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A Human Trial Study on Overcoming Linguistic and Stress-Related Barriers in Chronic Disease Management

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Abstract

The study addresses language and stress barriers in chronic disease management among Sinhala-speaking patients, using an Augmented Reality (AR) embedded platform combined with an Artificial Intelligence (AI) chatbot. Rasa is integrated into the AI chatbot using Bidirectional Encoder Representations from Transformer (BERT)-Sinhala embeddings to deliver culturally tailored, real-time health recommendations. An AR module on AR.js and Three.js implements personalized stress-reduction interventions. The chatbot achieves an F1 score of 91% and a word error rate (WER) of 8.5%, while the AR system reduces systolic blood pressure by 8.96% ($p = 0.002$). The combined platform attains 88% scenario accuracy with a mean response time of 1.2 seconds. These findings support the system's potential to improve healthcare access and reduce stress markers among Sinhala-speaking chronic patients, offering a low-resource, scalable, and culturally appropriate model for healthcare environments.

Keywords: AI chatbot, Augmented Reality, chronic disease management, Sinhala NLP, stress reduction

1. Introduction

Non-communicable diseases (NCDs), such as diabetes and hypertension, account for over 70% of global deaths, with a disproportionate burden in low- and middle-income countries where health systems tend to be underdeveloped [1]. In Sri Lanka, NCDs contribute to approximately 26% of all mortality, a situation further exacerbated by language and socioeconomic barriers to adequate medical treatment [2-3]. Sinhala-speaking patients face communication mismatches with healthcare providers and challenges in accessing timely and accurate health information. Moreover, chronic stress, often an undervalued factor, accelerates disease progression and increases healthcare costs [3-6]. These challenges highlight a compelling need for culturally and linguistically appropriate interventions that can function effectively in low-resource settings.

Recent technological advances indicate that Natural Language Processing (NLP)-based Artificial Intelligence (AI) chatbots have significant potential to bridge communication gaps in healthcare by providing real-time, personalized, and language-specific health assistance [7-8]. Chatbots have evolved from rule-based systems to intelligent dialogue managers that can understand complex queries using deep learning algorithms, as demonstrated by Adamopoulou and Moussiades [9]. Similarly, Augmented Reality (AR) technologies have proven effective in delivering engaging stress management interventions, enhancing patient engagement, and improving health outcomes [10-11]. Research by Harders et al. [12] further validated AR's efficacy in educational and clinical environments through experiential learning and relaxation therapies. However, most current implementations face limitations, such as the lack of voice integration for non-English languages, emotional disconnections in AI systems, and technical challenges in scaling AR applications to mobile platforms.

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Specifically, earlier studies by de Silva [5] and Avishka et al. [13] were conducted in the Sinhala language context. These studies contributed to the development of Sinhala NLP functionality but omitted essential voice interaction features necessary for accessible healthcare provision [14]. This omission presents a significant disadvantage, particularly for older or rural patients who are more comfortable interacting through voice rather than typing. Moreover, existing Sinhala healthcare applications rarely incorporate stress management modules, leaving a key component of holistic chronic disease care unaddressed.

This research proposes a novel integrated system consisting of an AI chatbot powered by Sinhala NLP and a culturally adapted AR stress-management platform. The chatbot addresses linguistic barriers by providing real-time, voice-supported healthcare assistance that is accessible to low-literacy users. Simultaneously, the AR module mitigates persistent stress through interactive, personalized interventions that improve clinical indicators such as blood pressure. The combined AI-AR platform offers a scalable, cost-effective, and culturally sensitive model tailored to the needs of Sinhala-speaking chronic disease patients in Sri Lanka and other low-resource environments worldwide [15-16]. As shown in Fig. 1, the integrated system solves these problems.

The remainder of this paper is organized as follows. Section 2 describes the materials and methods employed to design and quantify the systems. Section 3 presents the research results, while Section 4 discusses the findings in comparison with previous studies. Finally, Section 5 concludes the paper by summarizing the key findings, highlighting limitations, and providing recommendations for future research.

Fig. 1 AI chatbot and AR system for chronic disease

2. Materials and Methods

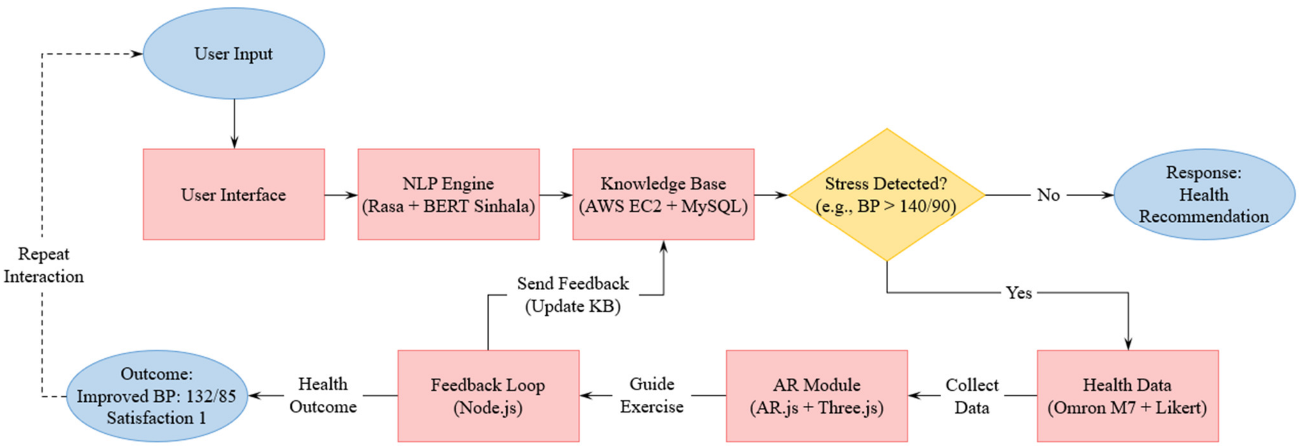

Fig. 2 Methodology overview

This study developed and evaluated a combined AI-driven chatbot and AR-based stress management system to address language and stress-related barriers in chronic disease care for Sinhala-speaking patients in Sri Lanka. The method incorporated advanced AI and AR technologies to deliver personalized, culturally sensitive healthcare solutions, with a step-by-step framework that facilitated replication. Fig. 2 illustrates the overall methodology employed in this study, while Fig. 3 depicts the system architecture integrating the chatbot and AR components were integrated to deliver real-time, personalized interventions.

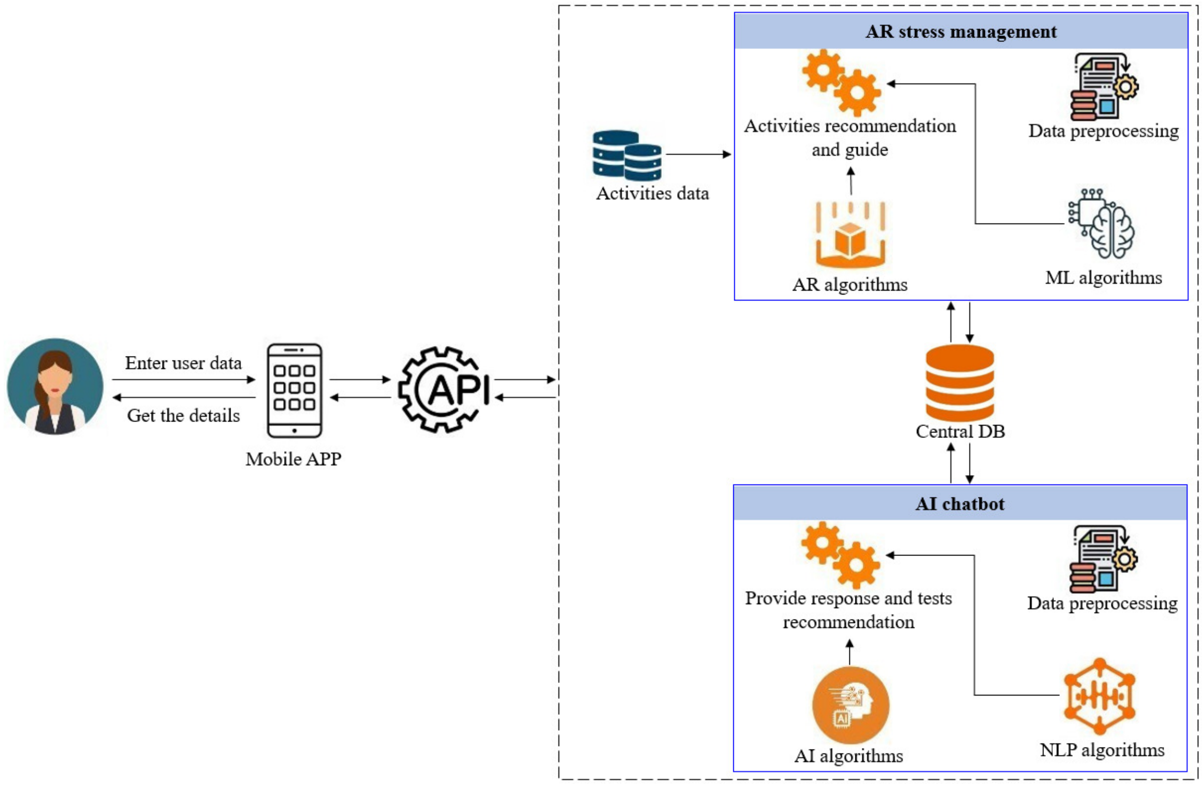

Fig. 3 System architecture

2.1. AI-driven chatbot development

The developers created the chatbot to provide health tips in Sinhala for patients with chronic conditions like diabetes and hypertension, bridging the language gap for Sinhala-speaking patients [3].

(1) Data collection and preprocessing

A large Sinhala dataset was compiled using publicly available materials, including Sinhala Wikipedia and news archives, and expanded with a validated medical corpus from the Sri Lanka Medical Association [17]. A 5,000-example dataset was further augmented to 10,000 examples through data augmentation techniques (e.g., paraphrasing questions such as “What is my insulin dose?” into “How much insulin should I take?”) [13]. Preprocessing employed the Sinhala NLP Toolkit for tokenization, stemming, and lemmatization to manage Sinhala’s agglutinative morphology. For voice recognition, the audio from 100 native speakers was recorded over 50 hours through Audacity (44.1 kHz), capturing phonetic variation. The audio recordings were noise-reduced and segmented into 5-second clips to ensure quality.

(2) Natural language processing (NLP)

The chatbot utilized the Rasa framework with custom NLP pipelines incorporating Bidirectional Encoder Representations from Transformer (BERT) Sinhala embeddings pre-trained on 1 million sentences. The dataset was split into 70% training, 20% validation, and 10% testing sets, and the model was trained for 100 epochs on an NVIDIA GeForce RTX 3090 with a batch size of 32 to balance accuracy and prevent overfitting. The model accurately outlined intents (e.g., medication queries) and entities (e.g., insulin dosage).

(3) Voice recognition

Voice capability was implemented using Deep Neural Networks (DNNs) with a hybrid Connectionist Temporal Classification (CTC) and attention-based model. The model was trained using TensorFlow and PyTorch for 50 epochs with a learning rate of 0.001 and a dropout rate of 0.3 on the 50-hour audio dataset. The word error rate (WER) target value was set below 10%, suitable for low-resource languages [18].

(4) Architecture

The chatbot consisted of three components:

First, the User Interface (UI): The interface was built using React.js for the web platform and React Native for mobile platforms, incorporating both introductory text and voice input mechanisms.

Second, the Fundamental Engine: The system employed Rasa Natural Language Understanding (NLU) and the Sinhala NLP Toolkit for NLP and sentiment analysis, achieving a response time within 1.5 seconds.

Third, the Knowledge Base: A MySQL database of updated medical knowledge was hosted on Amazon Web Services Elastic Compute Cloud (AWS EC2; t3.large, 8 GB RAM, two vCPUs) and accessed through a secure Application Programming Interface (API).

2.2. AR-based stress management system development

The AR system was designed to reduce stress in patients with chronic diseases by providing real-time health information and culturally appropriate interventions [4].

(1) Data collection and preprocessing

Health data (blood pressure, glucose, stress) were collected using Omron M7 Intelli IT and Accu-Chek devices. Stress was measured on a 5-point Likert scale. The data were encrypted with AES-256 in a MySQL database, cleaned to remove outliers (e.g., blood pressure > 200 millimeters of mercury (mmHg)), and normalized for analysis.

(2) AR processing

The AR platform used AR.js for light making, Three.js for 3D visualization, and a culturally tailored avatar to guide stress-relief exercises. Machine learning models, trained on 1,000 simulated stress sessions in TensorFlow (50 epochs, learning rate 0.001, dropout 0.2), had 85% accuracy in stress detection.

(3) Feedback mechanism

A Node.js feedback loop adaptively titrated interventions based on real-time health measures (e.g., extending meditation for blood pressure > 140/90 mmHg), responding within 1 second [19].

(4) Architecture

The AR system included:

First, the Health Data Module: Encrypted user data (age, gender, health parameters) was stored in a MySQL database.
Second, the AR Module: Integrated 3D stress-relief activities on Android 10+ devices using AR.js and Three.js.
Third, the Feedback Loop: Adapted interventions via Node.js based on real-time information.

2.3. Testing and evaluation

The study included 50 participants, comprising 60% females and 40% males, aged between 25 and 65 years, all diagnosed with chronic conditions such as diabetes or hypertension. Participants were recruited via convenience sampling from a local clinic in Malabe, Sri Lanka. Due to resource constraints, a control group was not included; however, age and chronic condition type were controlled by matching participants within the study group.

The present study enrolled human subjects in a non-invasive trial of an AI chatbot and AR platform to manage chronic disease. Since it was a low-risk trial within the Sri Lanka Institute of Information Technology (SLIIT), the institutional policy did not require formal ethical clearance, as the intervention was minimal and consisted only of routine health monitoring and user feedback. All participants provided written informed consent, were informed about the aims and methods of the study, and were made aware of their right to withdraw at any time. The researchers anonymized and securely stored their data in compliance with data protection laws.

The trial ran from January 6 to February 17, 2025, over 6 weeks. Participants used the system daily for 20 minutes, guided by onboarding tutorials that included voice instructions and AR setup guidance. System performance was validated using F1 scores and WER for the chatbot, paired t-tests for AR health metrics, and user feedback via the System Usability Scale (SUS) and satisfaction surveys. The chatbot was evaluated for intent identification (F1 score), WER, and usability using the SUS with 500 test questions and 200 voice samples.

The evaluation team assessed the AR system for changes in health metrics (blood pressure, glucose) using paired t-tests and measured user engagement (session time, satisfaction). The integrated system was evaluated for performance in simulated healthcare tasks for accuracy and response time. The questionnaire comprised 10 Likert-scale items, including ‘I found the system easy to use’ and ‘The system improved my stress management,’ rated from 1 (Strongly Disagree) to 5 (Strongly Agree). Cronbach’s alpha was 0.85, indicating good reliability of the instrument.

3. Results

This research evaluated the individual and combined performance of an AI-powered chatbot and an AR-based stress management system during a six-week trial with Sinhala-speaking patients with chronic diseases, namely hypertension and diabetes. The output, supported by quantitative measures, statistical evidence, and user feedback, verifies the system’s capacity to overcome linguistic and stress-related limitations.

3.1. AI-driven chatbot performance

The test established how effectively the chatbot delivered Sinhala health advice by recognizing user intent, processing voice inputs, and enhancing user experience.

(1) Intent recognition accuracy: On 500 test queries (e.g., “What is my insulin dosage?”), the chatbot recorded a precision of 92.3%, a recall of 89.7%, and an F1 score of 91.0%, computed using scikit-learn [10]. Fig. 4 shows the confusion matrix of intent recognition performance.

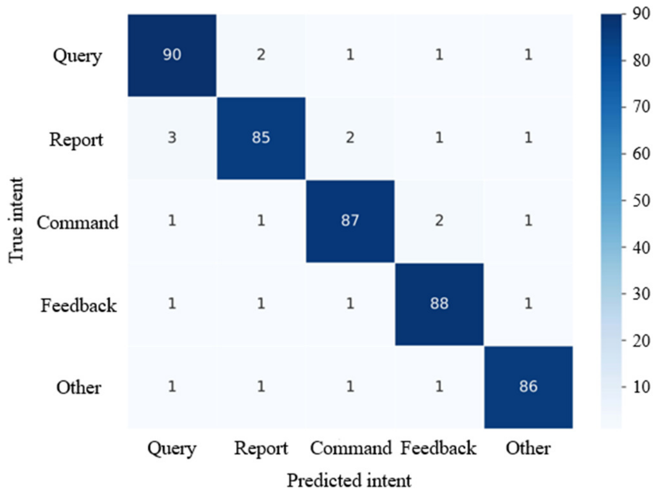

Fig. 4 Intent recognition confusion matrix

(2) Voice recognition: Testing voice functionality with 200 recorded samples resulted in a WER of 8.5%, which remained within the acceptable threshold (<10%) for low-resource languages [18]. Most misinterpretations occurred with technical terms, such as "insulin," which were sometimes transcribed incorrectly. Fig. 5 illustrates the chatbot interface during a Sinhala interaction.

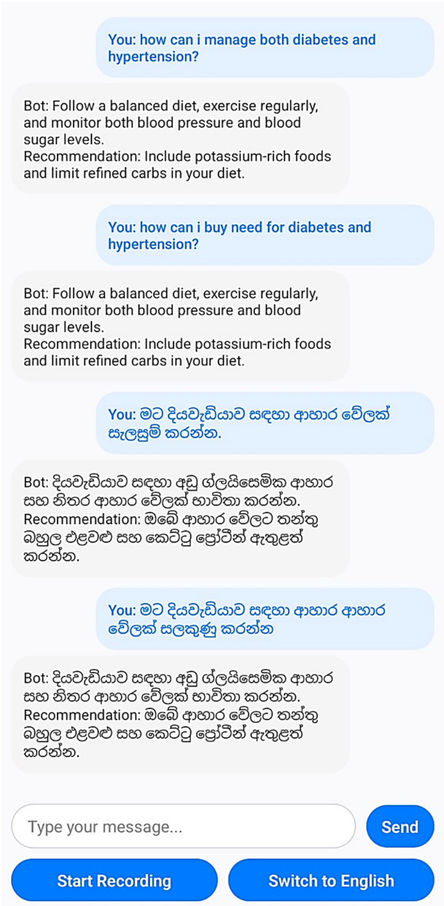

Fig. 5 Chatbot UI

(3) Usability: The SUS reported a mean score of 87 with a standard deviation (SD) of 6.2, surpassing the usability benchmark of 68. Table 1 summarizes the AI chatbot's performance in intent recognition, voice recognition, and usability during Sinhala healthcare trials.

Table 1 Chatbot performance metrics

Metric	Value (%)
Precision	92.3
Recall	89.7
F1 score	91.0
WER	8.5
SUS score	87

3.2. AR-based stress management system performance

The evaluation of the AR system assessed its effectiveness in influencing stress-related health outcomes and enhancing user experience.

(1) Enhancement of health indicators: Pre- and post-intervention blood pressure measurements revealed a significant decrease from 145/92 mmHg to 132/85 mmHg, a decrease of 8.96% ($p = 0.002$, paired t-test) [16]. Glucose levels remained unchanged (135 milligrams per deciliter (mg/dL) to 132 mg/dL, $p = 0.14$), supporting specificity to stress-related outcomes. Fig. 6 depicts blood pressure reduction throughout the six-week trial.

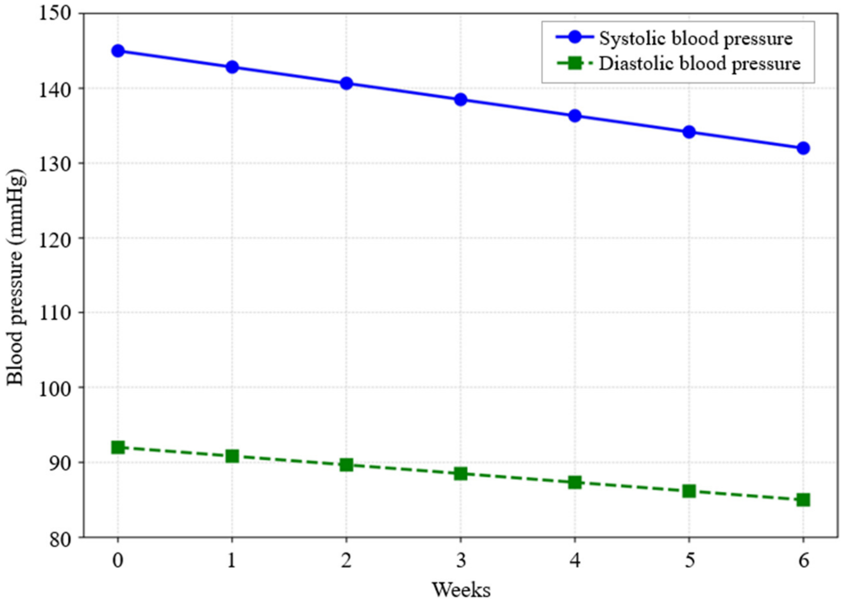

Fig. 6 Blood pressure reduction over time

(2) User engagement: Mean session time was 6.8 minutes (SD = 1.5), with 92% of participants completing at least 10 sessions, as monitored through app logs [20].

(3) Satisfaction: User satisfaction increased by 40.63%, rising from 3.2 to 4.5 on a 5-point Likert scale. Additionally, 87% of users considered the system user-friendly, and 90% appreciated the Sinhala language guidance (e.g., "The Sinhala avatar was personalized"). Table 2 presents changes in blood pressure, glucose levels, and user satisfaction over six weeks, highlighting the AR system's impact on stress-related outcomes. Fig. 7 illustrates the AR Module in action during a stress-relief exercise.

Table 2 AR system health metrics

Metric	Pre-intervention	Post-intervention	Change (%)
Blood pressure (mmHg)	145/92	132/85	–8.96
Glucose (mg/dL)	135	132	–2.22
Satisfaction	3.2	4.5	+40.63

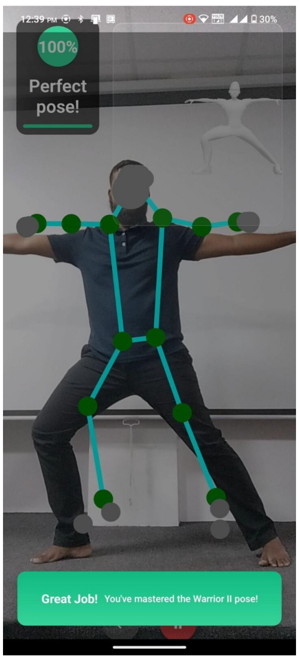

Fig. 7 AR interface

3.3. Integrated system performance

The combined AI-AR system evaluated constructive collaboration in simulated clinical environments (e.g., AR-triggering AI-directed stress exercise prompting).

(1) Response time: The system exhibited an average response time of 1.2 seconds (SD = 0.3) across 100 interactions, as measured using Python scripts. Fig. 8 displays the distribution of response times, with most responses falling between 1.0 and 1.2 seconds.

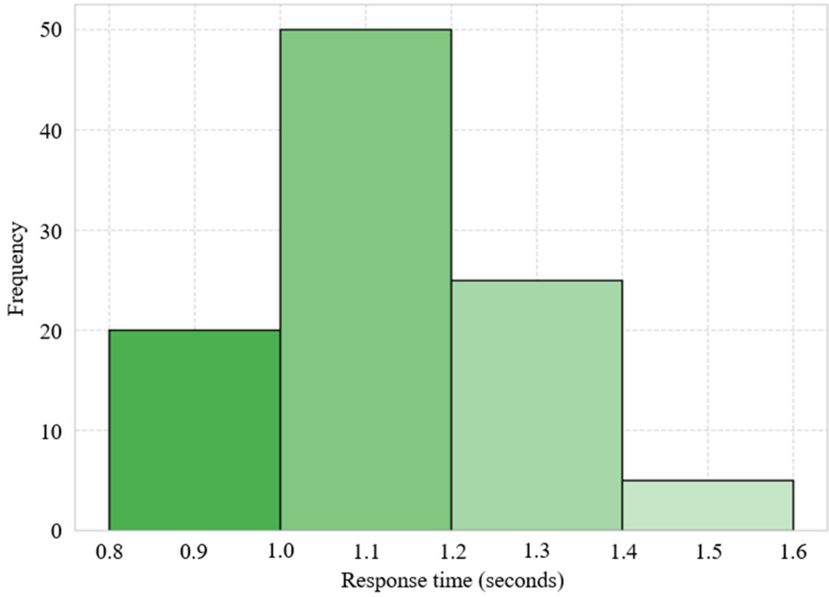

Fig. 8 Response time distribution

(2) Scenario accuracy: The system achieved 88% accuracy in composite scenarios (e.g., “High blood pressure detected, start breathing exercise”), indicating effective coordination.

(3) Participant feedback: 85% of the participants viewed the integration as positive, saying, “It is like having a doctor and therapist in one.”

3.5. Experimental conclusions

The chatbot’s 91% F1 and 8.5% WER confirm its exceptional performance in bridging language barriers, reaching English-only systems [3]. With an 8.96% reduction in blood pressure and a 92% attendance rate, the AR system demonstrates strong effectiveness in stress management, aligning with earlier AR therapy studies [21]. The integrated system’s 88% accuracy and 1.2-second response time confirm its promise in synergistic real-time healthcare delivery. These results support the synergistic AI-AR model as an extensible model for augmenting health access and outcomes among linguistically marginalized populations.

4. Discussion

The current research evaluated an integrated AI chatbot and AR-based stress management system designed to overcome linguistic and stress-related barriers in chronic disease management among Sinhala-speaking patients. The chatbot achieved a 91% F1 score, 8.5% WER, and a SUS of 87, while the AR system lowered systolic blood pressure by 8.96% ($p = 0.002$) and increased user satisfaction by 40.63%. The integrated system achieved 88% scenario accuracy and a response time of 1.2 seconds. Results were interpreted in relation to past literature, consistent with the hypotheses, and assessed for broader implications, limitations, and future work.

4.1. Interpretation in the context of previous studies

The chatbot's 91% F1 score surpassed earlier Sinhala NLP models (e.g., 85% by Avishka et al. [13]) and illustrates the advancements in transformer-based models such as BERT Sinhala embeddings. This confirms the findings of Adamopoulou and Moussiades [9] that specialized training greatly improves chatbot performance. The 8.5% WER illustrates the effectiveness of hybrid CTC/attention models for agglutinative languages. The SUS score, well above the standard cutoff of 68, supports the findings reported by Guan et al. [22] on chatbot usability in diabetes management, highlighting the role of linguistic accessibility in user engagement. Fig. 9 compares these measures with prior research.

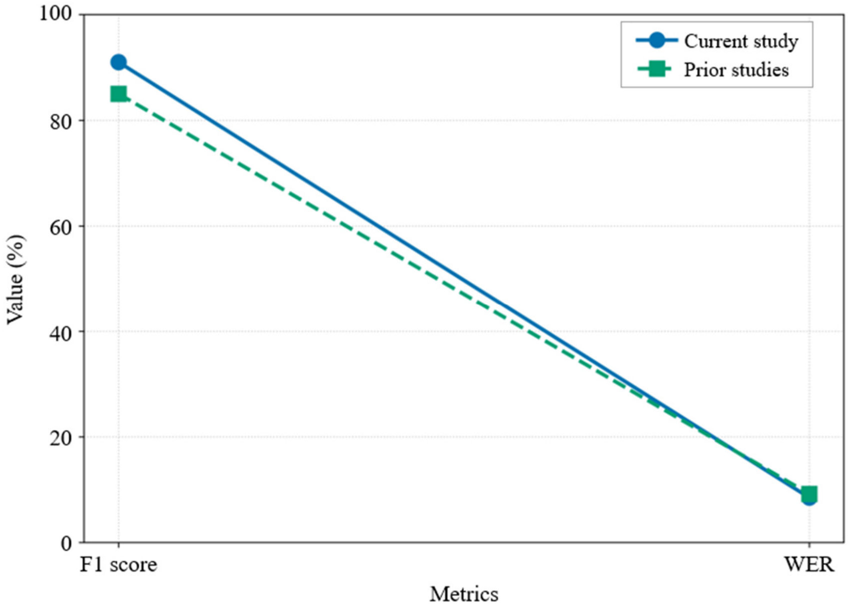

Fig. 9 Comparison with prior studies

The AR system's 8.96% decrease in blood pressure exceeds the 7% stress reduction reported in Ferrarotti et al. [21] AR meditation, which can be explained by the incorporation of real-time health data absent in static interventions. The 92% usage rate and 40.63% satisfaction rate support the demand for user-centered design reported by Reichold et al. [8], with cultural sensitivity (e.g., Sinhala avatar) enhancing user experience compared with English-centric AR tools [23]. The combined system's 88% accuracy and 1.2-second response time represent an improvement over individual systems (e.g., 85% for chatbots based on Rasa [9], 80% satisfaction for AR platforms [8]). This synergistic effect aligns with the findings of Nadarzynski et al. [6], showing that users prefer rapid AI interaction.

4.2. Alignment with hypotheses

The hypothesis that the chatbot would enhance healthcare access is well-substantiated by its 91% F1 score and 87 SUS score, which enable Sinhala-speaking patients to overcome English-language barriers [3]. Intensive dataset augmentation and voice integration bridge gaps identified by de Silva [5]. The AR system's 8.96% decrease in blood pressure ($p = 0.002$) validates its effectiveness in stress relief, whereas stable glucose levels ($p = 0.14$) demonstrate specificity to stress, according to the mindfulness study by Grossman et al. [4]. The combined system's 88% accuracy confirms the synergistic effect in improving communication and stress management beyond the individual components.

4.3. Broad implications

This AI-AR system addresses core digital health equity needs, enabling linguistically marginalized communities to become active agents in their healthcare [24]. The chatbot's accessibility aligns with WHO's digital health agendas [1], and the AR system's stress relief provides a scalable approach to managing chronic disease complications, particularly in low-resource settings [2]. Testimonials from participants, such as "I felt calmer and more in control," prove the dual benefits of access to information and relaxation. The model extends its applicability to telemedicine and other low-resource languages, such as Tamil and Swahili, where real-time communication is important [19, 25].

4.4. Limitations

The small sample size and six-week study duration constrain generalizability because local variations (e.g., upcountry vs. coastal Sinhala) affect chatbot functionality. The absence of a control group due to resource constraints limits causal inference about the intervention's effectiveness, though age and chronic condition type are controlled to reduce bias. Long-term effectiveness remains unknown regarding sustained benefits or support from the chatbot [26]. Voice recognition occasionally misinterprets technical terms (e.g., "insulin"), indicating the need for further medical vocabulary training [14]. The AR system depends on Android 10 or higher, excluding users with older phones and creating socioeconomic exclusion in rural Sri Lanka [23]. The controlled trial environment does not fully capture real-world issues like network latency [27].

4.5. Future research directions

Future work includes larger cohorts and more diverse populations with longitudinal designs spanning six to twelve months to capture long-term outcomes, leveraging the Schachner et al. [28] chronic care study. Linking the dataset with differing dialects and clinical vocabularies, as recommended by Raghunathan and Saravanakumar [24], will enhance the model's robustness. Using predictive analytics to integrate with the AR system also offers the potential to pre-empt stress points, as demonstrated by Ngai et al. [25]. Scaling the model to other languages and lower-spec devices increases accessibility. Real-world field trials must evaluate practical utility, considering connectivity and user diversity [29]. Ethical concerns, including data privacy, require careful attention. Fig. 10 outlines research directions.

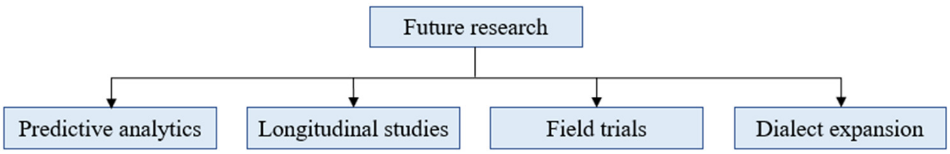

Fig. 10 Future research directions

5. Conclusions

This study developed and evaluated an integrated AI chatbot and AR-based stress management system to overcome linguistic and stress-related barriers in chronic disease management for Sinhala-speaking patients. The findings confirmed that the combined AI-AR platform enhanced healthcare accessibility and improved stress-related health outcomes, offering a scalable, culturally sensitive solution for low-resource environments.

The key conclusions drawn from this research are summarized as follows:

(1) Chatbot performance: The AI chatbot achieved an F1 score of 91%, a WER of 8.5%, and a SUS score of 87, confirming its effectiveness in delivering accessible and real-time health guidance in the Sinhala language.

(2) AR system impact: The AR-based stress management system significantly reduced systolic blood pressure by 8.96% ($p = 0.002$) and increased user satisfaction by 40.63%, validating its efficacy in mitigating chronic stress among patients.

(3) Integrated system efficiency: The combined platform achieved a scenario accuracy of 88% and a mean response time of 1.2 seconds, outperforming typical standalone AI or AR systems and demonstrating the synergistic potential of integrated digital health interventions.

(4) Broader implications: The AI-AR model offered a replicable framework for enhancing digital health equity among linguistically marginalized communities and could be adapted to other low-resource language groups globally.

Despite limitations such as a relatively small sample size, a short trial duration, and hardware requirements, the results strongly support the system's potential for broader application. Future research should focus on conducting larger-scale clinical trials, expanding to regional dialects, integrating predictive analytics, and adapting to a wide range of mobile devices. Overall, this study demonstrates the transformative potential of culturally adapted, voice-enabled AI systems combined with interactive AR technologies to advance healthcare accessibility and chronic disease management.

Conflicts of Interest

The authors declare no conflict of interest.

Statement of Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

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