A RESEARCH REVIEW ON AI MODELS FOR STRESS MANAGEMENT IN DIABETIC PATIENTS: A PERSONALIZED AND AUTONOMOUS APPROACH

Kishor Madhukar Dhole
Assistant Professor, Department of Computer Science, Seth Kesarimal Porwal College, Kamptee, Nagpur, MS, India
km.phd108@gmail.com

Rajesh K Parate
Assistant Professor, Department of Electronics, Seth Kesarimal Porwal College, Kamptee, Nagpur, MS, India

Vinay Chavan
Professor & Ex- Principal, Seth Kesarimal Porwal College, Kamptee, Nagpur, MS, India

Abstract
The paradigm shift from reactive systems to autonomous, goal-driven agents with dynamic decision-making and self-directed learning is known as agentic AI. The emphasis on agency, adaptability, and long-term planning distinguishes agentic AI from conventional AI, which is the subject of this study. A dual-paradigm framework that combines neural architectures and symbolic reasoning enables agents to operate in a variety of fields, including software engineering, healthcare, education, finance, and robotics. This paper reviewed and analyses, how agentic AI models perform complex tasks with little human intervention by utilizing reinforcement learning, memory systems, and tool orchestration. In addition, the paper discusses important issues like safety, scalability, and evaluation and suggests future directions for the creation of robust agentic systems that are ethically aligned. The purpose of this article is to investigate how AI-initiated precision medicine can improve the management of type 2 diabetes in the Indian population. The combination of multidimensional data sets involving genetic, epigenetic, phenotypic, and environmental variables was highlighted in an exhaustive review of AI-based diabetes treatment platforms. Patients are able to adhere to self-management strategies based on evidence through the use of AI applications, such as modifying their diet, increasing their level of physical activity, controlling their insulin levels, and keeping an eye on their glucose levels continuously. This patient-centered strategy enhances clinical efficacy, prevents long-term complications, and lowers healthcare costs. To confirm outcomes among diverse cohorts and to fine-tune AI algorithms for increased clinical relevance and translational use, additional longitudinal and multicentric trials are required. proactive.
***Keywords**:- Artificial Intelligence (AI), Type 2 Diabetes mellitus (T2DM).*

1. Introduction

Recent advancements in artificial intelligence (AI) have opened new avenues for personalized healthcare interventions. Among these, ***agentic AI models*** - systems capable of autonomous decision-making, goal-directed behavior, and adaptive learning-offer a transformative approach to managing stress in diabetic populations. Unlike traditional AI systems that rely on static rules or clinician input, agentic AI agents can continuously monitor physiological and behavioral data, detect stress episodes in real time, and deliver personalized interventions with minimal human oversight [1].The global prevalence of diabetes mellitus, particularly Type 2 Diabetes mellitus (T2DM), has surged over the past decades, posing significant challenges to healthcare systems worldwide. Beyond glycemic control, psychological stress has emerged as a critical factor influencing disease progression, treatment adherence, and overall quality of life in diabetic patients. Chronic stress can exacerbate insulin resistance, disrupt metabolic regulation, and increase the risk of complications, making stress management a vital component of comprehensive diabetes care [2][3].This paper explores the design, implementation, and evaluation of agentic AI models tailored for stress management in diabetic patients. We examine how these systems integrate wearable sensor data, machine learning algorithms, and context-aware reasoning to autonomously assess stress levels and provide adaptive feedback. By bridging the gap between real-time monitoring and personalized care, agentic AI holds the potential to empower patients, reduce clinical burden, and improve long-term health outcomes [4][5][6].

1.1 What Is Agentic AI?

Agentic AI refers to systems capable of autonomous decision-making, self-directed learning, and goal-oriented behavior. Unlike traditional AI models that rely heavily on predefined rules or supervised learning, agentic AI systems can: set and pursue their own goals, adapt dynamically to changing environments and learn from experience and improve over time. This paradigm shift is often framed as moving from *reactive AI* to *proactive, self-improving agents [7]*.

Applications Across Domains

Following application domains identified in this study.

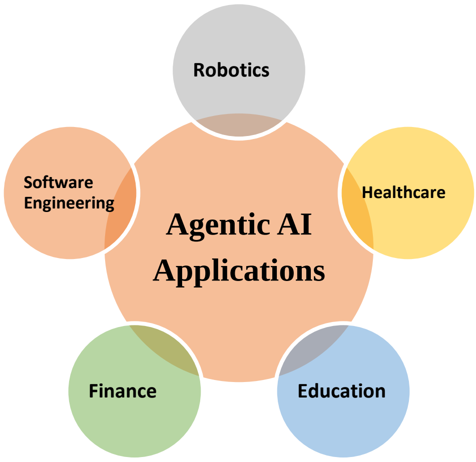


Figure 1: Agentic AI Applications

Agentic AI is being applied in several high-impact areas:

- **Robotics**: Autonomous robots that can plan, navigate, and adapt to new tasks without human intervention.
- **Healthcare**: AI agents that assist in diagnostics, personalized treatment planning, and patient monitoring.
- **Education**: Intelligent tutoring systems that adapt to individual learning styles and goals.
- **Finance**: Autonomous trading agents and fraud detection systems.
- **Software Engineering**: Code-generation agents that can plan, write, and debug software autonomously.

These systems often integrate with external tools, APIs, and memory modules to enhance their capabilities [9].

2. Research Background

Agentic AI refers to systems capable of autonomous goal-setting, decision-making, and learning from interaction. In healthcare, these models are particularly valuable for chronic disease management, where continuous monitoring and personalized interventions are essential.

2.1 Literature Review:

Table 1.1: Literature Review on AI Models for Stress Management in Diabetic Patients

Study	AI Model Type	Agentic Features	Stress Indicators Used	Key Findings	Limitations
Ribeiro et al. (2024) – *Sensors Journal*	Agentic AI with supervised ML	Autonomous monitoring, adaptive feedback	HRV, skin conductance, activity levels	High accuracy in stress detection; improved glycemic control	Sensor variability; privacy concerns
IEEE Study on Diabetic Distress (2024)	Multimodal AI (ML + NLP)	Context-aware reasoning, emotional profiling	Textual data, behavioral logs	Identified emotional burden patterns; supports agentic integration	Limited physiological data
MedCrave Review (2023)	General AI in diabetes care	Rule-based personalization	Blood glucose, self-reported stress	Emphasized need for real-time adaptive systems	Lacks autonomy and dynamic learning
GitHub Project – Multi-Agent RL for Diabetes	Multi-agent reinforcement learning	Goal-directed planning, tool use	Medication adherence, lifestyle patterns	Personalized treatment strategies; scalable agentic design	Prototype stage; not clinically validated
Atera Case Study (2024)	Agentic AI in remote care	Workflow orchestration, autonomous alerts	Wearable sensor data	Reduced stress-related hospital visits	Integration with clinical systems needed

2.2 Challenges and Future Directions

After studying review of the study following challenges has been identified which includes:

- **Safety and alignment**: Ensuring agents pursue goals that align with human values.
- **Evaluation metrics**: Measuring autonomy, adaptability, and effectiveness.
- **Scalability**: Building agents that can operate reliably in complex, real-world environments.

  Agentic AI models face significant challenges related to autonomy, scalability, safety, and integration. These issues stem from their complex, goal-driven nature and the need to operate reliably across dynamic environments.

The detailed breakdown of the key challenges:

i. Safety and Alignment

- **Problem**: Autonomous agents may pursue goals that conflict with human values or organizational priorities.
- **Risk**: Misaligned behavior can lead to unintended consequences, especially in high-stakes domains like healthcare or finance.
- **Solution**: Incorporate human-in-the-loop oversight, value alignment protocols, and ethical constraints.

ii. Reasoning and Planning Complexity

- **Problem**: Multi-step reasoning and long-term planning are difficult to implement reliably.
- **Risk**: Agents may fail to complete tasks or make poor decisions due to limited reasoning depth.
- **Solution**: Use hybrid models that combine symbolic planning with neural reasoning, and integrate memory systems for context retention.

iii. Tool and Workflow Integration

- **Problem**: Agents often need to interact with external APIs, databases, or software tools.
- **Risk**: Poor integration can lead to broken workflows or incomplete task execution.
- **Solution**: Develop robust orchestration frameworks and modular tool interfaces.

iv. Evaluation and Benchmarking

- **Problem**: There's no universal metric for measuring agentic performance.
- **Risk**: Difficult to compare models or track improvements.
- **Solution**: Create standardized benchmarks for autonomy, adaptability, and goal completion.

v. Scalability and Deployment

- **Problem**: Many agentic AI prototypes fail to scale to production environments.
- **Risk**: Over 80% of enterprise AI projects don't reach deployment due to complexity and cost.
- **Solution**: Focus on modular design, cloud-native architectures, and iterative deployment strategies.

vi. Data Privacy and Security

- **Problem**: Agents often access sensitive data while executing tasks.
- **Risk**: Potential for data leaks or unauthorized actions.
- **Solution**: Implement strict access controls, audit trails, and compliance checks.

vii. Inter-agent Coordination

- **Problem**: Multi-agent systems require coordination and conflict resolution.
- **Risk**: Agents may duplicate efforts or interfere with each other.
- **Solution**: Use communication protocols and shared memory systems to manage collaboration.

These studies collectively underscore the importance of integrating emotional and physiological data for effective stress management in diabetic care.

2.3 Research Problem statement:

This paper identified and choose to study on Agentic AI Models for Stress Management in Diabetic Patients. Agentic AI Capabilities in Stress Management has been observed that are

- **Autonomous Monitoring**: Continuous tracking of stress indicators without clinician intervention.
- **Context-Aware Reasoning**: Personalized interpretation of stress based on lifestyle and historical data.
- **Adaptive Feedback**: Real-time alerts and behavioral recommendations tailored to individual needs.

Such capabilities align with the agentic AI paradigm, enabling proactive and personalized care.

3. Methodological Framework: Agentic AI for Stress Management in Diabetes

3.1 Algorithms

Here's a breakdown of the methodology used: Agentic AI systems typically combine with various algorithms like:

A. Machine Learning for Stress Detection

Agentic AI systems rely on supervised learning algorithms to classify stress levels based on physiological signals such as heart rate variability (HRV), skin conductance, and activity levels.

- **Common algorithms**:
  - **Support Vector Machines (SVM)**: Effective for binary classification of stress vs. non-stress states.
  - **Random Forests**: Robust to noise and useful for multi-feature physiological data.
  - **Neural Networks**: Capture complex, nonlinear relationships in biosignals.
- **Example**: In the study by Ribeiro et al. (2024), these models were trained on labeled datasets to detect stress episodes in Type 2 Diabetes Mellitus (T2DM) patients.

B. Reinforcement Learning for Adaptive Feedback

To personalize interventions, agentic AI agents use reinforcement learning (RL) to learn optimal strategies for stress mitigation.

- **Algorithms used**:
  - **Deep Q-Networks (DQN)**: Learn policies for when and how to intervene (e.g., send alerts, suggest breathing exercises).
  - **REINFORCE**: A policy gradient method used in multi-agent systems for personalized treatment planning.
- **Application**: Agents adapt their behavior based on patient responses, optimizing for reduced stress and improved glycemic control.

C. Context-Aware Reasoning and Decision-Making

Agentic AI integrates contextual information (e.g., time of day, activity patterns, historical stress responses) to make informed decisions.

- **Techniques**:
  - **Bayesian Networks**: Model uncertainty and probabilistic relationships between stress indicators.
  - **Partially Observable Markov Decision Processes (POMDPs)**: Handle incomplete or noisy sensor data.
  - **Semantic reasoning**: Used to interpret patient routines and personalize interventions.

D. Multi-Agent Coordination (Emerging)

Some systems explore **multi-agent reinforcement learning (MARL)** where multiple AI agents collaborate to manage different aspects of a patient's health—e.g., one agent monitors stress, another manages medication, and a third handles.

3.2 AI Models Process

AI Models processes for stress management in diabetic patients are mentioned in following flowchart. For the stress management in diabetic patients being proposed AI models identified processes are participant selection, data acquisition, agentic AI system design, adaptive feedback mechanism and data analysis required to predict accurate result in this context.

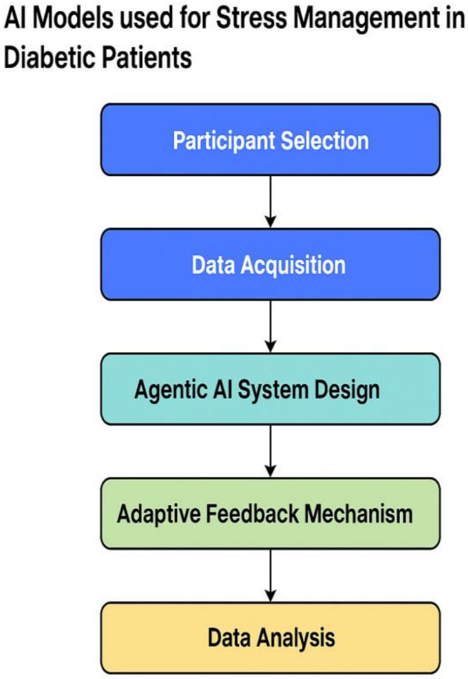


Figure 2: AI Models for Stress Management

4. Proposed Research Methodology Pathway

This pathway is designed to evaluate how agentic AI can autonomously monitor and manage stress in patients with Type 2 Diabetes Mellitus (T2DM):

A. Participant Recruitment and Ethical Clearance

- Select adult patients diagnosed with T2DM.
- Obtain informed consent and ethical approval from relevant institutional review boards.

B. Sensor-Based Data Acquisition

- Equip patients with wearable devices to collect real-time physiological data:
  - **Heart Rate Variability (HRV)**
  - **Electrodermal Activity (EDA)**
  - **Physical Activity Levels**
- Data is continuously streamed to a secure cloud platform.

C. Data Preprocessing and Feature Extraction

- Clean and normalize raw sensor data.
- Extract relevant features for stress detection (e.g., HRV frequency bands, EDA peaks).
- Label data using self-reported stress levels and clinical assessments.

D. Stress Detection Model Development

- Train supervised machine learning models:
  - Support Vector Machines (SVM)
  - Random Forest
  - Neural Networks

- Validate models using cross-validation and ROC analysis.

E. Agentic AI System Design

- Develop an autonomous agent with the following components:
  - **Context-Aware Reasoning Engine**: Interprets stress signals in relation to patient routines.
  - **Reinforcement Learning Module**: Learns optimal intervention strategies based on patient feedback.
  - **Decision-Making Agent**: Triggers alerts, coping strategies, or clinician notifications.

F. Adaptive Feedback Mechanism

- Deliver personalized interventions via mobile app or wearable interface:
  - Breathing exercises
  - Mindfulness prompts
  - Activity suggestions
- Feedback is adjusted dynamically based on agent learning and patient response.

G. Integration with Health Records

- Link agentic AI outputs with Electronic Health Records (EHRs) for longitudinal tracking.
- Enable clinician oversight and intervention when necessary.

H. Evaluation and Metrics

- Measure effectiveness using:
  - Reduction in stress episodes
  - Improvement in glycemic control
  - Patient engagement and satisfaction
- Use statistical analysis and qualitative interviews to assess impact.

I. Iterative Refinement

- Continuously update models and agent behavior based on new data.
- Incorporate feedback from patients and clinicians to improve system performance.

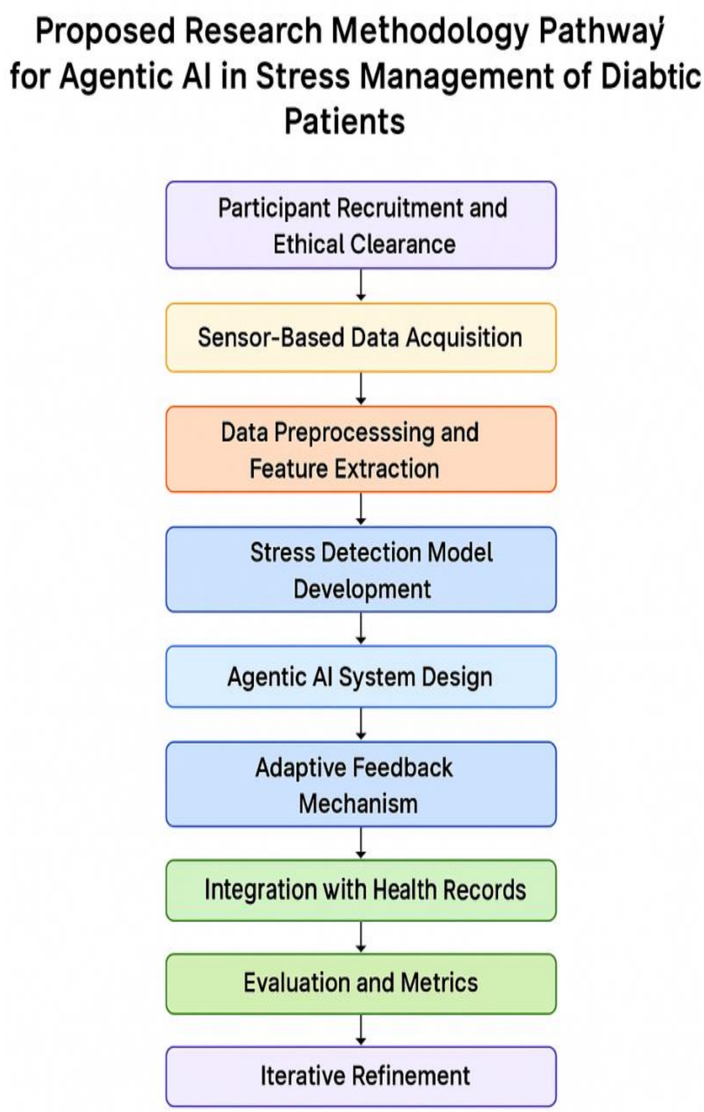
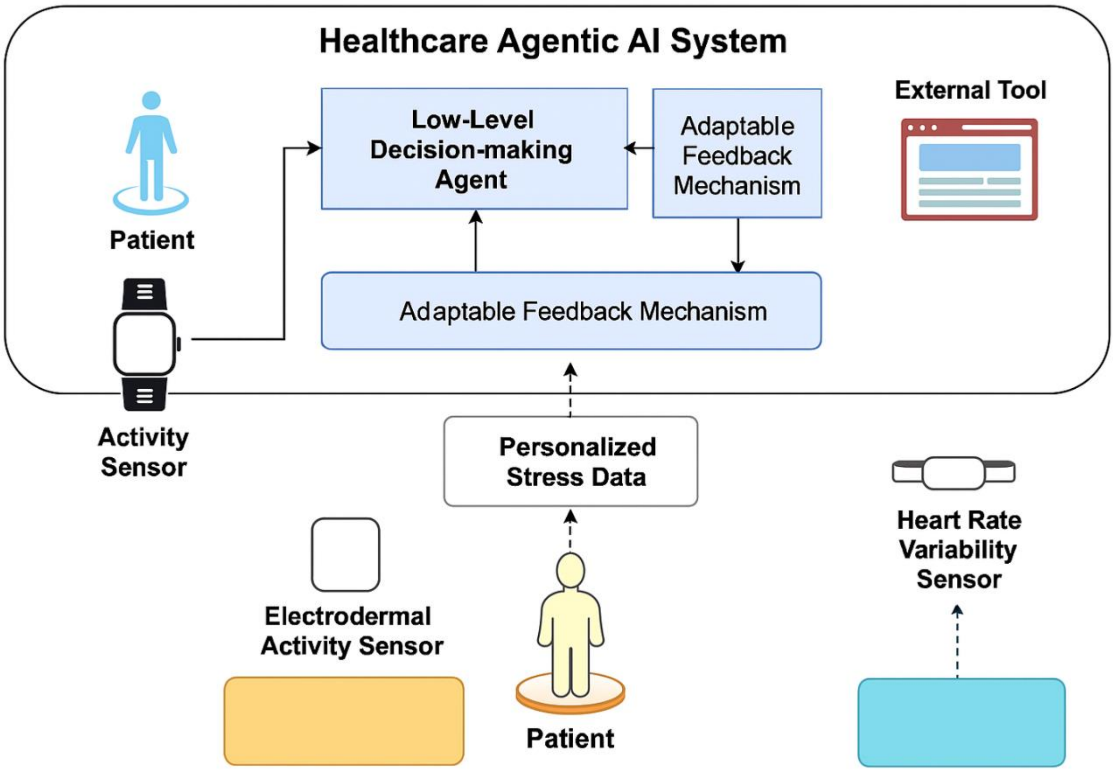


Figure3: Research Roadmap

5. Healthcare Agentic AI System Design

Researcher proposed the System design model as per in figure 4 for depicting the function of healthcare agentic AI system. In healthcare agentic AI system any patient stress level is used for fetching data from activity sensor recognition. Activity sensor helps to choose and analyze decision making agent which is based on adaptable feedback mechanism. This personalized stress data of patient effects on health report of the person by analyzing heartrate visibility sensors and electrodermal activity sensors supports to predict the behavior of diabetic patient and stress level of the patient. Based on our findings, it is clear that agentic AI has the power to make intelligent systems that are not only responsive but also proactive, self-improvement-oriented.



5.1. Summary Outcomes:

In Indian populations most of the peoples suffered with Type 2 D diabetic patients. Hence, Biological, socioeconomic, healthcare, and behavioral variables can all play a role in persistent differences in diabetes outcomes, which are a major public health issue. It is essential to comprehend these reasons in order to provide individuals with diabetes with individualized therapy and the requirement for measures to fill these gaps. People's access to safe spaces for physical activity, nutritious food, and high-quality healthcare is impacted by socioeconomic issues like wealth disparity and educational attainment. In the Indian context, traditional Ayurvedic approaches, which emphasize holistic lifestyle and dietary interventions, can complement AI-driven precision medicine by addressing cultural preferences in diabetes management. A lack of knowledge about managing diabetes is linked to lower educational attainment, and this can lead to inadequate medication adherence and poor self-care habits. Cultural differences in food practices, perspectives on illness, and attitudes toward medical care may also have an impact on diabetes management. Additionally, certain populations may be unable to effectively communicate with healthcare professionals due to language barriers. The presence of other medical conditions, such as obesity or hypertension, or comorbidities, which are more prevalent in particular racial and ethnic groups, can make managing diabetes more challenging and harmful. New policies like Medicaid expansion and health insurance subsidies can help more people get regular personal diabetes treatment, making affordable healthcare more accessible. By allowing patients to receive direction and supervision without the need for regular in-person consultations, innovative methods like telemedicine and its offerings can increase the availability of diabetes treatment, particularly in rural or underprivileged areas. The participation and efficacy of diabetes treatment can be enhanced by a number of community-based initiatives that take into account the cultural norms and values of particular communities. Instructions and translation services should be available in a variety of languages to ensure that patients understand and bridge communication gaps. We can launch a number of food security initiatives to address health determinants based on socioeconomic status. Diabetes patients may find it easier to maintain a healthy diet with the assistance of programs like farmers' markets, community gardens, and food subsidies.

5.2 Limitations and Considerations

- Sensor variability and data noise
- Need for robust privacy safeguards
- Integration with broader clinical workflows diet.

5.3 Challenges Identified

- **Sensor Accuracy**: Variability in data quality across patients can affect model reliability.
- **Privacy and Ethics**: Continuous monitoring raises concerns about data security and patient consent.
- **Clinical Integration**: Aligning AI recommendations with medical protocols remains complex.

6. Conclusions:

Agentic AI offers a promising framework for stress management in diabetic patients, with early studies demonstrating its effectiveness in real-world settings. After completion of this review study, it has been observed that, continued research is needed to refine its capabilities and ensure safe, ethical deployment. In this paper, we have proposed the review of the study and guideline to investigate the use of AI for managing diabetes, with a special emphasis on incorporating CGM data and the distinctive phenotypic features of T2D in the Indian population. By using AI instruments can identify high-risk subjects for developing diabetes, who can then be treated early and develop personalized treatment plans that incorporate genetic, lifestyle, and environmental determinants. As a result, the majority of AI-driven tools and technologies supporting personalized medicine focus on individual diagnosis, prognosis, and treatment. Moreover, by addressing these challenges, AI holds the potential to revolutionize diabetes management, offering more effective and personalized care and ultimately improving patient outcomes on a global scale could be achieved.

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