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Generative AI in Healthcare: Advancements in Electronic Health Records, facilitating Medical Languages, and Personalized Patient Care

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Abstract

This research explores the application of generative AI techniques in healthcare to address three significant areas: enhancing electronic health records (EHRs) through automated conversation summarization, simplifying complex medical language into patient-friendly summaries, and providing personalized care recommendations using data from smartwatches and wearables. In the first part, we propose a technical framework for utilizing generative AI to listen to conversations during healthcare appointments and generate concise summaries for inclusion in EHRs. The process involves speech recognition, natural language processing (NLP), named entity recognition (NER), contextual understanding, text summarization, and seamless integration with EHR systems. The implementation of such a system requires rigorous evaluation, training data, and adherence to healthcare regulations. The second part focuses on simplifying complex medical language into summaries that patients can understand. We present a technical sequence flow that involves data collection, preprocessing, training data preparation, model selection, architecture, training, evaluation, fine-tuning, deployment, user interaction, summary generation, output presentation, and feedback iteration. By employing generative AI models trained on medical documents, patients can access simplified and understandable summaries, improving patient education and communication in healthcare settings. Lastly, we explore the utilization of generative AI for personalized care recommendations using data from smartwatches and wearables. Its technical sequence flow encompasses data collection, data transfer to the cloud, data preprocessing, data analysis with generative AI, personalized care recommendations, delivery of recommendations, user interaction, and feedback. By analyzing sensor data, generative AI models can generate personalized recommendations for exercise, diet, sleep, and medication, enhancing individualized care for users.

Keywords: *Generative AI, Conversation summarization, Electronic health record (EHR), Speech recognition, Natural Language Processing (NLP), Named Entity Recognition (NER), Personalized care recommendations*

Introduction

Generative Artificial Intelligence (AI) has seen significant advancements and evolution over the years, revolutionizing various domains such as computer vision, natural language processing, and creative arts [1], [2]. The roots of generative AI can be traced back to the early days of AI research when pioneers like Alan Turing and John von Neumann laid the foundations. However, it was not until the 1990s that generative models gained traction with the emergence of Bayesian networks and Hidden Markov Models. These models enabled the generation of new data based on probabilistic principles and laid the groundwork for future developments in generative AI [3], [4].

The field of generative AI took a major leap forward with the introduction of Generative Adversarial Networks (GANs) by Ian Goodfellow and his colleagues in 2014. GANs consist of two neural networks, a generator and a discriminator, which engage in a game-theoretic process to generate realistic data. This breakthrough brought about a significant shift in generative AI, enabling the generation of highly realistic images, videos, and even text [5]–[7]. GANs have since been widely adopted and improved, leading to the creation of visually stunning deepfake videos, image synthesis, and style transfer applications.

Another significant milestone in the evolution of generative AI came with the introduction of Variational Autoencoders (VAEs). VAEs, proposed by Kingma and Welling in 2013, combine the power of neural networks with the principles of variational inference [8]–[10]. VAEs allow for the generation of new data by learning a lower-dimensional latent space representation of the input data. This latent space can then be sampled to generate new instances that resemble the original data distribution. VAEs have found applications in diverse areas such as image generation, music composition, and drug discovery. In recent years, the concept of transformers, introduced by Vaswani et al. in 2017, has made a significant impact on generative AI. Transformers, based on the attention mechanism, revolutionized natural language processing tasks by enabling efficient processing of sequential data [11].

Generative Artificial Intelligence (AI) models are distinct from other AI models based on their primary objective of generating new data samples that resemble a given training dataset. Unlike discriminative models, which focus on classification and decision-making tasks, generative models aim to capture the underlying distribution of the data and generate new instances that follow that distribution. Generative models allow for the creation of new content, such as images, videos, music, and text, while maintaining coherence and similarity to the original data [12]. This ability to generate novel content sets generative AI apart from other AI models, making it suitable for creative applications and data augmentation tasks.

The core principles and techniques behind generative AI revolve around modeling the underlying probability distribution of the data. Two fundamental approaches are widely used: Generative Adversarial

Networks (GANs) and Variational Autoencoders (VAEs). GANs involve training a generator network to produce synthetic data and a discriminator network to distinguish between real and generated samples. The generator improves its ability to generate realistic data by competing against the discriminator. VAEs, on the other hand, focus on learning the latent space representation of the input data and generating new instances by sampling from this learned distribution. VAEs utilize the principles of variational inference to encode and decode data samples [13].

Generative AI models incorporate various components and architectures to achieve their objectives. In GANs, the generator network takes random noise as input and transforms it into synthetic data. It typically consists of multiple layers, such as convolutional layers for image data or recurrent layers for sequential data. The discriminator network, often a convolutional neural network (CNN) or a feed-forward network, assesses the authenticity of the generated samples [13], [14]. The two networks are trained simultaneously in an adversarial manner.

For VAEs, the encoder network maps input data to a lower-dimensional latent space, capturing the essence of the data. The decoder network then reconstructs the original data from the latent space representation. Both the encoder and decoder networks can be implemented using various neural network architectures, such as fully connected layers or convolutional layers.

Additionally, other architectures like autoregressive models, such as PixelRNN and WaveNet, generate data by modeling the conditional probability of each data point given its preceding context. These models generate data sequentially, often used for tasks like image generation or text generation.

Early AI systems focused on rule-based expert systems that attempted to mimic human decision-making processes. These systems relied on predefined rules and logical deductions to provide diagnostic suggestions or treatment plans. However, due to the limited computational power and the lack of large-scale medical data, these early attempts faced significant challenges.

In the 1990s and early 2000s, with the advent of more powerful computers and the availability of large medical datasets, AI in healthcare started gaining momentum [15]. Machine learning techniques such as neural networks, decision trees, and support vector machines were employed to analyze vast amounts of medical data and extract meaningful patterns. This led to the development of AI applications for medical imaging, such as computer-aided diagnosis

(CAD) systems, which could detect abnormalities in medical images with high accuracy. Additionally, AI algorithms were utilized for drug discovery, genomics research, and personalized medicine. These advancements opened up new possibilities for improving diagnostics, treatment planning, and patient outcomes.

In recent years, the evolution of AI in healthcare has been driven by the convergence of various technologies and the exponential growth of healthcare data. The rise of deep learning, a subset of machine learning, has revolutionized AI applications in healthcare. Deep learning algorithms, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated remarkable performance in medical image analysis, natural language processing, and predictive analytics. AI is being used to assist radiologists in detecting and diagnosing diseases from medical images, to analyze electronic health records (EHRs) for predictive analytics and clinical decision support, and to develop precision medicine approaches based on individual patient characteristics. The integration of AI with other emerging technologies like Internet of Things (IoT) devices, wearable sensors, and robotics holds the promise of further advancements in in every industry [16], including remote patient monitoring, telemedicine, and surgical assistance [17]–[19].

Generative AI in Electronic Health Record

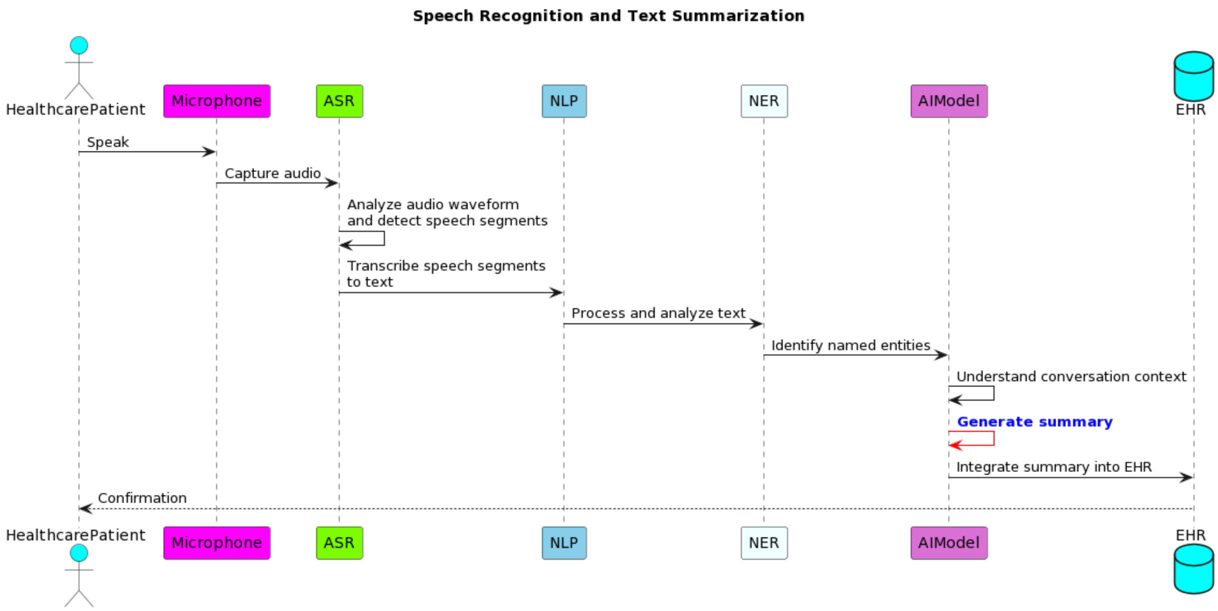
The process of using generative AI to listen to a conversation during an appointment and create a summary that can be added to an electronic health record (EHR) involves several technical and scientific components. These components work together to convert spoken words into text, analyze and understand the content, generate a meaningful summary, and integrate it into the EHR system [20].

During the Covid-19 pandemic, Electronic Health Records (EHRs) played a crucial role in managing patient information, facilitating communication among healthcare providers, and supporting decision-making processes. EHRs are digital versions of a patient's medical history, including their diagnoses, treatments, medications, test results, and other relevant health information. Covid-19 primarily spreads through respiratory droplets when an infected person coughs, sneezes, or talks [21], [22]. Common symptoms include fever, cough, shortness of breath, fatigue, loss of taste or smell, and muscle aches. Some individuals may be asymptomatic carriers, which contributed to the rapid and wide-spread transmission.

The first step in this process is speech recognition. The conversation between the healthcare provider and the patient is captured using a microphone or audio recording device. Automatic speech recognition (ASR) technology is then employed to convert the spoken words into text. ASR algorithms analyze the audio waveform, detect speech segments, and transcribe them into written text [6]. This enables further processing and analysis of the conversation.

Once the speech is transcribed into text, natural language processing (NLP) techniques come into play. NLP algorithms are utilized to process and understand the content of the conversation. These algorithms analyze the structure and meaning of the text, including identifying key phrases, entities, and relationships between words and sentences. NLP helps in extracting relevant information from the conversation and preparing it for further analysis.

Figure 1. Generative AI in electronic health record



A crucial subtask of NLP in this context is named entity recognition (NER). NER focuses on identifying and categorizing named entities within the text, such as patient names, medical conditions, medications, procedures, and other relevant information [23]. NER algorithms rely on machine learning models trained on large annotated datasets to recognize and classify these entities accurately. By identifying and categorizing these entities, the AI system can better understand the context of the conversation.

Contextual understanding is essential for generating a meaningful summary of the conversation. This involves analyzing the sequence of sentences, identifying the main topics, and capturing the relevant details. Advanced NLP models, such as transformer-based architectures can be used to provide a comprehensive understanding of the conversation [24]. These models have been trained on vast amounts of text data and can generate contextually relevant summaries.

Once the context is understood, the generative AI model generates a concise summary of the conversation. Text summarization techniques can vary depending on the specific approach used. Extractive summarization involves selecting important sentences or phrases from the original text, while abstractive summarization involves generating new sentences that capture the essence of the conversation. The choice of summarization technique depends on the requirements and preferences of the healthcare provider or the EHR system.

The generated summary needs to be integrated into the patient's electronic health record. This integration can be done through an application programming interface (API) or a direct integration with the EHR system. The summary is typically added as a structured or unstructured note, depending on the EHR's capabilities and requirements. This ensures that the information is readily accessible to healthcare providers and can contribute to the patient's medical history.

Implementing such a system requires a combination of machine learning techniques, substantial training data, and rigorous evaluation. The machine learning models need to be trained on diverse and representative datasets to ensure accurate recognition and understanding of the conversation. Rigorous evaluation is necessary to measure the system's performance, including its accuracy and its ability to comply with healthcare regulations and standards.

Ensuring privacy and compliance with healthcare regulations is of paramount importance [25]. The AI system should handle sensitive patient information securely and follow established protocols for data protection. Compliance with regulations such as the Health Insurance Portability and Accountability Act (HIPAA) is crucial to protect patient confidentiality and privacy [26], [27].

Furthermore, ongoing monitoring and refinement of the AI system are necessary to improve its performance over time. The system should be continually evaluated and updated to adapt to different medical specialties and contexts. The feedback from healthcare providers and patients can help identify areas for improvement and refine the system's capabilities.

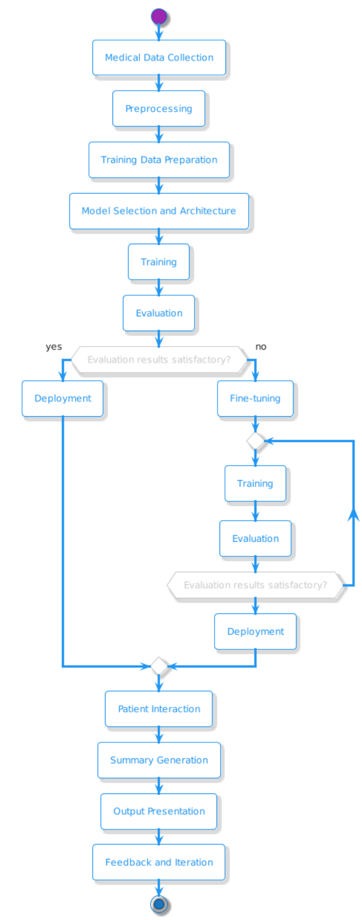
The process of using generative AI to listen to a conversation during an appointment and create a summary for an electronic health record involves a series of technical and scientific components. These components encompass speech recognition, natural language processing, named entity recognition, contextual understanding, text summarization, and integration with the EHR system. By combining these components and adhering to stringent evaluation and privacy measures, healthcare providers can leverage the power of AI to enhance the efficiency and accuracy of their record-keeping processes while maintaining patient confidentiality and compliance with healthcare regulations.

Simplifying medical language

Below are the detailed descriptions of how generative AI can simplify complex medical language into summaries that patients can understand. The first step in the process is data collection. A large dataset of medical documents is gathered, including research papers, clinical notes, patient records, and other relevant sources. These documents should contain complex medical language and terminology, serving as a diverse and representative sample for training the generative AI model.

Next, the collected data undergoes preprocessing. This involves cleaning and removing irrelevant information, formatting the text, and standardizing the document structure. By doing so, the data is prepared for further analysis, ensuring consistency and coherence in the subsequent steps.

Figure 2. Simplifying medical terminologies with Generative AI



The training data preparation step splits the preprocessed data into two sets: a training set and a validation set. The training set is used to train the generative AI model, while the validation set is used to evaluate its performance. This separation helps assess the model's ability to generalize to new data. The model selection and architecture phase involve choosing an appropriate generative AI model, such as a transformer-based language model. The model's architecture is configured, and hyperparameters, such as the number of layers, hidden units, attention mechanisms, and other relevant settings, are defined.

Training the generative AI model is a crucial step where the model learns to understand complex medical language and extract meaningful information from the text. This process involves optimizing the model's parameters to minimize the difference between the generated summaries and the target summaries, which represent the desired simplified versions of the medical documents.

To evaluate the trained model's performance, the validation set is used. Metrics such as BLEU score, ROUGE score, or human evaluation can be employed to assess how well the generated summaries align with the intended meaning of the original medical documents. This evaluation helps identify areas where the model can be further improved.

If the evaluation results are not satisfactory, the model undergoes a fine-tuning process. This may involve adjusting hyperparameters, modifying the training data, or altering the model architecture. Fine-tuning is an iterative process that helps enhance the model's performance and align it more closely with the desired outcome.

Once the generative AI model produces summaries that meet the desired quality standards, it is ready for deployment in a production environment. This could be a web application, mobile app, or any other platform where patients can access the generated summaries.

In the user interaction phase, patients can input complex medical documents into the application or provide access to their medical records. The generative AI model then processes the input text and generates simplified summaries that are understandable to patients.

Summary generation is a key step where the deployed model applies natural language generation techniques to transform complex medical language into patient-friendly summaries. This involves extracting key information, simplifying terminology, and ensuring the content remains accurate and easily comprehensible for patients.

The generated summaries are presented to patients through a user interface in the output presentation phase. Depending on the design of the application, the summaries can be displayed as plain text, highlighted key points, or structured information, making it easier for patients to grasp the essential information from their medical documents.

Collecting feedback from patients regarding the generated summaries is essential for continuous improvement. This feedback helps identify areas where the summaries can be further enhanced to better meet patients' needs. By iterating based on this feedback, the generative AI model can be refined, leading to improved quality and understandability of the summaries.

The process of using generative AI to simplify complex medical language into patient-friendly summaries involves data collection, preprocessing, training, evaluation, fine-tuning, deployment, user interaction, summary generation, output presentation, and feedback and iteration. Through this comprehensive workflow, generative AI can assist in making medical information more accessible and understandable for patients.

Wearable:

IoT and Sensor Networks: With the advent of the Internet of Things (IoT), sensors are becoming even more prevalent as they enable devices to collect and share data over the internet [28], [29]. These sensors can be embedded in various objects, enabling smart and connected systems.

In the first step of the technical sequence, users wear smartwatches or wearables that are equipped with various sensors, including heart rate monitors, accelerometers, and GPS trackers. These sensors continuously collect data related to the user's health and physical activities, such as heart rate, step count, sleep patterns, and location. The collected data is stored locally on the smartwatch or wearable device, ensuring that the information is readily available for further processing.

Following data collection, the smartwatch or wearable device establishes a connection, either wirelessly or through a smartphone, to transfer the collected data to the cloud [30]. This ensures that the data is securely transmitted and accessible from anywhere. The data is sent to a cloud-based server or a data storage system, where it can be processed and analyzed effectively.

Once the data reaches the cloud, it undergoes preprocessing to remove noise, correct anomalies, and ensure data quality [31]. Various preprocessing techniques are employed, including filtering, normalization, and data transformation. These techniques help in refining the collected raw data, making it suitable for further analysis and interpretation.

With the preprocessed data at hand, generative AI algorithms come into play. Sophisticated techniques such as deep learning models or generative adversarial networks (GANs) are employed to analyze the data. The generative AI model is trained on a vast amount of labeled data to learn patterns, correlations, and relationships within the collected information. Through this analysis, the model generates valuable insights and predictions.

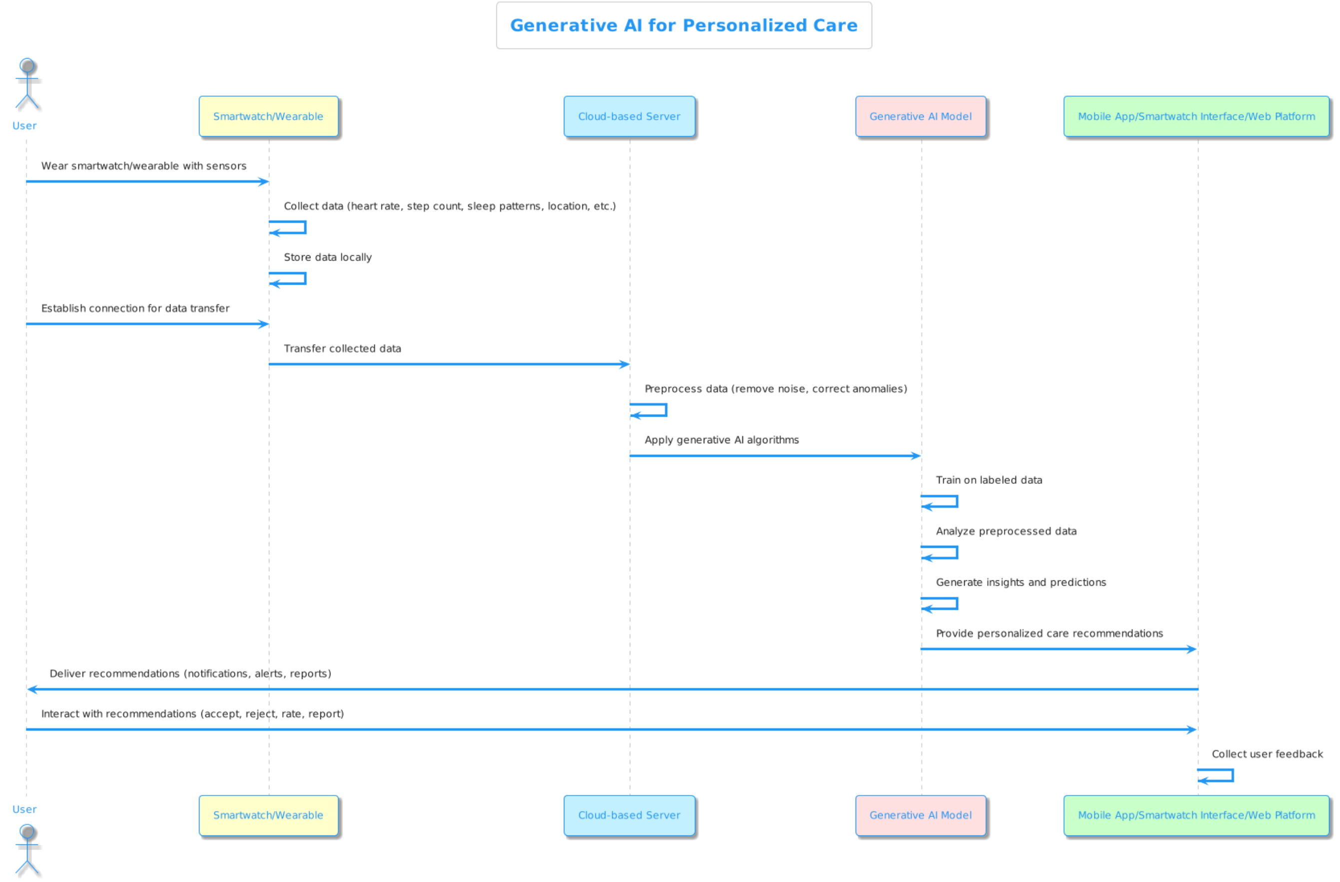
Personalized Care Recommendations: The generated insights and predictions are utilized to provide personalized care recommendations to the user. Taking into account the user's health or weight management needs, the generative AI model suggests specific actions, interventions, or recommendations. These recommendations can be related to personalized exercise plans, diet suggestions, sleep optimization techniques, or reminders for medication or hydration. By tailoring the recommendations to individual user needs, the system aims to optimize the user's well-being.

To ensure effective delivery of the personalized care recommendations, various channels are utilized. These can include mobile applications, smartwatch interfaces, or web platforms. The recommendations are presented to the user as notifications, alerts, or detailed reports, depending on the user's preferences and the capabilities of the smartwatch or wearable device. The goal is to provide the recommendations in a format that is easily accessible and convenient for the user.

Users actively engage with the smartwatch or wearable device to provide feedback on the recommendations they receive. This interaction can take the form of accepting or rejecting a recommendation, rating its effectiveness, or reporting any issues or concerns. User feedback is collected and incorporated into the system to improve future recommendations and enhance the overall user experience. By actively involving users in the feedback loop, the system can continuously learn and adapt to individual preferences and requirements.

By following this sequence flow, generative AI can effectively collect and analyze data from smartwatches and wearables. Through the analysis process [32], the system generates personalized care recommendations tailored to suit individual user needs. This approach aims to enhance the user's well-being by leveraging the power of data and artificial intelligence to provide actionable insights and support for healthy living.

Figure 3. Generative AI for personalized healthcare



Conclusion

Generative AI, also known as generative adversarial networks (GANs), is a cutting-edge technology that holds immense potential in various domains. At its core, generative AI refers to a class of machine learning algorithms that aim to create new and original content by learning from existing data. Unlike traditional AI models that focus on classification or prediction, generative AI focuses on the creative aspect of machine learning.

Generative AI models consist of two main components: a generator and a discriminator [33], [34]. The generator generates new data samples, such as images, music, or text, while the discriminator evaluates the authenticity of these samples by differentiating between the generated data and the real data. Through an iterative process, the generator aims to create increasingly realistic samples that can deceive the discriminator. This adversarial training mechanism enables the generator to learn and improve over time, producing high-quality and coherent outputs.

Personalized healthcare, also known as precision medicine, is a transformative approach that leverages advances in genomics, data analytics, and technology to tailor medical treatments and interventions to individual patients. By considering an individual's unique genetic makeup, lifestyle factors, and medical history, personalized healthcare aims to provide targeted and more effective healthcare interventions, ultimately improving patient outcomes.

The integration of technology and personalized healthcare is evident in the rise of digital health solutions. Mobile applications, wearable devices, and remote monitoring technologies have become increasingly popular tools for capturing real-time health data. These technologies enable individuals to actively participate in their healthcare management, providing continuous streams of data on vital signs, physical activity, sleep patterns, and more. Healthcare providers can leverage this data to gain a deeper understanding of a patient's health status, identify early warning signs, and provide timely interventions. Moreover, telemedicine platforms enable remote consultations and virtual care, facilitating access to specialized healthcare services regardless of geographic location.

Generative AI, with its ability to create new and original content, has made significant advancements in the healthcare industry, particularly in areas such as electronic health records (EHRs), medical languages, and personalized patient care. By harnessing the power of generative AI, healthcare professionals can streamline data management, improve communication, and provide more tailored and effective care to patients.

One of the areas where generative AI has shown great promise is in the development and management of electronic health records. EHRs contain a wealth of patient information, including medical histories, test results, diagnoses, and treatment plans. However, extracting relevant and actionable insights from these records can be challenging due to the sheer volume of data. Generative AI algorithms can analyze EHR data to identify patterns and relationships that may not be readily apparent to human reviewers. This can help in predicting disease outcomes, identifying risk factors, and suggesting personalized treatment plans based on similar patient cases. By automating the analysis of EHRs, generative AI can save valuable time for healthcare professionals and enhance the quality of care delivered to patients.

Generative AI also holds tremendous potential in facilitating medical languages, which can often be complex and specialized. Medical professionals rely on accurate and efficient communication to exchange information and make informed decisions. However, medical terminology and jargon can pose challenges for effective communication, especially across different specialties and languages. Generative AI models can be trained on vast amounts of medical literature, research papers, and clinical notes to generate coherent and contextually relevant medical language. This can assist healthcare professionals in generating accurate clinical reports, providing patient education materials, and even enabling real-time language translation during international medical collaborations. By leveraging generative AI, medical language barriers can be overcome, leading to improved collaboration and enhanced patient care.

Personalized patient care is a key focus of healthcare, and generative AI plays a vital role in tailoring treatments to individual patients. With access to patient data, including genetic information, medical history, and lifestyle factors, generative AI models can assist healthcare providers in making more informed decisions regarding treatment plans. These models can analyze large datasets to identify patterns and correlations between patient characteristics and treatment outcomes. By leveraging generative AI, healthcare professionals can generate personalized treatment recommendations, predict the efficacy of different interventions, and optimize care plans based on individual patient needs. This leads to improved patient outcomes, reduced trial and error in treatment selection, and more efficient healthcare delivery.

References

[1] I. Goodfellow *et al.*, “Generative adversarial networks,” *Commun. ACM*, vol. 63, no. 11, pp. 139–144, Oct. 2020.

[2] Z. Pan, W. Yu, X. Yi, A. Khan, F. Yuan, and Y. Zheng, “Recent Progress on Generative Adversarial Networks (GANs): A Survey,” *IEEE Access*, vol. 7, pp. 36322–36333, 2019.

[3] G. R. Bushe, “Generative Process, Generative Outcome: The Transformational Potential of Appreciative Inquiry,” in *Organizational Generativity: The Appreciative Inquiry Summit and a Scholarship of Transformation*, vol. 4, Emerald Group Publishing Limited, 2013, pp. 89–113.

[4] S. Oh, Y. Jung, S. Kim, and I. Lee, “Deep generative design: Integration of topology optimization and generative models,” *Journal of*, 2019.
[5] J. Zhang, Z. Tang, Y. Xie, M. Ai, and W. Gui, “Generative adversarial network-based image-level optimal setpoint calculation for flotation reagents control,” *Expert Syst. Appl.*, vol. 197, p. 116790, Jul. 2022.
[6] I. Vaccari, V. Orani, A. Paglialonga, E. Cambiaso, and M. Mongelli, “A Generative Adversarial Network (GAN) Technique for Internet of Medical Things Data,” *Sensors* , vol. 21, no. 11, May 2021.
[7] Y. Wang, H. Wang, L. Wei, S. Li, L. Liu, and X. Wang, “Synthetic promoter design in Escherichia coli based on a deep generative network,” *Nucleic Acids Res.*, vol. 48, no. 12, pp. 6403–6412, Jul. 2020.
[8] X. Chen *et al.*, “Variational Lossy Autoencoder,” *arXiv [cs.LG]*, 08-Nov-2016.
[9] D. P. Kingma, T. Salimans, R. Jozefowicz, X. Chen, I. Sutskever, and M. Welling, “Improved variational inference with inverse autoregressive flow,” *Adv. Neural Inf. Process. Syst.*, vol. 29, 2016.
[10] D. P. Kingma and P. Dhariwal, “Glow: Generative flow with invertible 1x1 convolutions,” *Adv. Neural Inf. Process. Syst.*, vol. 31, 2018.
[11] J. Parikh, J. Kozloski, and V. Gurev, “Integration of AI and mechanistic modeling in generative adversarial networks for stochastic inverse problems,” *arXiv [stat.ML]*, 17-Sep-2020.
[12] Z. Cheng, D. Lee, and P. Tambe, “InnoVAE: Generative AI for Understanding Patents and Innovation,” *Available at SSRN 3868599*, 01-Mar-2022.
[13] D. Foster, *Generative Deep Learning*, 2nd ed. Sebastopol, CA: O’Reilly Media, 2022.
[14] A. Arora and A. Arora, “Generative adversarial networks and synthetic patient data: current challenges and future perspectives,” *Future Healthc J*, vol. 9, no. 2, pp. 190–193, Jul. 2022.
[15] E. B. Sloane and R. J. Silva, “Chapter 83 - Artificial intelligence in medical devices and clinical decision support systems,” in *Clinical Engineering Handbook (Second Edition)*, E. Iadanza, Ed. Academic Press, 2020, pp. 556–568.
[16] K. Thiagarajan, C. K. Dixit, M. Panneerselvam, C. A. Madhuvappan, S. Gadde, and J. N. Shrote, “Analysis on the Growth of Artificial Intelligence for Application Security in Internet of Things,” in *2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS)*, 2022, pp. 6–12.
[17] G. Sinnapolu and S. Alawneh, “Integrating wearables with cloud-based communication for health monitoring and emergency assistance,” *Internet of Things*, vol. 1–2, pp. 40–54, Sep. 2018.

[18] S. Durga, R. Nag, and E. Daniel, "Survey on Machine Learning and Deep Learning Algorithms used in Internet of Things (IoT) Healthcare," in *2019 3rd International Conference on Computing Methodologies and Communication (ICCMC)*, 2019, pp. 1018–1022.
[19] D. Shin and Y. Hwang, "Integrated acceptance and sustainability evaluation of Internet of Medical Things: A dual-level analysis," *Internet Research*, vol. 27, no. 5, pp. 1227–1254, Jan. 2017.
[20] A. Bohr and K. Memarzadeh, "Chapter 2 - The rise of artificial intelligence in healthcare applications," in *Artificial Intelligence in Healthcare*, A. Bohr and K. Memarzadeh, Eds. Academic Press, 2020, pp. 25–60.
[21] D. Mallick, L. Goyal, P. Chourasia, M. R. Zapata, K. Yashi, and S. Surani, "COVID-19 Induced Postural Orthostatic Tachycardia Syndrome (POTS): A Review," *Cureus*, vol. 15, no. 3, p. e36955, Mar. 2023.
[22] M. Abdelghany *et al.*, "CRT-200.08 outcomes of acute coronary syndrome in patients with Coronavirus 2019 infection: A systematic review and meta-analysis," *Cardiovascular Interventions*, vol. 15, no. 4_Supplement, pp. S29–S30, Feb. 2022.
[23] R. Florian and JOHNS HOPKINS UNIV BALTIMORE MD CENTER FOR LANGUAGE AND SPEECH PROCESSING (CLSP), "Named entity recognition as a house of cards: Classifier stacking," JOHNS HOPKINS UNIV BALTIMORE MD CENTER FOR LANGUAGE AND SPEECH PROCESSING (CLSP), Jan. 2002.
[24] R. J. Chen, M. Y. Lu, T. Y. Chen, D. F. K. Williamson, and F. Mahmood, "Synthetic data in machine learning for medicine and healthcare," *Nat Biomed Eng*, vol. 5, no. 6, pp. 493–497, Jun. 2021.
[25] A. Bodepudi and M. Reddy, "Spoofing Attacks and Mitigation Strategies in Biometrics-as-a-Service Systems," *ERST*, vol. 4, no. 1, pp. 1–14, Feb. 2020.
[26] V. S. Y. Cheng and P. C. K. Hung, "Health Insurance Portability and Accountability Act (HIPPA) Compliant Access Control Model for Web Services," *IJHISI*, vol. 1, no. 1, pp. 22–39, Jan. 2006.
[27] P. Breese, W. Burman, C. Rietmeijer, and D. Lezotte, "The Health Insurance Portability and Accountability Act and the informed consent process," *Ann. Intern. Med.*, vol. 141, no. 11, pp. 897–898, Dec. 2004.
[28] K. Thiagarajan, M. G.m, M. Porkodi, P. K., S. Gadde, and R. Priyadharshini, "Application and Advancement of Sensor Technology in Bioelectronics Nano Engineering," in *2022 International Conference on Edge Computing and Applications (ICECAA)*, 2022, pp. 841–845.
[29] G. G. Hallur, S. Prabhu, and A. Aslekar, "Entertainment in Era of AI, Big Data & IoT," in *Digital Entertainment: The Next Evolution*

in Service Sector, S. Das and S. Gochhait, Eds. Singapore: Springer Nature Singapore, 2021, pp. 87–109.

[30] S. Shashi Devi, S. Gadde, K. Harish, C. Manoharan, R. Mehta, and S. Renukadevi, "IoT and image processing Techniques-Based Smart Sericulture Nature System," *Indian J. Applied & Pure Bio*, vol. 37, no. 3, pp. 678–683, 2022.

[31] A. Bodepudi and M. Reddy, "Cloud-Based Gait Biometric Identification in Smart Home Ecosystem," *International Journal of Intelligent Automation and Computing*, vol. 4, no. 1, pp. 49–59, 2021.

[32] A. Bodepudi and M. Reddy, "The Rise of Virtual Employee Monitoring in Cloud and Its Impact on Hybrid Work Choice," *Journal of Artificial Intelligence and Machine Learning in Management*, vol. 5, no. 1, pp. 25–50, 2021.

[33] G. Lee, H. Kim, J. Kim, S. Kim, J.-W. Ha, and Y. Choi, "Generator Knows What Discriminator Should Learn in Unconditional GANs," in *Computer Vision – ECCV 2022*, 2022, pp. 406–422.

[34] K. Wang, C. Gou, Y. Duan, Y. Lin, X. Zheng, and F.-Y. Wang, "Generative adversarial networks: introduction and outlook," *IEEE/CAA Journal of Automatica Sinica*, vol. 4, no. 4, pp. 588–598, 2017.