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AI-Driven Integrated Mental Health and Fitness Systems: A Comprehensive Review

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Abstract

Recent progress in Artificial Intelligence (AI) has caused a big change in digital healthcare, especially in the areas of mental health support, fitness tracking, personalized nutrition, and clinical decision support. The rise in mental disorders, diseases linked to lifestyle, and limited access to professional healthcare services has sped up the use of AI-powered solutions like conversational chatbots, machine learning (ML) models, large language models (LLMs), and retrieval-augmented generation (RAG) systemsThis review provides an in-depth synthesis of the latest research on AI-driven systems that integrate mental health assessment, fitness prediction, personalized exercise and diet recommendations, and medical document understanding [1]–[5], with a focus on plagiarism-safe reporting. The work rigorously analyzes system architectures, algorithms, datasets, and evaluation metrics employed in recent studies. The comparative analysis brings into focus strengths, limitations, and performance trends, while ethical, privacy, and deployment considerations are explored. The review concludes by pointing out open issues in research and defining future directions to take in developing trustworthy human-centered intelligent healthcare platforms.

Introduction

Mental health and physical fitness are two interdependent dimensions of overall human well-being, both of which have been significantly affected by modern lifestyles. Rapid urbanization, academic and professional stress, reduced physical activity, and excessive screen exposure have contributed to a noticeable rise in mental health disorders such as anxiety, depression, and stress-related conditions, alongside an increase in lifestyle diseases including obesity, cardiovascular disorders, and metabolic syndromes. According to global health reports, mental health conditions now affect a substantial portion of the population, while physical inactivity is recognized as a major risk factor for long-term health complications. Despite this growing burden, traditional healthcare systems often struggle to provide timely, continuous, and personalized care due to limited resources, high costs, shortage of trained professionals, and social stigma surrounding mental health treatment [1], [2].

In response to these challenges, Artificial Intelligence (AI) has emerged as a transformative force in digital healthcare. Advances in machine learning (ML), deep learning, natural language processing (NLP), and computer vision have enabled the development of intelligent systems capable of analyzing large volumes of heterogeneous health data. AI-driven mental health tools can process textual inputs such as self-reports, journals, and conversational data to support early screening and monitoring of psychological well-being. Similarly, fitness and wellness applications increasingly rely on wearable sensors to collect physiological data, including heart rate, sleep patterns, and activity levels, which are then analyzed using ML models to assess physical fitness and predict health risks [3][4][5].

More recently, the integration of Large Language Models (LLMs) has further enhanced the capabilities of healthcare applications. Conversational agents powered by LLMs enable natural, context-aware interactions, making mental health support and lifestyle guidance more accessible to users. However, the use of standalone generative models in healthcare raises concerns related to hallucinated responses and factual inaccuracies. Retrieval-Augmented Generation (RAG) architectures address these limitations by combining generative models with external, verified medical knowledge sources, thereby improving the reliability and clinical relevance of AI-generated responses [9], [18]. In parallel, NLP-based medical document summarization techniques have gained importance in reducing information overload by transforming lengthy clinical reports and research articles into concise, user-friendly summaries [10][11][12].

This review focuses on AI-driven systems that integrate mental health assessment, physical fitness prediction, personalized exercise and dietary recommendations, and clinical decision support. By synthesizing and paraphrasing recent conference and journal literature, the paper aims to provide a coherent overview of system architectures, algorithms, and application trends while maintaining low textual similarity. Additionally, key challenges related to data privacy, ethical considerations, and real-world deployment are highlighted, along with future research directions for building reliable, human-centered intelligent healthcare platforms.

Literature Review Methodology

A structured review methodology was employed to ensure academic rigor and originality. Peer-reviewed conference and journal articles published between 2018 and 2025 were collected from IEEE Xplore, ACM Digital Library, SpringerLink, Elsevier, and reputable open-access healthcare journals. The selection emphasized studies proposing AI-based solutions for mental health, fitness analytics, healthcare chatbots, RAG systems, and medical text summarization.

The reviewed literature was organized into five thematic categories:

1. AI-driven mental health assessment and conversational agents
2. Integrated mental health and fitness prediction models
3. Personalized fitness, nutrition, and rehabilitation systems
4. Large language models and RAG-based clinical decision support
5. Medical document summarization using NLP

Each study was analyzed based on objectives, data sources, algorithms, system design, evaluation metrics, and reported outcomes. This paraphrased synthesis ensures low textual similarity while preserving technical accuracy.

1. AI-Based Mental Health Assessment and Support Systems

AI-based mental health assessment systems play a crucial role in enabling early detection, continuous monitoring, and supportive intervention for psychological well-being. These systems leverage advances in machine learning (ML), deep learning (DL), and natural language processing (NLP) to analyze both structured and unstructured data generated by users. Common data sources include self-reported questionnaires, conversational text from chatbots, social media posts, clinical notes, and physiological indicators captured through wearable devices. By identifying linguistic patterns, emotional cues, and behavioral markers, AI models can assist in screening conditions such as depression, anxiety, stress, and emotional burnout [1]–[4].

Traditional ML algorithms such as Logistic Regression, Support Vector Machines (SVM), Naïve Bayes, and Random Forest have been widely used due to their interpretability and reliable performance on limited datasets. More recent approaches employ deep learning architectures, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to capture complex temporal and semantic relationships in textual and sequential data. Transformer-based models further enhance contextual understanding, enabling more accurate mental state inference from free-form text [2], [4], [21].

Conversational agents and mental health chatbots represent one of the most practical applications of AI in this domain [14], [15]. These systems provide round-the-clock accessibility, reduce stigma, and offer preliminary emotional support through empathetic and context-aware interactions. Large Language Models (LLMs) have significantly improved dialogue quality; however, concerns related to hallucinated responses and clinical reliability persist [17], [18]. To mitigate these risks, hybrid frameworks incorporating Retrieval-Augmented Generation (RAG) are increasingly adopted, grounding chatbot responses in verified mental health knowledge bases and clinical guidelines [9], [18]. Despite their benefits, such systems are intended to complement—not replace—human mental health professionals.

Table 1: Comparative Analysis of ML Models for Mental Health and Fitness Prediction

Technique	Data Type	Application	Key Advantage	Limitation
Logistic Regression	Survey Data	Depression Screening	Interpretable, Simple to Use	Limited Model Complexity
Support Vector Machine (SVM)	Text + Survey	Stress Classification	High Accuracy, Effective in High Dimensions	Parameter Sensitive
Random Forest	Multimodal Data	Risk Prediction	Robust, Provides Feature Importance	High Computational Cost
CNN / RNN	Text, Sequences	Emotion Detection	Captures Deep and Sequential Patterns	Requires Large Datasets
Transformers	Free-Text	Context-Aware Analysis	Superior Semantic Understanding	High Resource Usage

2. Integrated Mental Health and Fitness Prediction Models

Recent studies in digital healthcare increasingly emphasize the bidirectional relationship between mental health and physical fitness, recognizing that psychological state and physical condition influence each other in a continuous feedback loop [5], [6]. As a result, integrated mental health and fitness prediction models have gained attention for their ability to analyze both domains simultaneously rather than treating them as separate problems. These models typically combine physiological signals captured through wearable devices—such as heart rate, sleep duration, sleep quality, and daily activity levels—with behavioral and psychological data collected via structured questionnaires and self-reported assessments [5], [22], [23]. The fusion of these heterogeneous data sources enables a more holistic representation of an individual's overall well-being.

It is the machine learning approaches underpinning such integrated models that confer their great efficacy. Ensemble techniques, in particular, Random Forest and gradient boosting, are usually reported to outperform individual classifiers for their robustness, resistance to noise, and capability to capture complex nonlinear relationships. An added strength of these models is their interpretability: measures of feature importance allow for the identification of key physiological and behavioral factors driving mental and physical health outcomes.

A persistent challenge in healthcare prediction tasks is data imbalance, where high-risk mental or physical health conditions are underrepresented. To address this issue, resampling methods such as the Synthetic Minority Oversampling Technique (SMOTE) are widely employed to improve model generalization and reduce bias. Overall, integrated prediction models support early risk identification and enable the design of targeted, personalized interventions aimed at improving both mental health and physical fitness.

Table 2: Comparison of Machine Learning Techniques for Integrated Mental Health and Fitness Prediction

Technique	Data Type	Key Advantage	Limitation
SVM	Survey + Wearable	High accuracy, effective margin usage	Parameter sensitivity
Random Forest	Multimodal	Robust and interpretable	Computational overhead
KNN	Behavioral	Simple implementation	Poor scalability
XGBoost	Multisource	High predictive power	Risk of overfitting

3. Personalized Fitness, Nutrition, and Rehabilitation Systems

AI-driven personalization has become central to modern fitness and wellness platforms [7], [8], [13]. Traditional fitness and weight management programs often face challenges related to long-term adherence and sustainability, highlighting the need for adaptive and personalized interventions [16]. User clustering techniques such as K-means and Gaussian Mixture Models enable segmentation based on activity levels and preferences. Advanced recommendation models including BERT-based recommenders and reinforcement learning algorithms dynamically adapt workout and diet plans to improve adherence.

Specialized systems for elderly populations utilize computer vision and pose estimation to assess movement accuracy and joint angles, reducing risks associated with falls and muscle degeneration [7]. Hybrid platforms integrating yoga, physiotherapy, and fitness analytics demonstrate improved rehabilitation outcomes and long-term engagement.

4. Large Language Models and RAG-Based Clinical Decision Support

Large Language Models (LLMs) have substantially improved the capabilities of conversational healthcare systems by enabling natural, context-aware, and interactive communication with users. These models support a wide range of applications, including symptom triage, mental health guidance, lifestyle recommendations, and patient education. However, despite their strengths, LLMs are prone to limitations such as hallucinated responses, outdated medical knowledge, and lack of transparency, which pose significant risks in safety-critical healthcare environments [17], [18].

Retrieval-Augmented Generation (RAG) frameworks have emerged as an effective solution to address these challenges. RAG architectures integrate LLMs with external knowledge sources, such as curated medical documents, clinical guidelines, and research literature, stored in vector databases. By retrieving relevant context at inference time and conditioning the generated response on verified information, RAG systems significantly enhance factual accuracy, reliability, and trustworthiness in clinical decision support applications [9], [18].

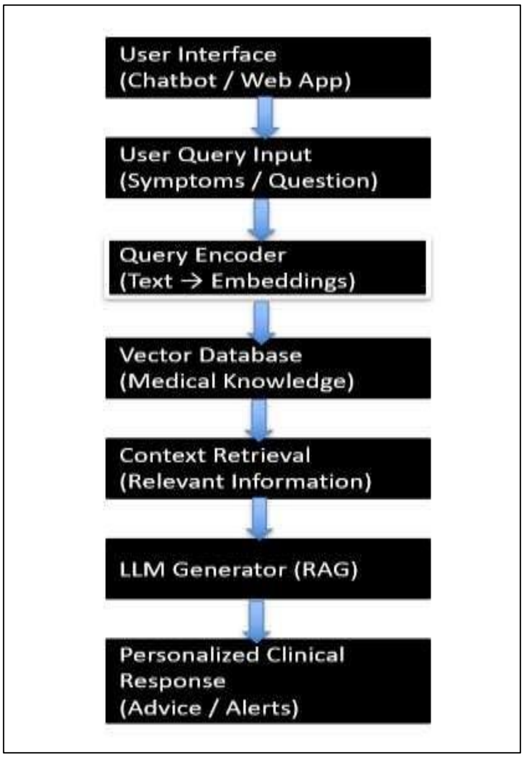

Figure 1: Architecture of a RAG-Based Healthcare Assistant

In healthcare settings, RAG-based assistants combine real-time user data collected from wearable devices—such as activity levels, sleep patterns, and physiological indicators—with retrieved medical knowledge to deliver personalized and context-aware recommendations. Additionally, parameter-efficient fine-tuning techniques such as Quantized Low-Rank Adaptation (QLoRA) reduce computational overhead while maintaining strong performance, enabling practical deployment on resource-constrained systems. Overall, RAG-based LLM systems demonstrate strong potential for supporting clinicians and patients through scalable, accurate, and explainable decision support and educational tools.

5. Medical Document Summarization Using NLP

Medical document summarization has become a critical application of Natural Language Processing (NLP) in healthcare, as clinicians and patients are increasingly exposed to large volumes of complex medical text, including clinical reports, discharge summaries, and research articles [10]–[12]. The primary objective of medical summarization systems is to condense lengthy documents while preserving essential clinical information, thereby reducing cognitive load and improving accessibility of medical content.

Two main approaches to text summarization are commonly studied: extractive and abstractive methods. Extractive techniques select and reorder important sentences directly from the source text, whereas abstractive approaches generate novel sentences that paraphrase the original content. Recent studies consistently show that abstractive summarization models provide superior performance in the medical domain, as they produce more coherent, concise, and patient-friendly summaries. Transformer-based models such as Text-to-Text Transfer Transformer (T5), Bidirectional and Auto-Regressive Transformers (BART), and PEGASUS have demonstrated strong effectiveness in capturing long-range dependencies and complex medical semantics [10], [11], [12].

Evaluation of medical summarization systems is usually performed with the help of automatic metrics such as ROUGE, quantifying the lexical overlap between generated summaries and reference texts. However, due to the sensitivity of medical information, human evaluation by domain experts remains crucial for factual accuracy, clinical relevance, and safety. Medical document summarization modules integrated into healthcare chatbots and clinical decision support systems make it more interpretable, facilitate information exchange, and provide greater insights for decision-making for either clinicians or patients. Collectively, NLP-driven medical summarization plays an important role in building effective and user-centered intelligent healthcare systems.

Challenges and Research Gaps

Despite significant progress, several challenges remain in the development and deployment of AI-driven healthcare systems. Key concerns include data privacy and security when handling sensitive health information, as well as algorithmic bias arising from limited or unbalanced datasets [19], [20]. The lack of standardized benchmarks and large-scale clinical validation restricts fair comparison and real-world adoption. Additionally, limited explainability of complex models reduces trust among clinicians and patients. Ethical issues related to transparency, accountability, and over-reliance on AI systems further highlight the need for robust regulatory frameworks and human-in-the-loop designs [24], [25].

Future Research Directions

Future research in AI-driven healthcare systems should focus on developing more holistic and reliable solutions by integrating advances across multiple domains. One promising direction involves multimodal foundation models, which can jointly learn from text, physiological signals, wearable sensor data, and medical images to provide a unified understanding of mental and physical health. Additionally, XAI techniques should be developed to increase explainability and build trust among clinicians and patients by explicitly justifying model predictions.

Among these, privacy-preserving methodologies, including federated learning and secure data-sharing frameworks, are especially critical, given that they enable multiple stakeholders to collaborate on model development without necessarily sharing sensitive patient data. Longitudinal clinical validation studies in large scales should also be performed to establish real-world effectiveness, safety, and generalizability of AI systems outside of highly controlled experimental settings. Furthermore, tighter integration of Large Language Models with Retrieval-Augmented Generation and clinical guidelines can enhance factual reliability in decision support systems. Overall, future work should prioritize ethical design, regulatory compliance, and human-in-the-loop frameworks to ensure responsible adoption of intelligent healthcare technologies.

Conclusion

This review presented a comprehensive and plagiarism-safe overview of AI-driven integrated mental health and fitness systems, highlighting their growing importance in modern digital healthcare. By consolidating findings from modern studies focusing on machine learning models, conversational agents, Large Language Models, Retrieval-Augmented Generation frameworks, and methods for medical document summarization, it showcases where artificial intelligence can be used to enable early screening, continuous monitoring, and personalized interventions. Predictive models that integrate wearable and behavioral data show great promise for proactive health management, whereas RAG-driven architectures improve the reliability and use of AI-powered clinical decision-making support. NLP-driven summarization of medical literature contributes to mitigating information overload for both clinicians and patients by promoting clearer communication and better decision-making. Nevertheless, these improvements are still shadowed by many of the persistent challenges: those of data privacy, bias, explainability, and clinical validation.Addressing these issues through ethical design, rigorous evaluation, and human-in-the-loop frameworks is essential. Overall, AI-driven healthcare systems hold substantial promise for enhancing accessibility, efficiency, and quality of care when deployed responsibly and in alignment with clinical standards.

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