iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** II **Month of publication:** February 2026

DOI: https://doi.org/10.22214/ijraset.2026.77710

Avasthi: Revolutionizing the Current Mental Healthcare System

Dr. Jisha P Abraham[1], Prof. Smitha Paulose[2], Acqulene Sara Thomas[3], Shraddha Sasikumar[4], Amritha M[5]
[1]Department of Computer Science and Engineering, Mar Athanasius College of Engineering (Autonomous), Kothamangalam

Abstract: Avasthi is an AI-powered mental health platform that offers per- sonalised stress management solutions. Users are classified as having low, medium, or high stress levels using the Perceived Stress Scale. Low and medium stress users interact with an AI chatbot based on Retrieval-Augmented Generation (RAG) for context-aware assistance and tailored recommendations, while high-stress users are connected to licensed psychologists through an integrated consultation system. Avasthi employs weighted vector fusion to combine behavioural cues explicit feedback, con- versational intent, and long-term preferences into a unified user profile. A knowledge graph–based recommendation engine uses deep contrastive learning (DCL) to create and compare activity embeddings via cosine similarity to rank optimal interventions. The platform also includes an AI fitness assistant that guides users through simple stress-bursting exercises and a diet module that provides nutri- tional guidance based on user preferences and requirements. Avasthi ensures scalable, transparent, and low latency interactions for holistic mental wellness support.

I. INTRODUCTION

Stress, anxiety, and depression continue to affect millions worldwide, yet many individuals hesitate to seek timely help due to high consultation costs, limited professional availability, and the persistent stigma surrounding mental health. As daily stressors accumulate, people often struggle to understand their emotional patterns, choose appropriate coping strategies, or determine when to seek clinical intervention. This creates a growing demand for intelligent digital systems capable of offering personalized guidance, answering user questions, and providing holistic support while respecting privacy and accessibility constraints.

Avasthi addresses this challenge by functioning as a self- scalable, AI-driven mental wellness platform that assists users across varying levels of psychological stress. The system is designed not only to deliver empathetic conversational support but also to adapt its behaviour based on user-specific profiles. When users interact with the platform, they are first guided through a Perceived Stress Scale (PSS) assessment. This enables Avasthi to categorize individuals into low, medium, or high stress tiers, thereby ensuring that responses and recommendations remain appropriate, safe, and context-aware. Users in the low or moderate stress ranges engage with Avasthi's Retrieval-Augmented Generation (RAG) chatbot. The chatbot integrates a vector database with carefully curated mental-health knowledge to deliver grounded, empathetic, and context-sensitive answers. Importantly, the system is designed to ask clarification questions—such as "How long have you felt this way?" or "Would you like guidance on relaxation or mood improvement?"—to better understand each user's emotional state and provide tailored support. This mirrors the goal-oriented reasoning found in modern therapist–client interactions and helps reduce ambiguity in user queries. To enhance personalization, Avasthi incorporates a knowledge-graph-driven recommendation engine. This engine models relationships among stress levels, user preferences, therapeutic activities, and emotional states. Using these relationships, it recommends suitable mental-health interventions such as breathing exercises, journaling prompts, guided meditation, mindfulness activities, mood-based music therapy, or cognitive reframing tasks. These recommendations evolve over time based on user behaviour and system-observed patterns.

The system also offers a specialized diet recommenda- tion module, which uses deep learning classifiers and graph- based clustering techniques—specifically the K-Clique algo- rithm—to generate customized nutrition plans that support emotional wellness. Foods known to influence mood stability, energy levels, and stress reduction are incorporated into these plans in a way that matches user preferences and dietary constraints.

For individuals who prefer physical activity as a coping mechanism, Avasthi includes an AI-powered fitness assistant capable of demonstrating and evaluating stress-relief exercises. Using computer vision and biomechanical analysis, the assis- tant guides users through routines such as stretching, yoga- inspired postures, or breathing-synchronized movements. This dual emphasis on physical and emotional regulation aligns with research highlighting the strong mind–body connection in mental-health improvement.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

When high stress levels are detected, Avasthi prioritizes user safety. Instead of relying solely on automated responses, it redirects these users to a secure online consultation interface where they can book sessions with licensed psychologists. This escalation mechanism ensures that the system remains ethically aligned and does not overstep its technological limits. Technically, Avasthi is implemented using FastAPI for back- end processing, React for interface rendering, and a vector database to store and retrieve semantic embeddings efficiently. The platform integrates multiple deep-learning models to support stress classification, personalized recommendations, natural-language understanding, and real-time guidance. To- gether, these components ensure low-latency, reliable, and confidential support for the user at every interaction stage.

Beyond individual mental-health assistance, Avasthi holds strong potential for broader applications in wellness tracking, workplace stress management, behavioral-health research, and large-scale telepsychology systems. Its ability to interpret user input, ask clarifying questions, deliver multimodal rec- ommendations, and escalate cases appropriately positions it as a promising innovation in AI-supported mental wellness ecosystems.

Overall, Avasthi represents a comprehensive, scalable path- way toward accessible mental-health care. By combining stress assessment, RAG-based conversational grounding, knowledge- graph personalization, diet and fitness guidance, and pro- fessional referral, it offers an integrated system capable of delivering meaningful, contextually relevant support to diverse users seeking emotional well-being.

II. RELATED WORKS

Recent literature in personalized recommendation, conver- sational AI, and digital health provides strong groundwork for AI-driven mental wellness platforms such as Avasthi. Research on conversational preference modelling shows that actively eliciting user preferences through dialogue leads to richer user profiles and improved recommendation accuracy. These systems demonstrate that preference discovery is an ongoing process, enabling recommendations to adapt as users' emotional states, habits, and needs evolve.

Knowledge-graph-based recommendation frameworks fur- ther strengthen personalization by embedding structured rela- tions among users, activities, nutritional items, and wellbeing factors. Such models help address data sparsity and enhance multi-task performance. Meanwhile, diversified contrastive graph learning methods (e.g., DCL) introduce mechanisms that prevent recommendation collapse into a narrow set of items, ensuring users receive varied and balanced suggestions—an important factor in mental wellbeing, where over-repetition can reduce effectiveness and engagement.

Work on text representation and semantic embeddings high- lights that contextual embedding models significantly improve natural-language understanding, which is core to Retrieval- Augmented Generation (RAG) chatbots. These studies also underline challenges such as bias, privacy, and model inter- pretability—issues that are particularly sensitive in mental- health contexts, where user trust and safety are critical.

Studies in human–AI interaction show that chatbots aligned with a user's communication style or personality traits yield higher satisfaction and engagement. Research on online health consultation interfaces similarly emphasizes accessibility, clar- ity, and the importance of reducing perceived power imbalance between users and virtual advisors. These findings guide the design of supportive, empathetic, and non-intimidating conversational systems.

In healthcare AI, surveys on generative models report substantial promise for personalized guidance but highlight risks like hallucination, misinformation, and inconsistent rea- soning. These concerns motivate the integration of RAG pipelines and safety-aware mechanisms, ensuring generated responses remain grounded, reliable, and context-appropriate. Complementary work on nutrition knowledge graphs (e.g., KG4NH) demonstrates the value of structured dietary and health information for generating accurate, interpretable diet recommendations—key for stress-related nutritional guidance. Hybrid recommendation approaches combining collabora- tive filtering, k-means clustering, LightGBM models, and Bayesian inference achieve strong performance under sparse feedback conditions. These systems show that blending mul- tiple predictive signals—behavioural, contextual, and proba- bilistic—produces more stable and personalized recommenda- tions, offering useful design principles for tailored stress-relief activities and diet plans.

A. Takeaway

Across these works, the literature con- verges on a practical recipe for AI-driven mental wellness platforms: (1) use strong text and user-representation models (modern embeddings + conversational preference modelling) as the backbone for understanding users and queries; (2) exploit knowledge graphs and diversified graph-based rec- ommenders (e.g., DCL, KG-enhanced methods) to deliver personalized yet diverse activity and diet suggestions; (3) adopt RAG-style architectures and safety-aware generative models to provide grounded, empathetic conversational sup- port; and (4) design user-centred, low-friction interfaces that acknowledge power asymmetry in digital health and provide clear pathways to human professionals when risk is high. Open challenges remain in ensuring fairness and privacy of sensitive mental-health data, improving interpretability of deep recommendation models, and rigorously evaluating long-term clinical impact rather than short-term engagement or recall metrics.

III. METHODS

The Avasthi platform follows a structured methodology that integrates stress assessment, conversational AI, personalized activity recommendations, and professional mental health sup- port. The workflow begins with user onboarding and pro- gresses through several interconnected modules designed to deliver adaptive, context-aware assistance based on user needs.

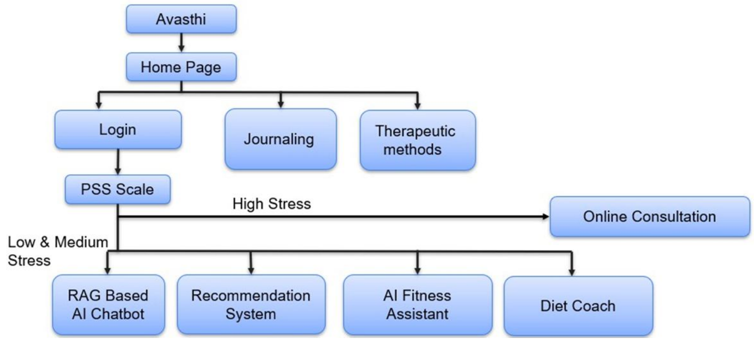


Fig. 1. Proposed workflow of Avasthi

A. *User Profiling and Stress Assessment*

- Users complete the Perceived Stress Scale (PSS) ques- tionnaire during onboarding.
- Based on standardized scoring rules, users are categorized into low, medium, or high stress groups.
- The system constructs a user profile by recording ques- tionnaire scores, basic demographic information, and interaction history.
- Low and medium stress users are directed to the AI- driven support system, while high-stress users access the consultation scheduling module.

B. *Conversational Processing and Emotional Understanding*

- User queries undergo preprocessing and sentiment under- standing through basic NLP techniques.
- Text inputs and interaction patterns help the system understand emotional tone and provide more empathetic responses.
- Conversation context is maintained across interactions to ensure continuity and relevance.

C. *Knowledge Retrieval Using RAG*

- The chatbot utilizes a Retrieval-Augmented Generation (RAG) approach to fetch relevant information from the mental health knowledge base.
- Retrieved information is matched with user queries to improve the relevance and clarity of responses.
- The RAG mechanism helps reduce hallucinations and supports more reliable guidance.

D. *Personalized Recommendation Generation*

- The system recommends suitable activities such as med- itation, journaling, breathing exercises, and mindfulness routines.
- Recommendations are based on user stress category, preferences, and previous interactions.
- Suggestions aim to help users build healthy coping mech- anisms and reduce stress levels over time.

E. *Chatbot Response Generation*

- The chatbot generates natural and supportive responses by combining retrieved knowledge, user sentiment, and ongoing conversation context.
- Response tone is adjusted according to the user’s emo- tional state and stress category.
- Users receive immediate guidance, reflective prompts, and wellness suggestions.

F. System Deployment and Data Security

- The platform backend is developed using FastAPI to ensure efficient processing and reliable communication.
- The frontend is implemented in React, enabling a user- friendly and responsive interface.
- Authentication and access control mechanisms protect sensitive user data, including chat logs and stress assess- ments.

G. Continuous Improvement Cycle

- User feedback on recommendations and interactions is collected to refine the quality of future responses.
- System components are periodically updated based on performance metrics such as response accuracy, latency, and user satisfaction.
- As the knowledge base expands, the system continuously improves its ability to deliver accurate and context-aware support.

H. AI Fitness Assistant Module

- The AI Fitness Assistant uses pose estimation to extract joint landmarks from live or recorded video streams.
- Key joint angles are computed and used as input fea- tures for a Random Forest classifier trained to recognize different exercises.
- The dataset is divided into 80% training and 20% testing to ensure robust model evaluation and generalization.
- The assistant provides real-time exercise classification and feedback, enabling users to perform physical activi- ties correctly as part of stress management.

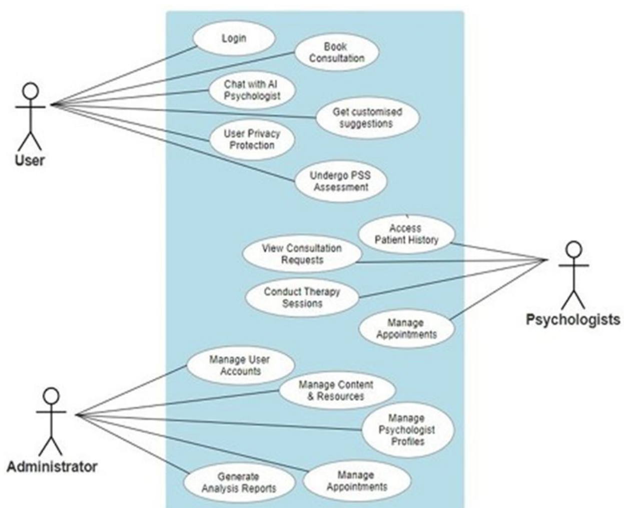


Fig. 2. Usecase Diagram

IV. DESIGN AND IMPLEMENTATION

Avasthi integrate multiple coordinated components to build a scalable, intelligent, and user-adaptive mental healthcare ecosystem. The platform combines a retrieval-augmented AI chatbot, a deep-learning–based recommendation engine, and a structured consultation module, all unified through a FastAPI backend and a React-based frontend. Each subsystem is sup- ported by a hybrid data architecture leveraging PostgreSQL for relational storage and Pinecone for vector-based semantic retrieval. Together, these components enable context-aware dialogue generation, personalized activity suggestions, and seamless escalation to professional support, forming a robust end-to-end framework for stress assessment and mental well- ness assistance.

A. Model Architecture

Avasthi follows a modular architecture where each subsys- tem operates through FastAPI endpoint services. The React frontend handles user interaction, while the FastAPI backend manages authentication, chatbot queries, recommendation re- quests, consultations, and journaling. PostgreSQL stores users, preferences, interactions, and therapist data, and Pinecone provides vector search for retrieval-augmented responses. The AI layer built using Llama-3, sentiment models, and sentence- transformer embeddings integrates directly with these backend services to deliver context-aware assistance and personalized recommendations.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

B. Chatbot Architecture

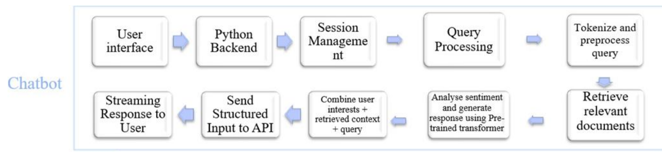


Fig. 3. Chatbot Architecture

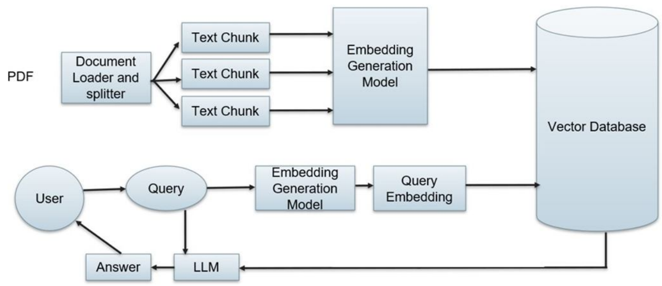


Fig. 4. RAG Architecture

The chatbot processes user queries through the following stages:

- Authentication and Session Context: Extracts the user's identity from the JWT token and retrieves recent chat history from the database.
- Query Understanding: Generates sentence embeddings, identifies sentiment using a pretrained transformer, and extracts scenario and role information using the Llama-3 model.
- Context Retrieval: Performs semantic search in Pinecone using the query embedding to fetch relevant prior interactions or knowledge snippets.
- Response Construction: Builds a dynamic instruction prompt incorporating sentiment, scenario, role, retrieved context, and past conversation history.
- LLM Response Generation: Invokes Llama-3 to pro- duce the final reply based on the constructed message set.
- Logging and Personalization: Stores the new interaction in PostgreSQL and extracts user preferences from the updated conversation for long-term personalization.

C. Recommendation System Architecture

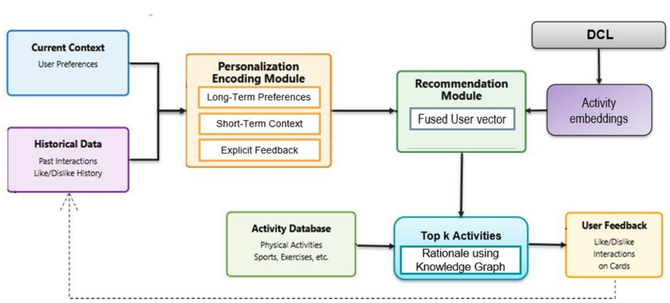


Fig. 5. Recommendation System Architecture

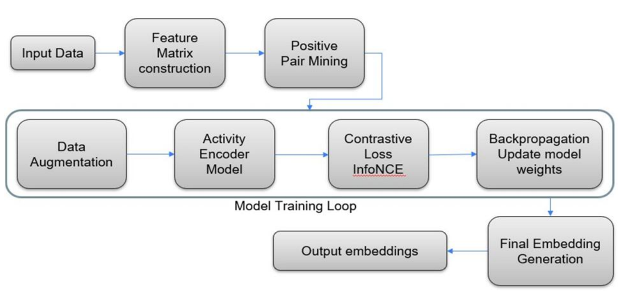


Fig. 6. DCL Architecture

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

- Activity and Knowledge Loading: The system loads activity metadata from activities.csv, pretrained activity embeddings, and knowledge-graph edges for ra- tionale generation.
- User Signal Retrieval: It fetches the user's long- term preferences, recent chat interactions, and explicit like/dislike feedback from the database.
- Vector Construction:

– *Feedback vector:* Computed by combining embed- dings of liked activities and subtracting those of disliked ones.
– *Short-term vector:* Generated by encoding recent messages using all-MiniLM-L6-v2.
– *Long-term vector:* Formed by averaging embeddings of activities matching the user's preferred modality.

- Weighted Fusion: The three vectors are merged using fixed weights (WLONG TERM, WSHORT TERM, WFEEDBACK) into a single normalized user profile.
- Similarity Computation: Each activity's embedding is compared with the fused profile using cosine similarity, and the top-k highest-scoring items are selected.
- Rationale Generation: Knowledge-graph attributes (e.g., modality, duration, environment) are formatted into short explanations for each recommendation.
- API Delivery: The /recommendations endpoint re- turns the ranked activities along with scores, descriptions, and rationales.

D. AI Fitness assistant Architecture

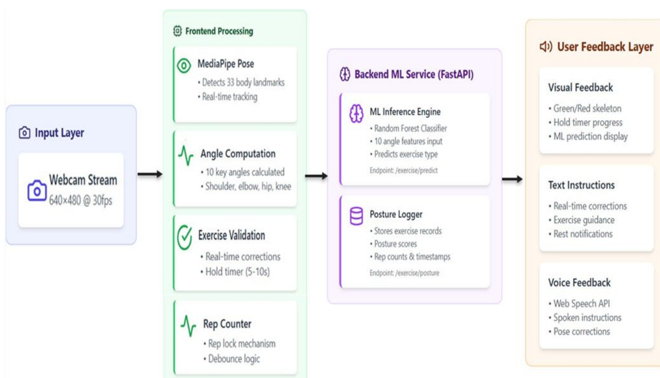


Fig. 7. AI Fitness assistant Architecture

- Exercise Selection and Video Capture: The user selects an exercise, upon which the system activates the device camera to capture live video frames of the user's move- ments.
- Pose Estimation and Keypoint Detection: A pose estimation model detects key body landmarks including shoulders, elbows, hips, knees, and ankles from the video stream.
- Angle Feature Extraction: Joint angles and joint-to- ground angles are computed from the detected keypoints, resulting in a fixed-length feature vector representing the user's posture and movement.
- Exercise Classification: The extracted angle vector is passed to a pretrained Random Forest classifier, which predicts the performed exercise using a label encoder to obtain the final exercise label.
- Posture and Movement Evaluation: The predicted ex- ercise is compared against reference posture patterns to evaluate movement correctness and calculate a posture score.
- Repetition Tracking and Feedback: Continuous motion tracking is used to count repetitions. If incorrect posture is detected, real-time corrective feedback is displayed to the user.
- Performance Logging: Exercise performance metrics including user ID, exercise type, posture score, and rep- etition count are stored via backend APIs for monitoring and analysis.
- API Integration: The /predict and /posture end- points facilitate communication between the frontend pose-estimation pipeline and the backend machine learn- ing services.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

E. Diet Recommendation Module Architecture

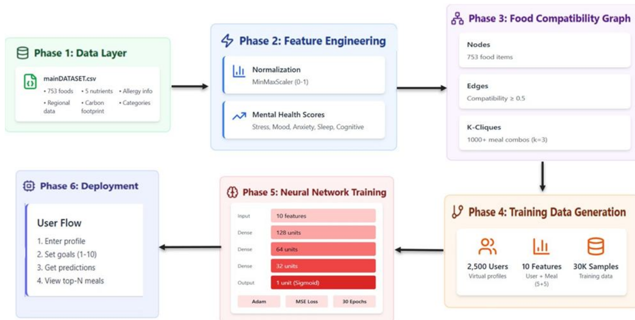


Fig. 8. Diet Recommendation Module Architecture

- User Profile and Preference Input: The user provides dietary preferences and mental wellness requirements such as stress relief, mood boost, anxiety reduction, sleep improvement, and cognitive function through the frontend interface, along with the number of required meal recommendations.
- API Request and Validation: The collected user inputs are validated using a structured request schema and sent to the backend through the /diet-recommend API endpoint for further processing.
- Feature Vector Construction: The backend converts the user's mental wellness preferences into a numerical feature vector. Aggregated mental-health benefit vectors of candidate meals are combined with the user vector to form a unified input representation.
- Data Normalization: The combined feature vector is normalized using a pretrained standard scaler to ensure compatibility with the trained deep learning model.
- Meal Combination Retrieval: A preprocessed dietary dataset containing nutritional, categorical, allergy, and re- gional attributes is loaded. Compatible meal combinations are retrieved from precomputed food groupings to ensure balanced and feasible recommendations.
- Meal Suitability Prediction: A pretrained deep neural network evaluates each candidate meal combination and predicts a suitability score indicating how well it aligns with the user's mental wellness requirements.
- Diversity-Aware Recommendation Ranking: To avoid repetitive suggestions, a diversity mechanism penalizes overlapping food items, similar categories, and closely matching calorie values, ensuring varied meal recommen- dations.
- Final Recommendation Generation: The top-ranked meal combinations are selected based on suitability and diversity constraints. Each recommendation includes food items, nutritional information, total calories, and a well- ness match score.
- Response Delivery and Integration: The final diet rec- ommendations are returned to the frontend as a structured JSON response for visualization and diet planning.

V. RESULTS

A. RAGAS-Based Evaluation of the Chatbot

To systematically evaluate the quality of responses gener- ated by Avasthi's RAG-based chatbot, the RAGAS (Retrieval-Augmented Generation Assessment) framework was applied. This framework scores the accuracy and usefulness of re- sponses by analysing how well the retrieved context con- tributes to the final answer. The evaluation considered cor- rectness, contextual alignment, and answer relevance.

- Context Precision: The chatbot consistently retrieved relevant past interactions and Pinecone semantic matches, achieving high precision in context selection. This demonstrates that the retrieval layer correctly matches semantically similar user inputs.
- Faithfulness Score: Responses closely followed the re- trieved context and avoided hallucination. Because the prompt explicitly embeds retrieved text, RAGAS scores showed strong alignment between evidence and output.
- Answer Relevance: The chatbot produced responses directly tied to user queries, benefiting from the scenario and role extraction module. RAGAS relevance ratings indicated coherent and appropriately scoped answers.
- Semantic Similarity: High similarity between model responses and expected supportive behaviour confirmed that the empathetic tone and structure were preserved across scenarios.
- Retrieval Recall: Although most queries returned strong matches, emotionally abstract queries sometimes pro- duced fewer relevant retrievals, revealing an improvement area in embedding diversification.

B. Ablation Study on the Recommendation System

The evaluation uses a set of synthetic test profiles seeded into the database, where each user is associated with a predefined *held_out _item* that represents the target activity the system is expected to recommend. For each profile, the recommender generates the top $k = 8$ activities, and a hit is recorded if the held-out activity appears in this list. Two metrics are computed across all test users:

- Recall@8: the fraction of users for whom the correct held-out activity appears in the top eight recommenda- tions.
- Average Response Time: the mean time taken (in mil- liseconds) to generate recommendations per user, mea- suring system efficiency.

Four model variations are evaluated:

- Full Model: all three signals (short-term context, long- term preferences, and feedback) are enabled.
- No-Short-Term: recommendations are generated with- out recent interaction context (use_short_term = False).
- No-Long-Term: long-term modality preferences are dis- abled (use_long_term = False).
- No-Feedback: explicit like/dislike feedback is excludedfrom the fused profile (use_feedback = False).

C. Evaluation of the AI Fitness Assistant

The AI Fitness Assistant was evaluated to assess its ef- fectiveness in recognizing and classifying physical exercises based on human pose estimation. The system employs a su- pervised machine learning approach, where a Random Forest classifier is trained on joint angle features extracted from body landmarks.

The dataset consists of pose angle measurements corre- sponding to different exercises and was split into training and testing subsets using an 80:20 ratio to ensure unbiased performance evaluation.

- Model Architecture: A Random Forest classifier was chosen due to its robustness to noise and ability to model non-linear relationships between joint angles and exercise classes.
- Feature Representation: Input features include key joint angles such as shoulder, elbow, hip, and knee orientations, which effectively capture movement patterns across ex- ercises.
- Training and Testing Split: 80% of the dataset was used for training the model, while the remaining 20% was re- served for testing to evaluate generalization performance.
- Confusion Matrix Analysis: A confusion matrix was used to analyse class-wise prediction performance, re- vealing high accuracy for well-defined exercises and minor misclassifications in visually similar poses.
- Classification Performance: The model demonstrated strong precision and recall across most exercise cate- gories, indicating reliable pose recognition suitable for real-time fitness assistance.

Overall, the evaluation confirms that the AI Fitness Assistant can accurately classify exercise movements using pose angle features, supporting its use as an intelligent real-time feedback system for guided workouts.

VI. CONCLUSION

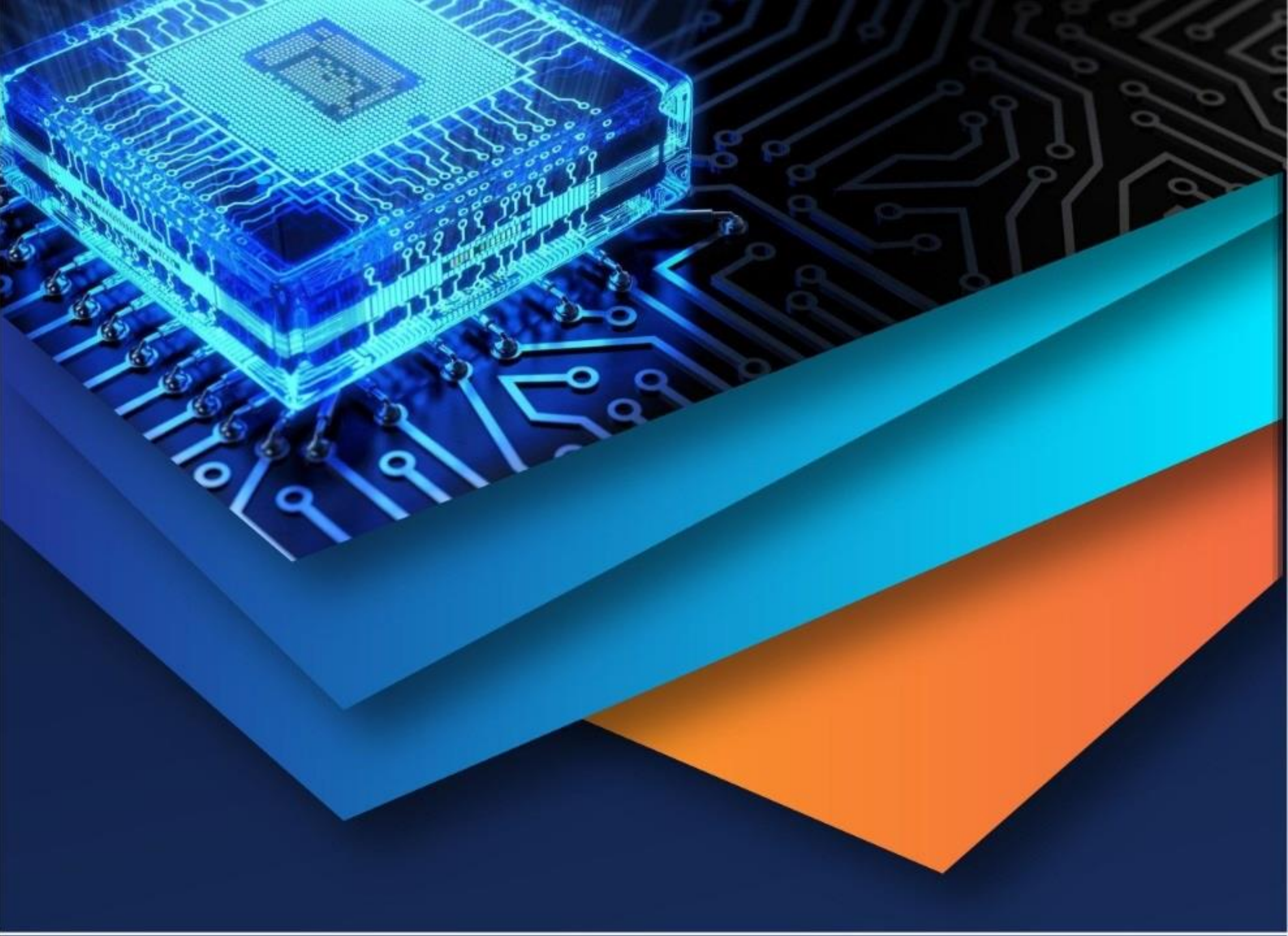
Avasthi is a comprehensive and scalable mental health ser- vice that combines accessible psychological care with cutting- edge AI technologies. In order to provide highly individ- ualised interventions, the platform integrates a RAG-based conversational assistant, knowledge graph-driven personalised recommendations, AI-powered fitness and mood regulation modules, and a scientifically based diet recommendation sys- tem that uses deep learning and the K-Clique algorithm. Stress reduction and emotional management are reinforced by the AI fitness assistant's guided physical activity and posture-aware workout support. High-stress customers are given priority by Avasthi, which links them with qualified experts while continuously offering AI-driven advice to others. Avasthi, which is positioned as a revolutionary solution for improving mental well-being worldwide, successfully connects profes- sional mental healthcare with digital self-help tools thanks to its safe, low-latency infrastructure.

VII. FUTURE WORKS

Based on the observed gaps, several improvements are planned to increase robustness, safety, and personalization. The retrieval pipeline will be strengthened by incorporating hybrid retrieval methods that combine dense and keyword- based search along with multi-query expansion to reduce retrieval failures and improve contextual accuracy. Scenario extraction will be enhanced by fine-tuning the Llama-3 clas- sifier or replacing it with a compact supervised model better suited for handling ambiguous inputs. To broaden accessibility, the system will be extended to support multiple languages as well as speech-based input and output. Finally, a human- in-the-loop framework will be integrated, enabling automatic alerts and escalation mechanisms that notify licensed mental health professionals when high-risk language patterns are detected.

REFERENCES

[1] L. Zhang, J. Zhan, V. K. W. Wan, and Y. Wang, "Designing and evalu- ating online health consultation interfaces: A perspective of physician- patient power asymmetry," IEEE Access, vol. 12, pp. 124 111–124 127, 2024.
[2] S. Sai, A. Gaur, R. Sai, V. Chamola, M. Guizani, and J. J. P. C. Ro- drigues, "Generative ai for transformative healthcare: A comprehensive study of emerging models, applications, case studies, and limitations," IEEE Access, vol. 12, pp. 31 078–31 106, 2024.
[3] B. Zhang, Z. Yan, X. Song, Y. Liao, and P. Li, "Influence of free consultation services on patients' willingness to pay in online medical platforms," International Journal of Crowd Science, vol. 8, no. 1, pp. 28–37, 2024.
[4] R. Ren, M. Zapata, J. W. Castro, O. Dieste, and S. T. Acun˜a, "Exper- imentation for chatbot usability evaluation: A secondary study," IEEE Access, vol. 10, pp. 12 430–12 464, 2022.
[5] S. Elmajali and I. Ahmad, "Toward early detection of depression: Detect- ing depression symptoms in arabic tweets using pretrained transformers," IEEE Access, vol. 12, pp. 88 134–88 145, 2024.
[6] Y. B. Sree, A. Sathvik, D. S. Hema Akshit, O. Kumar, and B. S. P. Rao, "Retrieval-augmented generation based large language model chatbot for improving diagnosis for physical and mental health," in Proceedings of the 2024 6th International Conference on Electrical, Control and Instrumentation Engineering (ICECIE), Pattaya, Thailand, 2024, pp. 1– 8.
[7] R. Patil, S. Boit, V. Gudivada, and J. Nandigam, "A survey of text representation and embedding techniques in nlp," IEEE Access, vol. 11, pp. 36 120–36 146, 2023.
[8] M. Amin Kuhail, M. Bahja, O. Al-Shamaileh, J. Thomas, A. Alkazemi, and J. Negreiros, "Assessing the impact of chatbot-human personality congruence on user behavior: A chatbot-based advising system case," IEEE Access, vol. 12, pp. 71 761–71 782, 2024.
[9] A. N. Ngaffo, W. E. Ayeb, and Z. Choukair, "A bayesian inference based hybrid recommender system," IEEE Access, vol. 8, pp. 101 682–101 701, 2020.
[10] C. Arihta, D. Fujiono, Veronica, J. V. Moniaga, and I. D. Rianto, "A re- view of gamification related to mental health treatment," in Proceedings of the 2022 3rd International Conference on Electrical Engineering and Informatics (ICon EEI), Pekanbaru, Indonesia, 2022, pp. 172–176.
[11] F. Wu, G. Zhao, T. Li, J. Shen, and X. Qian, "Improving conversational recommendation system through personalized preference modeling and knowledge graph," IEEE Transactions on Knowledge and Data Engi- neering, 2024.
[12] D. Su, B. Fan, Z. Zhang, H. Fu, and Z. Qin, "Dcl: Diversified graph recommendation with contrastive learning," IEEE Transactions on Com- putational Social Systems, vol. 11, no. 3, pp. 4114–4126, 2024.
[13] L. Guo et al., "Knowledge graph-based personalized multitask enhanced recommendation," IEEE Transactions on Computational Social Systems, 2024.
[14] C. Fu, X. Pan, J. Wu, J. Cai, Z. Huang, F. van Harmelen, W. Zhao, X. Jiang, and T. He, "Kg4nh: A comprehensive knowledge graph for question answering in dietary nutrition and human health," IEEE Journal of Biomedical and Health Informatics, 2023.
[15] X. Li, "Design of a web content personalized recommendation system based on collaborative filtering improved by combining k-means and lightgbm," Journal of Web Engineering, vol. 24, no. 2, pp. 267–290, 2025.
[16] W. Lei, X. He, M. de Rijke, and T.-S. Chua, "Conversational rec- ommendation: Formulation, methods, and evaluation," in Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, 2020, pp. 2425–2428.
[17] D. Jannach, A. Manzoor, W. Cai, and L. Chen, "A survey on conversa- tional recommender systems," ACM Computing Surveys, vol. 54, no. 5, pp. 1–36, 2021.
[18] W. Lei et al., "Estimation-action-reflection: Towards deep interaction between conversational and recommender systems," in Proceedings of the 13th International Conference on Web Search and Data Mining, 2020, pp. 304–312.
[19] Q. Chen et al., "Towards knowledge-based recommender dialog system," in Proceedings of the Conference on Empirical Methods in Natural Language Processing and the International Joint Conference on Natural Language Processing, 2019, pp. 1803–1813.
[20] K. Zhou, W. X. Zhao, S. Bian, Y. Zhou, J.-R. Wen, and J. Yu, "Improving conversational recommender systems via knowledge graph- based semantic fusion," in Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2020, pp. 1006–1014.
[21] Y. Lu et al., "Revcore: Review-augmented conversational recommen- dation," in Proceedings of the Annual Meeting of the Association for Computational Linguistics, 2021, pp. 1161–1173.
[22] C.-M. Wong et al., "Improving conversational recommender system by pretraining billion-scale knowledge graph," in Proceedings of the IEEE 37th International Conference on Data Engineering, 2021, pp. 2607– 2612.
[23] G. Penha and C. Hauff, "What does bert know about books, movies and music? probing bert for conversational recommendation," in Proceedings of the 14th ACM Conference on Recommender Systems, 2020, pp. 388– 397.
[24] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," in Pro- ceedings of the Annual Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 2019, pp. 4171–4186.
[25] Y. Zhang et al., "Dialogpt: Large-scale generative pre-training for con- versational response generation," in Proceedings of the Annual Meeting of the Association for Computational Linguistics, 2020, pp. 270–278.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY