Empowering Patient-Centered Care: AI-Driven Pre-Visit Tool to Enhance Patient Engagement and Diagnostic Accuracy

Amirreza Gholami[1] [0009-0006-5585-374X], Eelko Ronner[2] [0000-0002-4032-7863], Jun Hu[1] [0000-0003-2714-6264], and Panos Markopoulos[1] [0000-0002-2001-7251]

[1] Department of Industrial Design, Eindhoven University of Technology
{a.gholami,j.hu,p.markopoulos}@tue.nl
[2] Reinier de Graaf Groep, Delft, Netherlands

Abstract. Efficiently gathering relevant patient information before a medical visit can enhance diagnosis, streamline consultations, and improve patient care. Traditional methods rely on in-person questioning, which can be time-consuming, inconsistent, and prone to biases. This study explores an AI-powered pre-visit system designed to collect the information doctors typically ask for during consultations,enabling a more structured and efficient diagnostic process. The system features an AI-driven questionnaire that dynamically adapts to patient responses using Natural Language Models and Retrieval-Augmented Generation (RAG). Additionally, an interactive 3D body representation tool allows patients to visually indicate symptoms, improving communication and anatomical precision. By generating structured pre-visit reports, the system provides physicians with key insights before consultations, allowing them to focus on diagnosis and treatment rather than information gathering. This AI-driven approach aims to reduce consultation time, enhance diagnostic accuracy, and improve doctor-patient communication, ultimately improving patient outcomes.

Keywords: AI in Healthcare · Pre-Visit Tools · Patient-Centered Care · Digital Health Tools

1 Introduction

Accurate medical history-taking is widely recognized as one of the most powerful and versatile tools in a physician's diagnostic process. [1] Studies estimate that nearly 70 percent of diagnoses for certain diseases are based solely on information gathered during the patient interview. [2] Given this critical role, enhancing how patient histories are collected has the potential to significantly improve both clinical efficiency and diagnostic accuracy. Research shows that implementing structured pre-visit questionnaires can support more thorough history-taking and reduce the time physicians spend on data collection during appointments. [3] These tools have also been associated with improved communication; patients who believed their clinicians reviewed their responses reported higher levels of shared decision-making and overall satisfaction with care. [4] Additionally, automated history-taking tools can help alleviate the documentation burden on healthcare professionals, allowing them to focus more on clinical reasoning and patient interaction. [5, 6]

Building on this, the principles of patient-centered care (PCC) emphasize active patient involvement, shared decision-making, and effective communication—all of which are enhanced when patients are engaged prior to their consultation. [7, 8] PCC encourages a shift from physician-led decision-making to a more collaborative approach, where patients contribute essential context about their symptoms, medical history, and lifestyle. Pre-visit tools support this model by enabling patients to reflect on and communicate their concerns in a structured manner ahead of time. [9] This preparatory step helps create more focused and efficient consultations, empowering clinicians to interpret data more effectively and respond to individual patient needs. [9]

Recent advances in artificial intelligence, particularly the development of Large Language Models (LLMs), have opened new possibilities for enhancing the way pre-visit data is collected and interpreted. These models are capable of processing vast amounts of complex medical information, including symptoms, diseases, and treatment options, allowing them to understand and generate context-aware medical content. [10] One such application is the use of AI-powered systems for pre-visit assessments, where LLMs dynamically adapt to patient responses and generate clinically relevant questions in real time. [11] Chatbots based on this technology can assist from the earliest stages of consultation by engaging patients in preliminary assessments and delivering structured, relevant data to clinicians to support diagnosis and treatment planning. [11]

In this study, we propose a creative and engaging web-based system for collecting patients' medical histories prior to doctor visits. Our goal is to reimagine the pre-consultation experience by developing a platform that not only gathers essential clinical information, but also promotes patient engagement through an intuitive and interactive interface. The system integrates adaptive AI-driven questionnaires powered by LLMs with a 3D body model that allows patients to visually indicate symptoms, enriching the context and clarity of the information provided. By generating structured pre-visit reports, this solution aims to streamline the diagnostic process, improve communication, and ultimately contribute to more accurate and patient-centered clinical encounters.

2 Related Works

In the evolving landscape of AI-assisted healthcare, several systems have been developed to enhance patient-provider interactions. Here's a comparative overview highlighting how this project distinguishes itself from existing solutions:

System	Focus	Methodology	Limitations
Talk2Care [12]	Facilitates asynchronous communication between older adults and health-care providers.	Utilizes LLM-powered voice assistants for patients and dashboards for providers.	Primarily targets older adults; lacks structured clinical frameworks like SOCRATES; limited to asynchronous settings.
Dr. A.I. [13]	Conducts pre-visit patient interviews and drafts clinical notes.	Leverages generative AI to create differential diagnoses and clinical notes.	Focuses on note generation; lacks interactive symptom localization tools; does not emphasize structured questioning.
Bayesian LLM Framework [14]	Enhances history-taking for recurrent medical conditions.	Integrates LLMs within a Bayesian framework for iterative diagnostic refinement.	Tailored for recurrent conditions; may not address acute or diverse medical scenarios; lacks real-time patient interaction tools.
Chatbot-Based Symptom Checker [15]	Pre-visit symptom screening, notably for COVID-19.	Employs chatbot interfaces to collect symptom data before consultations.	Limited to specific conditions; lacks integration with advanced AI models; does not provide dynamic follow-up questioning.
German Outpatient Documentation System [16]	Structured medical history documentation in outpatient settings.	Uses tablet-based workflows to guide patients through history-taking.	Relies on static questionnaires; lacks AI-driven adaptability; does not include visual symptom mapping.

Table 1. Comparison of various AI-driven healthcare systems

In contrast to existing projects, our proposed RAG-based system, which is still a work in progress, combines Retrieval-Augmented Generation (RAG) with LLMs to create a highly adaptive and personalized medical history collection process. By leveraging past patient data from a secure database, it generates dynamic, context-aware follow-up questions and provides real-time, interactive symptom localization through a 3D model. This system addresses the limitations of existing approaches by integrating structured frameworks like SOCRATES and offering real-time, personalized engagement, making it more comprehensive and interactive than the alternatives outlined in the table.

3 Methodology

This section outlines the technical and design methods used in developing an AI-powered medical history collection system. The goal is to create an adaptive, user-friendly platform that collects comprehensive patient information before a clinical consultation. The methodology is divided into five key components: questionnaire development and AI integration, 3D body representation, user interface design, Retrieval-Augmented Generation (RAG) and Database Integration, and data collection and reporting. Each component contributes to improving the accuracy, clarity, and completeness of the medical history while reducing the time and cognitive load on both patients and healthcare providers.

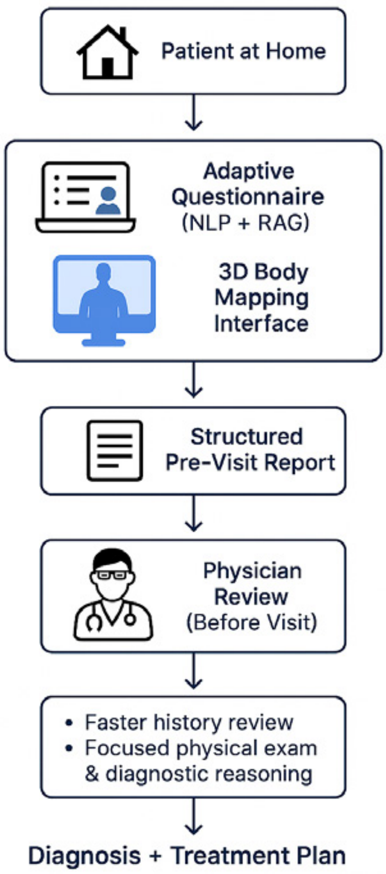

Fig. 1. System architecture showing the interaction between components.

3.1 Questionnaire Development and AI Integration

The system's questionnaire is developed based on clinically validated resources and established medical literature that guide history-taking in professional practice. [17] These questions are aligned with the formats typically used by healthcare providers during consultations and adhere to widely recognized protocols for comprehensive medical interviews. The content covers essential areas such as the patient's current complaints, past medical history, ongoing treatments, general health, lifestyle factors, and family medical background.

To operationalize this within the system, the questionnaire is deployed through an AI-driven interface that leverages a Large Language Model (LLM) to enhance adaptability and relevance. Patient responses dynamically influence the progression of questions, enabling real-time generation of personalized follow-ups. Furthermore, the SOCRATES framework is integrated into the symptom analysis process to ensure a structured, clinically grounded evaluation of patient-reported complaints.

3.2 3D Body Representation

To facilitate more accurate symptom description, the system includes an interactive 3D model of the human body. Patients can use this model to visually indicate the exact location of pain or discomfort. This spatial input enhances the clarity of patient-reported symptoms and minimizes potential miscommunication. The 3D model is built using open-source libraries such as Three.js or Babylon.js, and it integrates directly into the web application interface. The system encodes and stores the spatial information as part of the structured health data for physician review.

3.3 Retrieval-Augmented Generation (RAG) and Database Integration

To further enhance the accuracy and personalization of the medical history collection system, Retrieval-Augmented Generation (RAG) is integrated with a database of patient medical records. This methodology allows the system to both retrieve relevant past data and generate contextually aware responses or follow-up questions, resulting in a more tailored and efficient user experience.

3.3.1 Patient Data Storage and Retrieval The system stores patient medical data securely in a relational or NoSQL database. This data includes:

– Personal details (age, gender, etc.)
– Medical history (previous conditions, treatments, surgeries)
– Symptoms and diagnoses
– Medications and prescriptions
– Responses to previous questionnaire entries

By using a retrieval system the AI model can quickly access and retrieve relevant data based on patient inputs. For example, if a patient mentions experiencing symptoms similar to a past condition, the system can automatically retrieve and reference previous relevant data from the database.

3.3.2 Contextual Question Generation Once relevant data is retrieved, the Large Language Model (LLM) is used to generate follow-up questions. This ensures that the system remains contextually aware of the patient's history, allowing for more precise symptom analysis. For example, if a patient previously had a heart condition, the system may ask targeted follow-up questions such as, "Given your history of hypertension, have you noticed any changes in your blood pressure?"

This process of combining information retrieval with generative AI ensures that the system's questions are relevant, timely, and specific to the patient's unique medical background.

3.3.3 Continuous Memory and Update As patients complete their questionnaires and update their medical history, the system automatically updates the database with new responses, treatment changes, or any additional relevant information. This allows the AI model to "remember" and reference the patient's evolving medical profile, ensuring that future interactions build upon the most up-to-date information.

The memory system allows the AI to adapt to changes in a patient's condition, reducing repetitive questioning and enhancing the overall consultation efficiency. This also helps streamline diagnosis and treatment planning by providing healthcare providers with a comprehensive view of the patient's ongoing health journey.

3.4 User Interface Design

The system is delivered through a web-based interface that prioritizes accessibility, usability, and intuitive navigation. The interface is designed following Human-Centered Design (HCD) principles.

3.5 Data Collection and Reporting

After completing the questionnaire, the system automatically generates a structured report summarizing the patient's medical history. This report includes both text-based answers and annotated visual data from the 3D body representation. The report is delivered to the physician in advance of the consultation, allowing for informed pre-assessment and efficient diagnostic conversations. This structured and integrated approach improves data accuracy and helps streamline the clinical workflow.

4 Expected Outcomes

4.1 Improved Medical Histories

The AI-driven system will provide doctors with comprehensive, unbiased, and consistent medical histories, reducing the likelihood of diagnostic errors.

4.2 Reducing Confirmation Bias

AI-driven pre-visit tools reduce confirmation bias by generating follow-up questions based on patient input rather than physician expectations. This ensures a more objective and comprehensive data collection process, minimizing diagnostic tunnel vision.

4.3 Patient-Signed Medical Histories

Allowing patients to self-complete and sign off on their medical history increases accuracy and accountability. Unlike physicians, who may overlook or deprioritize certain details, patients can ensure all relevant symptoms and concerns are documented.

4.4 Enhanced Symptom Communication

The inclusion of the 3D body representation allows patients to visually indicate the areas of discomfort, improving their ability to communicate symptoms accurately.

4.5 Enhanced Patient Experience

Patients will be able to provide their medical information in a less stressful environment, improving the accuracy and completeness of their responses. The interactive 3D tool will also make the process more engaging and easier for patients to use.

4.6 Efficiency in Healthcare Delivery

Doctors will save time during consultations by receiving pre-compiled, detailed medical histories, along with visual representations of the patient's symptoms, allowing them to focus on diagnosis and treatment.

5 Conclusion

The proposed AI-powered medical history collection system, combined with a 3D body representation, represents a significant advancement in healthcare delivery. By reducing biases, improving data accuracy, and streamlining the diagnostic process, this system has the potential to enhance patient outcomes and increase efficiency in medical consultations. The 3D tool offers an additional layer of precision, allowing patients to visually communicate their issues, which reduces the chance of misinterpretation.

Moreover, the integration of Retrieval-Augmented Generation (RAG) and a structured patient database introduces a form of contextual memory, enabling the system to generate dynamic, personalized follow-up questions based on previously recorded information. This memory-driven interaction supports continuity of care, minimizes redundant questioning, and allows for more informed, efficient consultations. Overall, this project not only addresses current limitations in medical history collection but also lays the foundation for more intelligent, adaptive, and patient-centered AI solutions in future healthcare environments.

6 Acknowledgments

This work is supported by the STRAP consortium, a collaboration between three leading universities with complementary expertise, two healthcare organizations, and six innovative small- to medium-sized enterprises. The consortium aims to drive technological innovation in healthcare. In partnership with the eScience Center, STRAP focuses on developing big data solutions to improve the prevention and diagnosis of heart disease. Their continued support and interdisciplinary collaboration are essential to the progress of this research.

About Amirreza Gholami

Amirreza is currently pursuing an Engineering Doctorate (EngD) at Eindhoven University of Technology, The Netherlands, with a focus on the application of technology and AI in healthcare. He is an active member of the STRAP consortium, working on leveraging emerging technologies and artificial intelligence for healthcare applications, all while emphasizing human-centered design.

He holds a Master's degree in Medical Informatics with a specialization in applied AI. With a background in software development and a strong passion for both technology and healthcare, Amirreza's work aims not only to enhance operational efficiency but also to improve patient outcomes—making healthcare services more accessible, effective, and personalized.

References

1. Tu T, Schaekermann M, Palepu A, Saab K, Freyberg J, Tanno R, et al. Towards conversational diagnostic artificial intelligence. Nature. 2025:1-9.

2. Roshan M, Rao A. A study on relative contributions of the history, physical examination and investigations in making medical diagnosis. The Journal of the Association of Physicians of India. 2000;48(8):771-5.
3. Gomez J, Mazzoleni M, Calugar A, Pol-Rodriguez M, Ko JM, Bailey EE. Optimizing virtual visits and reducing inbox messages using a pre-visit questionnaire: a quality improvement project. Journal of the American Academy of Dermatology. 2023;88(6):1363-4.
4. Wilson MM, Broglio K, Vergo MT, Barnato AE, Cullinan AM, Doherty JR, et al. An electronic pre-visit agenda-setting questionnaire in ambulatory palliative care is feasible and acceptable to patients, care partners, and clinicians: A mixed methods evaluation. Palliative Medicine. 2025:02692163251321327.
5. Zhakhina G, Tapinova K, Kainazarov T, Kanabekova P. Pre-consultation history taking systems and their impact on modern practices: Advantages and limitations. Journal of Clinical Medicine of Kazakhstan. 2023;20(6):26-35.
6. Hauber R, Schirm M, Lukas M, Reitelbach C, Brenig J, Breunig M, et al. Computer-assisted medical history taking prior to patient consultation in the outpatient care setting: a prospective pilot project. BMC Health Services Research. 2024;24(1):1616.
7. Flach SD, McCoy KD, Vaughn TE, Ward MM, BootsMiller BJ, Doebbeling BN. Does patient-centered care improve provision of preventive services? Journal of general internal medicine. 2004;19(10):1019-26.
8. Ghabowen IK, Bhandari N. Concordance and patient-centered care in Medicaid enrollees' care experience with providers. Journal of Patient Experience. 2021;8:23743735211034028.
9. Gholamzadeh M, Abtahi H, Ghazisaeeidi M. Applied techniques for putting pre-visit planning in clinical practice to empower patient-centered care in the pandemic era: a systematic review and framework suggestion. BMC health services research. 2021;21(1):458.
10. Yu Q, Jin M, Shu D, Zhang C, Fan L, Hua W, et al. Health-LLM: Personalized Retrieval-Augmented Disease Prediction System. arXiv preprint arXiv:240200746. 2024.
11. Abbas SA, Yusifzada I, Athar S. Revolutionizing Medicine: Chatbots as Catalysts for Improved Diagnosis, Treatment, and Patient Support. Cureus. 2025;17(3).
12. Yang Z, Xu X, Yao B, Rogers E, Zhang S, Intille S, et al. Talk2care: An llm-based voice assistant for communication between healthcare providers and older adults. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies. 2024;8(2):1-35.
13. Rutledge GW, Sivura A. A Generative AI-Based Virtual Physician Assistant. In: Proceedings of the AAAI Symposium Series. vol. 3; 2024. p. 64-5.
14. Suraj T. A Bayesian framework for LLM-enhanced History-Taking in Recurrent Medical Conditions to Improve Treatment Outcomes: An Empirical Evaluation. SSRN Electronic Journal. 2025. Available from: https://ssrn.com/abstract=5160698.
15. Mahlknecht A, et al. A study of patient and physician attitudes in Italian general practice. Journal of Medical Internet Research. 2023;25:e10476397. Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10476397/.
16. Hauber R, et al. Feasibility and perceived usefulness of a novel medical history documentation system in a German cardiological outpatient practice. Journal of Medical Systems. 2023;47:e59617. Available from: https://link.springer.com/article/10.1007/s10916-023-59617.
17. Chatten K, Howe M, Marks G, Smith T, Tufton H, Sturrock A, et al.. Guide to History Taking and Examination; 2015. MBBS Year 4. Available

from: https://www.ucl.ac.uk/epidemiology-health-care/sites/epidemiology-health-care/files/history-exam.pdf.