAA and (General Data Protection Regulation) GDPR. Hence, this paper aims to push the limits of personalized healthcare by addressing the drawbacks of traditional filtering methods and utilizes generative AI to provide data-driven, ethical and intelligent recommendations that simultaneously enhance patient satisfaction and health outcomes.

II. BACKGROUND & RELATED WORK

A. Overview of Recommender System

Recommender systems (RS) are high-level tools created to assist users make decisions by recommending items based on their preferences and behaviours. These systems are highly beneficial in multiple industries, such as e-commerce, healthcare and entertainment. As for the healthcare domain, an emerging trend is the importance of recommendation technologies development for patients to monitor and maintain their health effectively based on the patient's medical history, genetic traits and lifestyle habits. However, with the growth of the emergent user base, performance maintenance has become increasingly difficult [1]. Additionally, new users or items lack sufficient data for effective recommendations, which causes a cold start [2] and data sparsity is present when uneven distribution of user-item interactions complicates the recommendation process [1]. While RS significantly enhance user experience by personalizing content, they also face ongoing challenges that necessitate continuous research and innovation to improve their effectiveness and efficiency [3]. Therefore, to overcome those challenges, future advancements are needed to enhance further RS's role in revolutionizing healthcare.

According to Abdullah *et al.* [4], HRS focuses on providing tailored medical advice based on patient conditions and histories. For instance, if a patient is diagnosed with a heart disease, the HRS suggests a less vigorous exercise routine that is suitable for the patient. Moreover, there are RS that are specifically targeted to recommend medication to their patients. It analyses symptoms and demographics to suggest appropriate medications, enhancing patient outcomes during critical times [5]. For instance, if a patient is iron deficient, the RS suggests a supplement that contains ferrous sulphate to treat iron-deficiency anaemia after analyzing the patient's medical history and allergies. Furthermore, RS utilizes K-nearest neighbour algorithms to suggest rehabilitation exercises, achieving high accuracy through user feedback [6]. As an illustration, patients suffering from stroke attacks may receive at home physiotherapy exercises from the RS to regain their strength, but if a patient submits negative feedback, the RS will constantly try to improve the suggested exercise to achieve the best user experience.

Some of the common methodologies and technologies used are machine learning techniques and data processing. Algorithms like decision trees and K-means clustering are employed to classify and analyze patient data, to ensure personalized recommendations [4, 5]. Data processing includes data cleaning, preprocessing and training the recommender engine to improve prediction accuracy [7]. The first step in data cleaning, is to maintain accuracy and quality by fixing errors and inconsistencies. Data preprocessing transforms raw data into a usable format for analysis and the final step is training the recommender engine. The final step is to build and optimize a model to generate accurate and personalized recommendations.

While RS show trust in enhancing healthcare services, challenges like cold-start problem is agreed by António *et al.* [6] as well because early iterations of RS often struggle with accuracy due to insufficient data. Besides, extracting relevant recommendations become complex with the vast amount of online health information [8]. Similarly, data privacy and algorithm bias are becoming a concern as the healthcare domain constantly evolves. In essence, continuous optimization is vital for future research and development of HRS.

B. Phases in Recommender System

HRS have evolved in both traditional and generative AI approaches throughout the digital age. Traditional systems mainly focus on data-driven recommendations, unlike generative AI introduces innovative methods for personalized healthcare solutions. Traditional RS focuses on historical data and user preferences, whereas generative AI creates new insights and enhances personalization in healthcare recommendations, which is a more dynamic approach. This shift has both advantages and challenges, particularly in ethical considerations and data privacy [9]. Figure 1 provides an overview of these phases in traditional recommendation process whereas Fig. 2 provides an overview of phases in generative AI recommendation process.

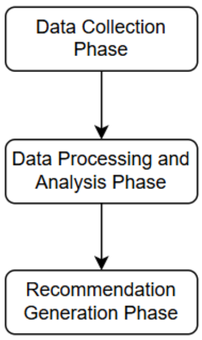


Fig. 1. Phases in traditional RS.

The first phase is the data collection phase, includes gathering both external and user-specific data. This consists information from wearable technology as well as information added by users themselves such as health goals, symptoms and medical history. For instance, wearable gadgets that monitor metrics like heart rate, sleep quality, physical activity and preferences is crucial for tailoring recommendations [10]. Furthermore, Electronic Health Records (EHRs) offer clinical data such as laboratory findings, diagnoses and treatment records.

The second phase is data processing and analysis, uses machine learning algorithms to analyze the collected data, in order to identify patterns and user behaviour. It implements methods like collaborative filtering and content-based filtering [10]. The first steps involve standardization of formats to achieve consistent analysis and data cleaning to remove inaccuracies. Subsequently, to identify key trends as well as characteristics such as diabetic levels and BMI.

The final phase involves personalized recommendation generation based on the insights derived from the data processing and analysis phase, which often utilizes hybrid models for improved accuracy [10]. In addition to preventative care alerts for screenings and individualized treatment programs, these recommendations may also involve lifestyle changes like food or workout plans.

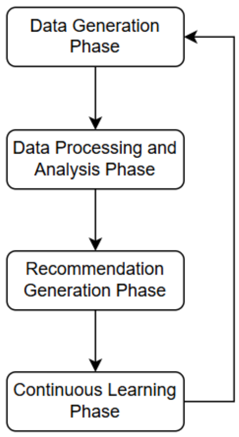


Fig. 2. Phases in Generative AI RS.

The first phase, generative AI utilizes algorithms like GANs and VAEs to create new medical data, which enhances the trained datasets for a better model performance [11].

The second phase, is by multi-modal patient data analysis, generative AI can uncover patterns that lead to tailored treatment approaches that improve patient outcomes [9]. As a result, a variety of techniques are used like clustering to link individuals with similar health profiles and matrix factorization for interpretation of user interactions. Reason being generative AI models mimic human thought processes to provide intricate predictions that are beneficial. By correlation revelations like the one between sedentary lifestyles and specific health issues, these analyses lay the foundation for suggestions that are specifically customized to each individual.

In the recommendation generation phase, the effectiveness of the system's recommendations is evaluated during the evaluation phase. Accuracy, precision and user satisfaction are important criterias that guarantee system reliability. This is because different recommendation systems are compared using techniques like A/B testing and user feedback. Similarly, engagement analysis shows how successfully users respond to the recommendations. This phase is important to verify the system's efficiency as well as identify areas in need of improvement.

The system's continued applicability and effectiveness are ensured by the last stage, which is the continual learning and improvement phase. In order to ensure accuracy, models are updated to incorporate new data and future recommendations are modified in response to user comments. The latest medical guidelines and research are incorporated into the system. Furthermore, it continuously adapts to user behaviours, preferences and health state changes. As the RS evolves, it becomes more proficient at addressing the individual healthcare requirements of each user. Thus, it enables them to make sensible decisions and enhance their health.

C. Recommender System Techniques

1) Traditional RS apply content-based, collaborative, hybrid-based and semantic-based approaches to enhance user experience and precision in EHRs.

The Content-based filtering technique (CB) depends on the use of patient information, which includes medical history and personal preferences. In order to recommend a service or treatment in healthcare based on attributes and the user's preferences [12]. Thus, an exact match with what the patient needs is able to be provided [13].

Collaborative filtering (CF) is a technique that generates recommendations from the behaviours of similar users. In the context of healthcare, especially personalized medicine and disease management, it has been quite effective when dealing with the cold-start and sparse-data problems [14].

The accuracy of the recommendation is improved with hybrid-based filtering (HB) by combination of CB and CF techniques. It further improves healthcare by integration of patient likes and dislikes with the attributes of the items for personalized recommendations. HB also gives better recommendations for medical services by seeding semantic relationships [15].

Semantic-based filtering techniques improve the recommendation by using ontologies and semantic relationships between medical conditions and treatments [16]. This would address the problems of new items and data sparsity, thus improving the accuracy of HRS as well as patient satisfaction [17].

Despite the fact that these methods significantly improve the capabilities of HRS, they also come with disadvantages such as possible biases in suggestions and privacy issues. Additionally, it brings up concerns about patient confidentiality and data security. Furthermore, the number and quality of available data determine how effective these systems are and these factors might vary throughout healthcare settings.

2) Generative AI techniques have notable benefits over traditional methods. GANs and VAEs have become effective tools in HRS. These generative models tackle important issues such as the lack of data, cold-start issues and the requirement for tailored suggestions. GANs and VAEs improve the precision and effectiveness of healthcare recommendations as it makes use of their distinct capabilities. Thus, it offers a more resilient and flexible framework than traditional techniques.

GANs are most useful in synthetic data generation to augment small datasets, which is a common issue in healthcare. This helps overcome data scarcity and improve training without invasion of patient privacy [18, 19]. GANs have been applied to enhance the accuracy of medical diagnoses, such as detection of COVID-19 from chest X-rays, because of their ability to generate high-fidelity synthetic images that improve model training and validation [20]. Even though the data generated by GANs are realistic, they must be managed carefully to ensure compliance with privacy conditions, which are very important in healthcare applications [18].

VAEs are effective in overcoming cold-start issues by generation of meaningful item representations in a continuous latent space. This allows the system to make recommendations even for new users or items with limited historical data [21]. Additionally, VAEs can improve cross-domain recommendation systems by capture and transfer of user preferences between domains. This enhances the system's ability to suggest more relevant medical services or products.

In contrast to traditional RS techniques that often struggle with apprehending complex user preferences, generative models like VAEs and GANs overcome these limitations by modelling user preferences in a more nuanced manner [21]. In addition, traditional methods that rely heavily on historical data and simple filtering techniques are not very flexible compared to generative models that offer great scalability in managing vast and diverse datasets [10]. Moreover, deep learning techniques like GANs and VAEs are able to provide more personalized recommendations, which are crucial in healthcare for tailoring treatments and interventions to individual patient needs [22, 23].

Even though GANs and VAEs offer significant advancements compared to traditional RS, they also have disadvantages such as the need for large computational resources and the complexity of model training. Moreover, careful consideration of ethical and regulatory issues, particularly data privacy and security, needs to be taken into account when implementation of these models in existing healthcare systems. These challenges are important to address to fully realize the potential of generative models in transformation of HRS.

Table I. Summary of Recommender System Techniques.

Filtering Techniques	**Advantages**	**Limitations**
Content-Based (CB)	Recommends items based on the characteristics of items and user preferences [12].	Limited to user's historical preferences, leading to a lack of novelty in recommendations.
Collaborative Filtering (CF)	Effective in handling cold-start and sparse-data problems by leveraging community data [14].	In terms of popularity bias, CF tends to favour popular items, which can overshadow niche content.
Hybrid-Based (HB)	Combines CB and CF to enhance recommendation accuracy and address individual limitations [15].	HB typically requires higher computational power, adding to the system's processing requirements.
Semantic-Based (SB)	Leverages semantic relationships and ontologies to enhance recommendation processes [16].	Semantic-based filtering requires detailed and accurate ontology creation.
Variational Autoencoder-based (VAE)	VAEs overcome cold-start issues by creating meaningful representations in latent space [21].	VAEs require extensive training data and computational resources, which can be a barrier for smaller datasets.
Generative Adversarial Networks (GAN)	GANs generate synthetic data to augment small datasets, improving model training without compromising privacy [18, 19].	GANs are known for their training instability and susceptibility to mode collapse, where the generator produces limited diversity in outputs. This is a significant challenge in applying GANs to recommendation systems.

D. Related Work

Pahune and Rewatkar [24] proposed a paper that discusses the growing role of generative AI and large language models (LLMs) in healthcare that focuses on their potential to reform healthcare applications. It highlights the use of models like GPT-3, Visual ChatGPT, GANs and VAE to address significant healthcare challenges. The paper suggests using LLMs and generative AI for various healthcare applications such as medical text analysis, information extraction from EHRs and medical images production. The dataset employed is a publicly accessible database called "A Multimodal Clinical Dataset," which includes masked clinical data from intensive care units. This dataset incorporates information from EHRs, medical imaging and other modalities. Generally, generative AI and LLMs offer powerful tools for medical data exploration because they improve diagnosis accuracy and the development of personalized treatment plans. They have the potential to reduce the burden of medical paperwork by creation of visit notes, treatment codes and medical summaries. These technologies can revolutionize healthcare by providing better healthcare outcomes and improved patient experience, which fundamentally impacts medical research, diagnosis and patient care. The paper acknowledges ethical issues and data privacy concerns as significant challenges in the application of generative AI and LLMs in healthcare. Reason being without human oversight, generative AI applications could potentially spread false information or produce damaging content at an unprecedented scale.

In another work, Shambour *et al.* [16] suggested Hybrid Semantic-based Multi-Criteria Collaborative Filtering (HSMCCF), which is a medication recommendation system to assist patients in locating the right drugs for their illnesses. The method makes use of a WebMD dataset of patient reviews on medications. It has two primary modules: a multi-criteria filtering module that takes patient preferences into account across a number of rating criteria and a semantic filtering module that organizes medications by medical condition. Unlike the multi-criteria module, which increases recommendation accuracy, the semantic module deals with data sparsity. In order to increase the number of comparable medications taken into consideration, a medicine's reputation score is also utilized. According to experiments, the HSMCCF technique outperforms benchmark methods in terms of prediction accuracy and coverage, particularly for novel medications with low ratings and sparse datasets.

Roy and Dutta [25] proposed HRS provide individualized medical advice based on a patient's medical history, lifestyle choices and other attributes. Various types of HRS are described, including systems for recommending healthcare professionals, health status prediction systems, nutrition and physical exercise suggestions and diagnosis decision support systems. The article then reviews the body of research on these several HRS, outlining their methods, characteristics, uses and challenges. It draws attention to areas that require greater investigation, including integrating a wider range of data sources, enhancing algorithm openness and customization and carrying out thorough assessments of the effect of HRS on patient outcomes. Finally, the study offers recommendations for enhancing HRS as well as a summary of HRS research trends.

Ooi *et al.* [7] outlined the framework for the HRS that encompasses various RS techniques. The datasets used and evaluation metrics are employed in the healthcare domain. Moreover, the paper emphasizes the significance of accurate medical recommendations and the potential of RS to enhance patient care as well as decision-making processes. It also presents insights into the theoretical framework, dataset, data cleaning process, recommender engine and user interface that offers a comprehensive overview of the entire system's development and evaluation.

Shambour *et al.* [17] proposed a hybrid system based on content-based and collaborative filtering to address the challenge of finding the best-suited doctors for patients despite the vast amount of available healthcare information. The proposed system incorporates a multi-criteria collaborative filtering approach to help patients accurately identify doctors that align with their preferences. It utilizes multi-criteria decision-making, whereby doctor reputation scores and doctors' content information to improve recommendation quality and mitigate the impact of data sparsity. Their evaluation results demonstrate the effectiveness of the proposed approach with regards to predictive accuracy and coverage under extreme levels of sparsity.

Ghebrehiwet *et al.* [26] proposed the use of generative AI, specifically deep generative models (DGMs) like GANs and VAEs, to revolutionize personalized medicine. These models are used to create realistic, privacy-preserving synthetic patient data because they can address challenges in data collection, costs and privacy in precision medicine. The review follows PRISMA guidelines to analyze studies from databases such as Scopus and PubMed. It focuses on the impact of AI in precision medicine and the applications of DGMs in synthetic data generation. The paper highlights the use of advanced deep learning techniques to produce novel and realistic outputs by replicating patterns found in existing data. However, the paper does not specify a particular dataset used in the studies reviewed. Instead, it mentions the use of real-world clinical and genomic sources for generating synthetic patient data, such as in the case of myeloid malignancies. The evaluation metrics include precision and recall, particularly in the context of assessing the performance of LLMs like ChatGPT in providing treatment recommendations. The paper also discusses the use of a synthetic validation framework to evaluate the fidelity and privacy of synthetic data.

Generative AI models tackle challenges like data scarcity and privacy issues by synthetic patient data generation that maintains realism and authenticity. These models enhance data analysis and interpretation because of advanced precision medicine, which improves synthetic data generation, accuracy and privacy. LLMs provide valuable complementary insights in complex medical fields, such as radiation oncology, despite not reaching human expertise levels. Thus, the accuracy of foundation models like LLMs in digital diagnostics is a noted limitation, as it indicates the need for further development to improve diagnostic precision. However, there is a need for more interdisciplinary research to advance the application of generative AI in personalized medicine that addresses existing limitations and enhances model robustness and generalizability.

Bengesi *et al.* [27] proposed a comprehensive review of state-of-the-art generative AI models like GANs, GPT, Autoencoders, Diffusion Models and Transformers. The aim is to fill the gap in understanding these models by exploring their technical and mathematical foundations, applications, challenges and future prospects. The paper examines commonly used GAI models, researching into their technical and mathematical backgrounds.

Additionally, it categorizes tasks, describes applications and discusses areas of impact, challenges and future prospects. The review includes an exploration of the theoretical and mathematical foundations of these models. For the Generative Pretrained Transformer (GPT), the initial model (GPT-1) was trained on the BooksCorpus dataset, which consists of over 7,000 unique unpublished books in various genres. This dataset allows the model to learn from long stretches of contiguous text. The paper does not explicitly mention specific evaluation metrics used for the models reviewed. However, it notes that GPT-4 was compared with state-of-the-art models using the Measuring Massive Multitask Language Understanding (MMLU) benchmark, which covers 57 tasks across various domains. The reviewed models, such as GPT-4, exhibit high performance comparable to humans in several professional and academic benchmarks, including passing bar and medical exams. Figure 3 shows the structure of self-attention architecture of GPT.

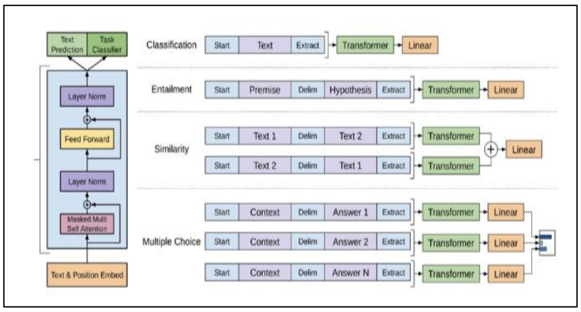


Fig. 3. The Self-attention Architecture of GPT [27].

Kancharla [28] proposed the use of synthetic test data generation through generative AI techniques such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) to address challenges in healthcare data usage. This approach aims to surpass the statistical properties of real healthcare data while ensuring patient confidentiality and compliance with privacy regulations. The paper discusses the use of regularization techniques like dropout and weight decay to prevent overfitting during the training of generative models. These techniques help the models generalize better to unseen data so that they perform well in real-world scenarios. The synthetic data is iteratively refined based on statistical analyses and clinical evaluations to ensure accuracy and usefulness. This process supports better decision-making in healthcare research and practice. Once validated, the synthetic data is used in various healthcare applications, including machine learning model development, software testing and research initiatives. Thus, the specific datasets employed in the study are not detailed in the provided paper. The focus is on synthetic datasets generation that mirror real-world healthcare data. The paper emphasizes rigorous validation through statistical and clinical methods, but specific evaluation metrics are not explicitly mentioned in the provided contexts, as shown in Fig. 4.

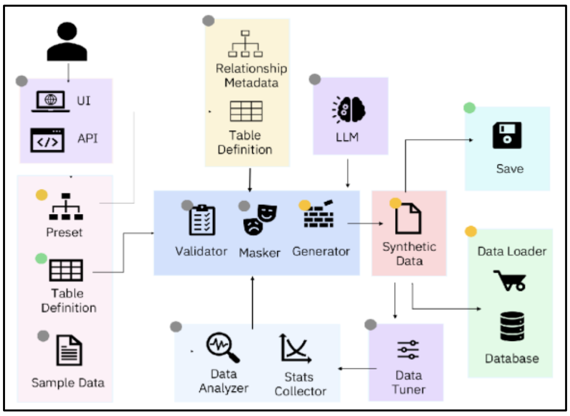


Fig. 4. The Technical Architecture for the Synthetic Data Preparation of Sensitive Healthcare Data [28].

Moreover, generative models enhance patient privacy by elimination of risks associated with real data usage and reduce costs by minimizing the need for real data acquisition. Timelines can be shortened by instant access to diverse datasets. Additionally, generative models facilitate responsible data usage and innovation in data-driven decision-making. Therefore, there is a need for further refinement of algorithms to achieve higher realism in synthetic datasets because of ethical implications and potential biases in synthetic datasets that could affect clinical decision-making.

Gupta *et al.* [29] proposed an automatic diagnosis system that recommends preventative measures based on patient symptoms. This system leverages machine learning algorithms, categorical data conversion and speech data extraction to enhance diagnostic accuracy. The system records patient voice data using a microphone and assesses the performance of speech recognizers. It was observed that text data often provides more accurate results than categorical data. The accuracy of the system improves when classifiers have access to a large feature vector. The dataset for the current study was taken from Kaggle. The dataset includes separate files for symptoms and safety measures. The evaluation of Gupta *et al.*'s method is conducted using several metrics, F1-score, Recall, Precision and Accuracy.

The system shows improved accuracy when using text data and a large feature vector. Combination of both speech and text data, the system provides a more comprehensive analysis of patient symptoms. The specific limitations of Gupta *et al.*'s system are not explicitly mentioned in the provided contexts. However, general limitations in such systems could include challenges in handling diverse accents in speech data, data privacy concerns and the need for large datasets to train machine learning models effectively.

Navin *et al.* [30] proposed a model of a knowledge-based RS that uses adaptive fuzzy logic systems to diagnose illnesses and suggest treatments. For sub-medical diseases, it offers an architecture made up of several parallel "fuzzy blocks" that function as fuzzy rule-based classifiers. The outputs of these fuzzy blocks are combined using a rule base by a knowledge-based combiner segment to produce comprehensive diagnosis and treatment suggestions. A sample patient dataset is used to configure and assess the system for the diagnosis of fundamental lung diseases. The findings are in good agreement with professional assessments.

Table II. Summary of related works.

References	**Findings**	**Evaluation Metrics**
Pahune & Rewatkar [24] Healthcare: A Growing Role for Large Language Models and Generative AI	Medical imaging has significantly improved through the use of generative AI, particularly in the analysis of MRI and X-ray data. More precise diagnoses can result from improvement of medical images by GANs. Research, diagnosis and customized treatment are also being advanced by the use of multimodal AI, which integrates information from genomes, clinical records and images. This is a significant advancement in the use of natural language processing (NLP) in the biomedical field. In contrast, without human oversight, generative AI and LLMs may result in inaccuracies or harmful outputs. Thus, it causes ethical and data privacy concerns in the healthcare domain.	MME (Multimodal Model Evaluation) and SEED-Bench for assessing the effectiveness of multimodal large language models (MLLMs).
Shambour *et al.* [16] Medicine Recommender System Based on Semantic and Multi-Criteria Filtering	Medicine recommendation system called HSMCCF to help patients find appropriate medications based on their medical conditions. However, the system still faces challenges with limited user feedback and its applicability in the industry.	Accuracy.
Roy & Dutta [25] A Survey on Personalized Health Recommender Systems for Diverse Healthcare Applications	The survey provided an overview of HRS research trends and guidance to improve HRS. However, HRS lack transparency, personalization and comprehensive evaluations of the real impact on patient after diagnosis.	Various evaluation metrics were surveyed.
Ooi *et al.* [7] A Healthcare Recommender System Framework	Proposed the framework for the HRS, encompassing various RS techniques, datasets used and evaluation metrics employed in the healthcare domain.	Similarity score, word count.
Shambour *et al.* [17] A Doctor Recommender System Based on Collaborative and Content Filtering	Used a doctor's reputation score and the substance of their medical practice as multiple decision-making factors to improve the quality of their suggestions and lessen the impact of data sparsity.	Prediction coverage, RMSE and MAE.
Ghebrehiwet *et al.* [26] Revolutionizing Personalized Medicine with Generative AI: A Systematic Review	Generative AI helps solve problems like limited data and privacy concerns by generation of realistic synthetic patient data. This improves data analysis, supports precision medicine and leads to better treatment outcomes. Models like VAEs and GANs assist in identifying important genes, whereas LLMs support decision-making in cancer care and radiation therapy.	Precision and recall,
Bengesi *et al.* [27] Advancements in Generative AI: A Comprehensive Review of GANs, GPT, Autoencoders, Diffusion Model and Transformers	The paper reviews the latest generative AI models like GANs, GPT, Autoencoders, Diffusion Models and Transformers. It explains how they work, their development and future potential. Generative AI is creating new opportunities in fields like business, healthcare, education, entertainment and media. The paper also highlights generative AI's major impact on the 5th Industrial Revolution and how it is changing job markets.	Measuring Massive Multitask Language Understanding (MMLU) benchmark.
Kancharla [28] Synthetic Test Data Preparation using Generative AI & Usage in Secured Healthcare Practice	The paper proposes the usage of generative AI methods like GANs and VAEs to generate synthetic healthcare data. As it helps overcome data limitations but protect patient privacy and follows legal guidelines. Additionally, it covers the use of regularization techniques to avoid overfitting, in order the models to work well with new real-word data. Further algorithm refinement is needed because synthetic datasets may still carry biases and lack realism which may potentially affect clinical decisions.	Rigorous validation through statistical and clinical methods, but specific evaluation metrics are not explicitly mentioned in the provided contexts.
Gupta *et al.* [29] Detecting Thyroid Disease Using Optimized Machine Learning Model Based on Differential Evolution	Introduced an automated healthcare system that can successfully take the place of a physician at the first stage of diagnosis and contribute to time savings by advising the appropriate measures. Some of the challenges mentioned in the paper were speech variability, privacy concerns and the need for large and diverse datasets to ensure reliable model training.	Accuracy, precision and F1 score.
Navin *et al.* [30] Knowledge Based Recommender System for Disease Diagnostic and Treatment Using Adaptive Fuzzy-Blocks	Disease diagnosis and treatment recommendations using adaptive fuzzy logic, which utilizes rule base to provide holistic diagnoses and treatment recommendations.	Expert evaluation.

III. THEORETICAL FRAMEWORK

A. Variational Autoencoder (VAE)

VAE is a generative model that has been applied in RS to overcome challenges such as data sparsity and the need for robust latent representations. It is because VAEs model the underlying distribution of data using a probabilistic framework, they are especially well-suited to managing the sparse and complex datasets that are typical in recommendation settings. In order to predict user preferences and increase suggestion accuracy, RS use VAEs to create latent representations of users and items.

VAEs are proficient at handling implicit feedback, which is often sparse and biased. For instance, the VAE-IPS model uses inverse propensity scoring to lessen selection bias in implicit feedback because it leads to more accurate recommendations [31]. Likewise, VAE revisits the annotation of positive and negative samples in implicit feedback to enhance recommendation performance [32].

HRS can enhance patient care and resolution by the implementation of VAEs' generative capabilities to generate precise and tailored recommendations. The capability of VAEs to model complex distributions and produce new data makes it especially useful in the healthcare industry because they frequently struggle with a lack of labelled data. VAEs are used to create personalized healthcare recommendations by examination of deep latent representations of user profiles and item contents like healthcare providers' description. This approach allows for the extraction of implicit relationships between users and items to improve recommendation accuracy [33]. Additionally, VAEs address the cold-start problem by precise estimation of the interest probabilities of newly introduced users and resources. This is made possible by VAEs' generative nature, which allows them to create new data points using learnt distributions [34]. Furthermore, in HRS, VAEs facilitate a balance between recommendation of known items and exploration of new options. This is achieved by construction of user-specific subgraphs that capture both observed interactions and potential new interests.

Some of the advantages of using VAEs in HRS are effective handling of data sparsity, improved recommendation performance and bias mitigation and explainability. VAEs are effective in overcoming data sparsity, a common issue in healthcare data because of amortized inference to generate recommendations even with limited data. On top of that, VAEs can be extended to generate explainable recommendations, which then provides natural language explanations that improve user trust and understanding of the recommendations [35]. Subsequently, more accurate and reliable recommendations are generated with the integration of VAEs in HRS compared to traditional methods [33]. Besides, VAEs can be trained using methods like inverse propensity scoring to reduce biases inherent in implicit feedback, such as popularity or position bias because it leads to more unbiased recommendations [31].

In an HRS, VAEs streamline the feature extraction process. They begin by preprocessing patient data to a standard format and then utilize encoder layers to learn latent representations of health indicators. The encoder maps complex patterns in patient data into a lower-dimensional latent space, in order to capture essential features such as lifestyle factors, medical history and biometrics. The decoder then reconstructs patient profiles to ensure meaningful feature extraction. The recommender engine can evaluate similarities and forecast diabetes stages or individualized health suggestions thanks to the latent space's output, which is a reduced depiction of a patient's health condition.

B. Generative Adversarial Networks (GAN)

GANs are a class of machine learning frameworks designed to generate new data samples that mimic a given dataset. A generator and a discriminator are two neural networks that are trained simultaneously through adversarial processes. Model training without compromising patient privacy can be done by using synthetic data. Besides, GANs are used in HRS to improve the quality and fairness of recommendations. Approaches such as data sparsity and bias in healthcare datasets can be overcome by GANs implementation.

Moreover, GANs are used to generate synthetic Electronic Health Records (EHRs) that preserve the statistical properties of real data while protecting patient privacy. This is crucial when training healthcare models without compromission of sensitive information [36]. Additionally, to generate reasonable synthetic health data by correlations and ensure accurate subgroup representation, techniques like Bias-transforming GANs (Bt-GAN) are developed. This helps to reduce bias during healthcare prediction generation [37]. Subsequently, to ensure that synthetic data generation does not interrupt patient privacy, Local Differential Privacy (LDP) is integrated with GANs to protect training data from malicious attacks [38].

In HRS, GANs are implemented to create personalized healthcare recommendations by combination of user and item features like demographics and medical history. For instance, conditional GANs are customized to individual needs. Furthermore, issues such as data sparsity in HRS can be addressed using Variational Collaborative GANs (VCGAN) because it leverages auto-encoders to produce latent vectors. Thus, improvement of correlation between generated samples and real-world data [39]. On top of that, in order to improve model efficiency and reduce model complexity while maintaining accuracy can be achieved with a compact GAN [40].

Furthermore, it is essential to tackle such issues in order to ensure that GANs can be successfully integrated within HRS. It is also important to be familiar with fairness in healthcare predictions and the construction of fairness. Plus, unbiased synthetic data generation method such as Bt-GAN is a notable ongoing progress. Therefore, with ongoing research, it is anticipated that GANs will continue to play a crucial role in enhancing the accuracy and reliability of HRS.

C. Evaluation Metrics

In order to guarantee efficacy and dependability in clinical contexts, generative AI-based HRS are evaluated using a range of criteria. These criteria are essential in evaluating how well AI models perform in producing precise and practical suggestions for patients as well as healthcare providers. The evaluation metrics can be categorized into traditional performance metrics and those specifically tailored for healthcare applications.

1) Accuracy

Accuracy measures the number of correct predictions made by the model out of all predictions. It is a fundamental metric. However, it is not always sufficient, especially in imbalanced datasets that are common in healthcare domains. For instance, in healthcare datasets, the number of positive cases may be much smaller than the number of negative cases [41]. In such cases, accuracy can be misleading because the model predicting the majority class most of the time may still appear to perform well.

2) Precision

Precision represents the proportion of correctly predicted positive cases out of all predicted positive cases. It is crucial in healthcare domains to minimize false positives. The reason is that a high precision score ensures that the model does not incorrectly classify negative cases as positive, thereby preventing unnecessary treatments or interventions.

3) Recall (Sensitivity)

Recall (sensitivity), measures the model's ability to correctly identify all actual positive cases. In healthcare, high recall is critical because missing actual positive cases (false negatives) can be harmful to patient outcomes. Therefore, a model with high recall ensures that as many relevant cases as possible are identified and the chances of undiagnosed conditions are reduced.

4) F1 Score

The F1 score is the harmonic mean of precision and recall as it provides a balanced measure between the two. It is particularly useful when there is an imbalance between positive and negative cases, which ensures that both false positives and false negatives are considered in the evaluation process [42].

5) Root Mean Square Error (RMSE)

As for Root Mean Square Error (RMSE), it is used to compare the differences between predicted and observed values. It helps forecast ratings for a test dataset of user-item pairs for which the rating values are already known, which involves calculating the RMSE as it is one method for accuracy evaluation. Alternatively, the difference between the actual and anticipated values would establish the error. The RMSE can be calculated by squaring all of the test set error values to find the average (or mean) and then taking the square root of that average. It is very useful for regression tasks in RS for healthcare [7]. The computation of RMSE is detailed in Eq. (1) within the documentation of the Surprise library.

$$RMSE = \sqrt{\frac{1}{|\hat{R}|}\sum_{\hat{r}_{ui\in\hat{R}}}(r_{ui} - \hat{r}_{ui})^2} \qquad (1)$$

, where:

$\hat{R}$ = Number of records

rui = Actual rating of the item i by user u

$rui\hat{}$ = Predicted rating of the item i by user u

Even though these evaluation metrics offer a thorough framework for HRS assessments based on generative AI, it is important to take each application's unique needs and context into account. For instance, metrics like recall and precision might be more important than others in situations when patient safety is the top priority. Furthermore, integration of user-centred metrics like trust and empathy can enhance the review process, which guarantees that AI systems not only function well technically but also in harmony with moral and human-centred principles in the healthcare industry.

IV. RESEARCH METHODOLOGY

A. Implementation

The project is designed for two types of users which are the administrator (researcher) and the customer (patient). All work will be conducted within Jupyter Lab, where the administrator will analyze, preprocess and prepare the dataset for model development.

The primary focus is on Exploratory Data Analysis (EDA) and data preprocessing using the Diabetes Health Indicators Dataset. This involves dataset's structure exploration, missing values identification and a cleaned dataset. A well-structured data eases model training. The first step will be to load and explore the dataset in order to examine its characteristics such as size, features and data types. In case of any missing values, redundant or inconsistent records will be removed to maintain data integrity. Additionally, duplicate entries will be recognized and dropped to avoid complications during next phase of implementation.

EDA will be done to identify patterns and trends within the dataset. Subsequently, descriptive statistics such as mean, median, standard deviation and skewness will be calculated to summarize the data distribution. On top of that, visualization techniques like histograms and box plots will be used to analyze the spread and variability of key health indicators. Correlation analysis using heat maps will help identify relationships between various variables and provide insights into which features may be relevant for future modelling. Furthermore, outlier detection techniques such as Z-score, interquartile range (IQR) and box plot analysis will be done to identify and address anomalies in the dataset. Figure 5 shows a flowchart of the prototype for administrator.

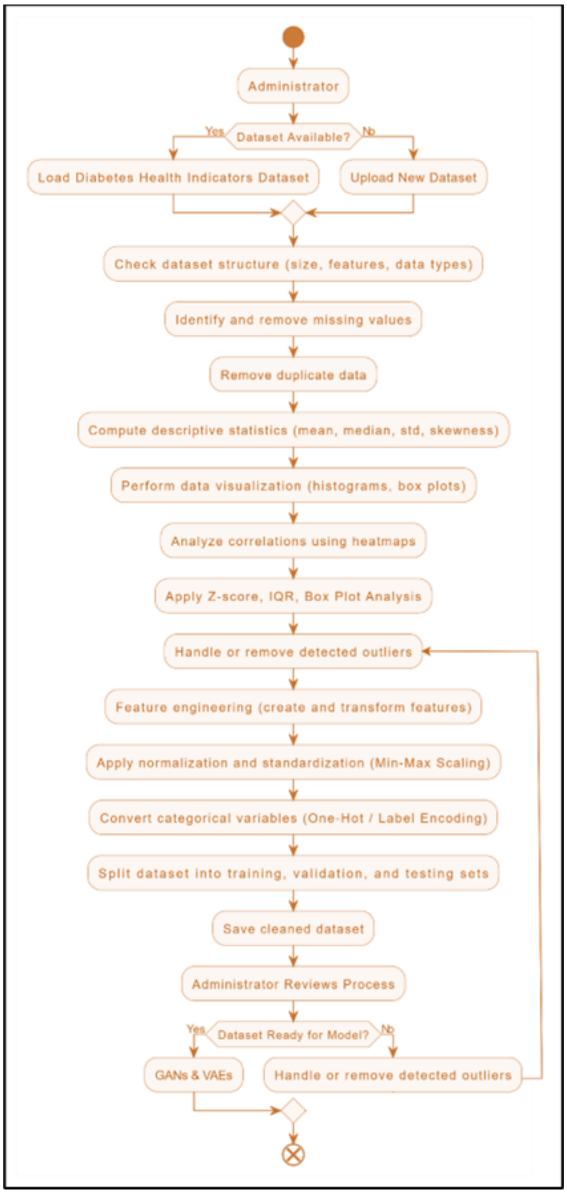


Fig. 5. Flowchart of prototype for administrator.

Once the dataset has been thoroughly analyzed, it will undergo data preprocessing to ensure it is optimized for model training. New relevant features may be created and existing ones transformed to improve the dataset's quality during feature engineering. Normalization and standardization techniques such as Min-Max Scaling will be applied to numerical features to maintain consistency across different variables. However, if categorical variables are present, it will be converted into numerical representations using one-hot encoding or label encoding to ensure compatibility with machine learning models. As for a balanced representation across different health conditions for fair model evaluation, the dataset will then be split into training, validation and testing sets.

All data exploration, visualization and preprocessing tasks will be conducted within Jupyter Lab since no GUI will be developed. The cleaned dataset and analysis findings will be saved and well-documented using markdown cells to maintain clarity and reproducibility. Generative AI models such as GANs and VAEs will be implemented to develop a personalized healthcare recommendation system. The final outcome will be a cleaned, well-structured dataset along with detailed exploratory analysis, ensuring that when generative AI techniques are applied, they are trained on high-quality, well-prepared data, ultimately improving the effectiveness of personalized healthcare recommendations. Figure 5 visualizes a flowchart of the prototype for an administrator.

B. Dataset

The prototype's model training dataset is a healthcare-related dataset, "Diabetes Health Indicators Dataset" on Kaggle. This dataset was cleaned and consolidated and it was created from the Behavioural Risk Factor Surveillance System 2015 (BRFSS) dataset already on Kaggle. The BRFSS is a health-related telephone survey that is collected annually by the Center for Disease Control and Prevention (CDC). Each year, the survey collects responses from over 400,000 Americans on health-related risk behaviours, chronic health conditions and the use of preventative services. It has been conducted every year since 1984. For this project, a csv of the dataset available on Kaggle for the year 2015 was used. It is a clean dataset of 70,692 survey responses to the CDC's BRFSS2015. It has an equal 50-50 split of respondents with no diabetes and with either prediabetes or diabetes. The target variable Diabetes binary has 2 classes. 0 is for no diabetes and 1 is for prediabetes or diabetes. This dataset has 21 feature variables and is balanced. This original dataset contains responses from 441,455 individuals and has 330 features. These features are either questions directly asked of participants or calculated variables based on individual participant responses. Table III illustrates the descriptions of attributes of the used dataset.

Table III. Attributes descriptions of the selected dataset.

Attributes	**Details**	**Field Type**
Diabetes_binary	Indicates whether a person has diabetes (1) or no diabetes (0)	Integer (0/1)
HighBP	Indicates whether a person has high blood pressure (1) or no high blood pressure (0)	Integer (0/1)
HighChol	Indicates whether a person has high cholesterol (1) or no high cholesterol (0)	Integer (0/1)
CholCheck	Indicates whether a person has checked their cholesterol levels in the last 5 years. Yes (1), No (0)	Integer (0/1)
BMI	Body Mass Index (BMI)	Float

Smoker	Indicates whether a person has ever smoked at least 100 cigarettes [5 packs = 100 cigarettes]. Yes (1), No (0)	Integer (0/1)
Stroke	Indicates whether a person has history of stroke. Yes (1), No (0)	Integer (0/1)
HeartDiseaseorAttack	Indicates whether a person has coronary heart disease (CHD) or myocardial infarction (MI). Yes (1), No (0)	Integer (0/1)
PhysActivity	Indicates whether a person practices regular physical activity in past 30 days - not including job. Yes (1), No (0)	Integer (0/1)
Fruits	Indicates whether a person consumes fruit at least once per day. Yes (1), No (0)	Integer (0/1)
Veggies	Indicates whether a person consumes vegetables at least once per day. Yes (1), No (0)	Integer (0/1)
HvyAlcoholConsump	Indicates whether a person heavily consumes alcohol. (adult men >=14 drinks per week and adult women>=7 drinks per week). Yes (1), No (0)	Integer (0/1)
AnyHealthcare	Indicates whether a person has any kind of healthcare coverage, including health insurance, prepaid plans such as HMO, etc. Yes (1), No (0)	Integer (0/1)
NoDocbcCost	Indicates whether a person could not see a doctor due to cost in the past 12 months. Yes (1), No (0)	Integer (0/1)
GenHlth	Self-reported general health (1 = excellent, 2 = very good, 3 = good, 4 = fair, 5 = poor)	Integer (1-5)
MentHlth	Indicates number of mentally unhealthy days in the past 30 days experienced by a person.	Integer
PhysHlth	Indicates number of physically unhealthy days in the past 30 days experienced by a person.	Integer
DiffWalk	Indicates whether a person difficulty in walking or climbing stairs due to health issues. Yes (1), No (0)	Integer (0/1)
Sex	Indicates a person's sex. Male (1), Female (0)	Integer (0/1)
Age	Indicates a person's age group. 13-level age category (1 = 18-24…9 = 60-64…13 = 80 or older)	Integer (1-13)
Education	Indicates a person's education level. 6-level education category (1 = Never attended school or only kindergarten…6 = College graduate)	Integer (1-6)
Income	Indicates a person's income level. 8-level income scale (1 = less than $10,000…5 = less than $35,000…8 = $75,000 or more)	Integer (1-8)

C. Exploratory Data Analysis (EDA)

Before the dataset is cleaned, the first step involves analyzing and exploring the raw dataset. This beginning phase allows us to understand the structure of the dataset before working on it.

- Step 1: Identifying the shape of the raw dataset (refer Figure 6).

```
df.shape
[4]:
(70692, 22)
```

Fig. 6. The shape of raw dataset.

- Step 2: Calculating skewness and plot histograms to analyze key health indicators (refer Figures 7 & 8).

```
Diabetes_binary          0.000000
HighBP                  -0.255908
HighChol                -0.102950
CholCheck               -6.119271
BMI                      1.719180
Smoker                   0.099031
Stroke                   3.626499
HeartDiseaseorAttack     1.984703
PhysActivity            -0.888732
Fruits                  -0.458804
Veggies                 -1.414969
HvyAlcoholConsump        4.522548
AnyHealthcare           -4.387510
NoDocbcCost              2.784235
GenHlth                  0.171991
MentHlth                 2.388110
PhysHlth                 1.657304
DiffWalk                 1.138002
Sex                      0.172657
Age                     -0.545923
Education               -0.681621
Income                  -0.645073
dtype: float64
```

Fig. 7. The skewness of key indicators.

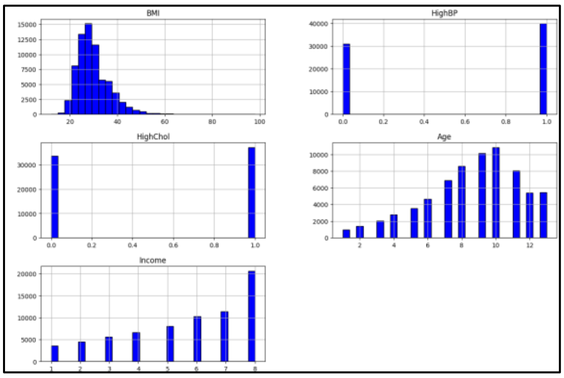


Fig. 8. Histograms of key indicators.

- Step 3: Use the correlation heatmap to analyze the relationship of each attribute (refer Figure 9).

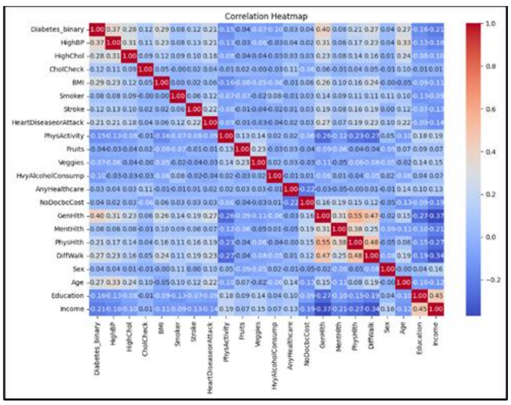


Fig. 9. The Correlation Heatmap of each attribute.

D. Data Cleaning

The next step involves data cleaning. This essential phase uses a streamlined pipeline to ensure the data is properly prepared and optimized for subsequent training steps.

- Step 1: Handling missing data (refer Figure 10).

```
Diabetes_binary         0
HighBP                  0
HighChol                0
CholCheck               0
BMI                     0
Smoker                  0
Stroke                  0
HeartDiseaseorAttack    0
PhysActivity            0
Fruits                  0
Veggies                 0
HvyAlcoholConsump       0
AnyHealthcare           0
NoDocbcCost             0
GenHlth                 0
MentHlth                0
PhysHlth                0
DiffWalk                0
Sex                     0
Age                     0
Education               0
Income                  0
dtype: int64
```

Fig. 10. Missing data in each attribute.

- Step 2: Remove duplicated data (refer Figure 11).

```
# Checking and drop duplicated data

df.duplicated().sum()

[18]:

np.int64(1635)

[19]:

df.drop_duplicates(inplace = True)
df.duplicated().sum()

[19]:

np.int64(0)
```

Fig. 11. The removal of duplicated data.

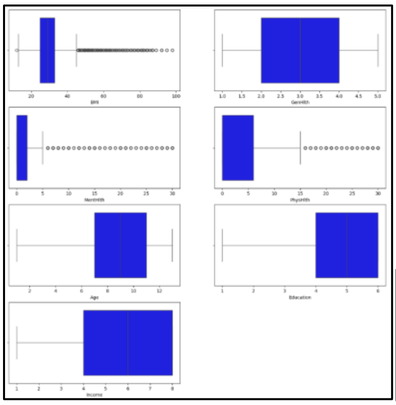
- Step 3: Converting all data to integers (refer Figure 12).

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 70692 entries, 0 to 70691
Data columns (total 22 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Diabetes_binary       70692 non-null  float64
 1   HighBP                70692 non-null  float64
 2   HighChol              70692 non-null  float64
 3   CholCheck             70692 non-null  float64
 4   BMI                   70692 non-null  float64
 5   Smoker                70692 non-null  float64
 6   Stroke                70692 non-null  float64
 7   HeartDiseaseorAttack  70692 non-null  float64
 8   PhysActivity          70692 non-null  float64
 9   Fruits                70692 non-null  float64
 10  Veggies               70692 non-null  float64
 11  HvyAlcoholConsump     70692 non-null  float64
 12  AnyHealthcare         70692 non-null  float64
 13  NoDocbcCost           70692 non-null  float64
 14  GenHlth               70692 non-null  float64
 15  MentHlth              70692 non-null  float64
 16  PhysHlth              70692 non-null  float64
 17  DiffWalk              70692 non-null  float64
 18  Sex                   70692 non-null  float64
 19  Age                   70692 non-null  float64
 20  Education             70692 non-null  float64
 21  Income                70692 non-null  float64
dtypes: float64(22)
memory usage: 11.9 MB
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 70692 entries, 0 to 70691
Data columns (total 22 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Diabetes_binary       70692 non-null  int64
 1   HighBP                70692 non-null  int64
 2   HighChol              70692 non-null  int64
 3   CholCheck             70692 non-null  int64
 4   BMI                   70692 non-null  int64
 5   Smoker                70692 non-null  int64
 6   Stroke                70692 non-null  int64
 7   HeartDiseaseorAttack  70692 non-null  int64
 8   PhysActivity          70692 non-null  int64
 9   Fruits                70692 non-null  int64
 10  Veggies               70692 non-null  int64
 11  HvyAlcoholConsump     70692 non-null  int64
 12  AnyHealthcare         70692 non-null  int64
 13  NoDocbcCost           70692 non-null  int64
 14  GenHlth               70692 non-null  int64
 15  MentHlth              70692 non-null  int64
 16  PhysHlth              70692 non-null  int64
 17  DiffWalk              70692 non-null  int64
 18  Sex                   70692 non-null  int64
 19  Age                   70692 non-null  int64
 20  Education             70692 non-null  int64
 21  Income                70692 non-null  int64
dtypes: int64(22)
memory usage: 11.9 MB
```

Fig. 12. The conversion of all data to integer.

- Step 4: Checking for outliers using boxplot (refer Figure 13).



```
BMI            801
GenHlth          0
MentHlth      4373
PhysHlth         0
Age              0
Education       75
Income           0
dtype: int64
```

Fig. 13. The Outliers using boxplot.

- Step 5: Compute the Interquartile Range (IQR) and remove outliers (refer Figure 14).

```
BMI           2181
GenHlth          0
MentHlth     11816
PhysHlth     10624
Age              0
Education        0
Income           0
dtype: int64
```

```
Original dataset: 70692 rows
Cleaned dataset: 51793 rows
```

Fig. 14. The IQR and removed outliers.

E. Healthcare Recommender System (HRS)

After the data preprocessing process, the VAEs and GANs modelling techniques are now prepared to be fitted into the RS. Combining VAEs with GANs in a RS allows leveraging the strengths of both: VAEs utilize a probabilistic framework to model complex distributions, whereas GANs enhance healthcare recommendations by generating realistic synthetic data while protecting patient privacy, making them particularly effective in tailored healthcare recommendations. In addition, there are multiple helpful built-in features to construct a RS, such as train-test split and various metrics. This model performance is evaluated using various evaluation metrics as shown in Fig. 15.

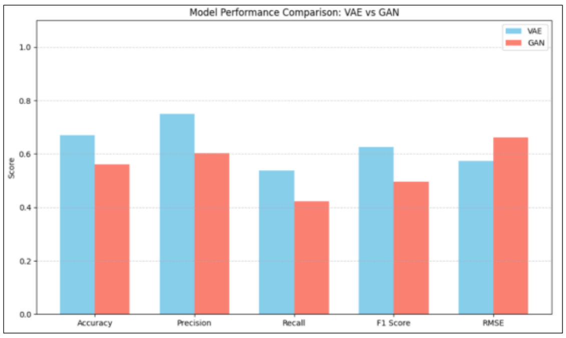


Fig. 15. Model performance comparison between VAE and GAN.

Furthermore, the dataset is divided into train, validation and test sets. The proportions for these sets are 60%-20%-20%. The ‘stratify’ parameter ensures that the splits of the dataset maintain the same distribution of certain categories as the original dataset. Specifically, the dataset is being stratified based on the Diabetes_binary attribute to preserve the proportion of diabetic and non-diabetic individuals across the splits. VAEs are implemented to generate synthetic health data and refine personalized healthcare recommendations for model training. This is because after evaluating the model performance in Fig. 15, VAEs outperforms GANs in all key metrics such as accuracy, precision, recall, F1 score and has a lower RMSE score, which indicates better prediction and less error. Subsequently, the algorithm is trained using the training set and the validation set is used to compare the performances between the models. The model with the best performance will then be used in the test set. Precision, accuracy and RMSE are the primary metrics used to assess the models' effectiveness in achieving accurate recommendations.

In order to have an enhanced visualization, dashboards are developed to represent relationships between health indicators efficiently. Histograms and box plots will be used to analyze the spread and variability of key health indicators. Correlation analysis using heatmaps will help identify relationships between different variables. Therefore, it provides insights into which features may be relevant for future modelling and to reveal complex connections between health attributes, which aids a clearer understanding of disease patterns and risk factors.

V. CONCLUSION

This review offered insightful information about the limitations of traditional recommendation methods that emphasize the necessity of VAEs and GANs to enhance personalized medical recommendations. VAEs were leveraged to address cold-start issues, whereas GANs were utilized for data augmentation and enhancing the diversity of generated recommendations.

One possible avenue for further research is hybrid methods combining VAEs and GANs with knowledge graphs for richer contextual understanding of patient information and more accurate recommendations. Also, domain-specific eXplainable AI (XAI) approaches for generative models might help build confidence in personalized medical recommendations by making them transparent enough for doctors and patients to understand and verify the proposed treatments easily.

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