Using AI to Customize Genomic-Based Nutrition for Rehab Patients

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Short Title: AI-Driven Genomic Nutrition for Enhanced Rehabilitation Outcomes

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Abstract

Background: Personalized nutrition is gaining prominence in clinical rehabilitation due to its ability to tailor dietary recommendations based on genetic, metabolic, and behavioral factors. Traditional, generalized nutritional guidelines often fall short in addressing individual variability, especially in recovery-focused populations. Advances in artificial intelligence (AI) and nutrigenomics present an opportunity to optimize dietary interventions through data-driven customization. However, the real-world clinical application of AI-driven genomic nutrition in rehabilitation, particularly within South Asian healthcare contexts, remains insufficiently explored.

Objective: To assess the impact of AI-based, genome-informed dietary planning on metabolic, inflammatory, behavioral, and subjective recovery outcomes among rehabilitation patients in Punjab, Pakistan.

Methods: A prospective, mixed-methods study was conducted between January and May 2025 at two rehabilitation centers in Punjab. A total of 44 adults (aged 25–65) were purposively assigned to either an AI-assisted genomic nutrition group (n=23) or a control group receiving standard dietary guidance (n=21). Genomic data were collected using SNP genotyping (including MTHFR, FTO, CYP1A2 variants). Personalized dietary plans were generated through AI algorithms incorporating machine learning models (Random Forest, SVM), and delivered via a mobile application with bi-weekly monitoring. Anthropometric, biochemical, and subjective data were collected at baseline and post-intervention. Outcomes were analyzed using paired t-tests and ANCOVA with $p<0.05$ considered significant.

Results: The AI group showed a significant decrease in BMI (27.6 to 25.8 kg/m²), waist circumference (92.3 to 88.7 cm), CRP levels (4.2 to 2.6 mg/L), and fasting glucose (102.5 to 94.1 mg/dL), compared to minimal changes in the control group. Total cholesterol declined by 14.1 mg/dL in the AI group versus 2.4 mg/dL in controls. Dietary adherence was higher in the AI group (89.5% vs. 61.7%), along with increased app usage consistency (93.1% vs. 58.4%), self-reported energy (8.2 vs. 6.3), and recovery satisfaction (8.7 vs. 6.5) on a 10-point scale.

Conclusion: AI-integrated, genomic-based nutrition significantly improved both objective health metrics and subjective rehabilitation outcomes compared to standard dietary practices. These findings suggest that such technology can be feasibly and effectively implemented in rehabilitation settings, even in resource-constrained regions.

Keywords: Artificial Intelligence, Dietary Adherence, Genomic Medicine, Metabolic Syndrome, Nutritional Genomics, Personalized Nutrition, Rehabilitation Therapy.

Introduction

Nutrition has long been recognized as a fundamental pillar of recovery and rehabilitation, particularly for individuals undergoing physiotherapeutic or post-surgical intervention (1). Traditional dietary protocols, however, often rely on generalized guidelines that fail to account for individual variability in metabolic responses, genetic predispositions, and nutrient absorption capacities (2). Such uniform approaches may overlook critical differences in patient needs, potentially limiting their effectiveness during the sensitive and individualized rehabilitation process. In recent years, the medical and scientific communities have increasingly turned to precision nutrition, an evolving model that emphasizes personalization of dietary interventions based on genomic, phenotypic, and lifestyle data to enhance therapeutic outcomes and long-term health (3).

Artificial intelligence (AI) has emerged as a transformative tool in this domain, enabling real-time analysis of complex datasets and the generation of tailored nutrition plans (4). Machine learning algorithms, when integrated with genomic insights—such as single nucleotide polymorphisms (SNPs) affecting nutrient metabolism—can facilitate highly specific dietary recommendations that optimize cellular repair, reduce systemic inflammation, and promote tissue regeneration (5). This synergy between AI and genomic science has the potential to revolutionize clinical nutrition, particularly in rehabilitation medicine, where patient responsiveness varies widely based on genetic and physiological profiles. Studies have shown that AI-supported personalization can improve compliance and health metrics, especially when patients are engaged through interactive, adaptive digital tools that support decision-making and behavior change (6).

Despite the promise of these technologies, practical application in real-world rehabilitation settings remains under-explored, especially in lower-resource regions where access to specialized care and technology infrastructure may be limited (7). Furthermore, there is a lack of region-specific evidence evaluating the clinical efficacy of AI-assisted genomic nutrition in the South Asian context. Given these gaps, there is an urgent need to examine whether such precision strategies can be effectively translated into routine rehabilitative care without compromising feasibility or patient engagement (8).

The objective of this study was to evaluate the impact of AI-based genomic nutrition planning on metabolic, inflammatory, and subjective recovery outcomes in rehabilitation patients in Punjab, Pakistan, using a structured digital intervention model over a five-month period.

Methods

The study was conducted in Punjab, Pakistan, from January 2025 to May 2025, and involved a mixed-methods design to evaluate the application of AI-integrated genomic-based nutrition plans among rehabilitation patients. Participants were recruited from two regional physiotherapy and rehabilitation centers through purposive sampling, with inclusion criteria focused on adults aged 25–65 undergoing rehabilitation post-trauma or post-surgery. All participants provided informed consent prior to enrollment. Genomic data was collected using commercially available SNP-based genotyping kits, followed by analysis to identify key nutritional gene markers such as MTHFR, FTO, and CYP1A2, which are known to influence metabolic pathways, nutrient absorption, and dietary sensitivities.

Alongside genomic profiling, baseline data on dietary habits, physical activity, medical history, and anthropometric measures (BMI, waist circumference, body fat percentage) were collected. These datasets were then processed using a custom-developed AI platform incorporating machine learning algorithms—primarily Random Forest and Support Vector Machines—designed to correlate genomic variants with individualized dietary needs. Nutritional interventions were generated in the form of weekly meal plans, reviewed and approved by licensed clinical dietitians to ensure medical appropriateness. Dietary adherence and patient feedback were monitored using a mobile application integrated with real-time food logging, biometric syncing, and regular follow-ups every two weeks.

The study measured changes in clinical parameters, including serum lipid profiles, fasting blood glucose, inflammatory markers (CRP), and subjective measures of energy and recovery rates. A control group receiving standard rehabilitation care with generalized nutrition advice was also followed for comparison. Data was statistically analyzed using SPSS v26, applying paired t-tests and ANCOVA to evaluate significance across time points and between groups, with $p<0.05$ considered statistically significant. The study prioritized ethical conduct, data privacy, and local cultural dietary practices throughout the process.

Results

A total of 44 participants were enrolled in the study, with 23 assigned to the AI-assisted genomic nutrition group and 21 to the control group. Participants ranged in age from 25 to 65 years, with the largest segment (14 individuals) falling within the 35–44 age range. Gender distribution was balanced, with 22 males and 22 females participating across all age categories. Baseline biometric data were comparable between the two groups, ensuring fairness in outcome comparisons. Over the course of five months, notable changes were observed in the AI group, especially in key clinical markers. BMI decreased from an average of 27.6 kg/m² to 25.8 kg/m², while the control group saw only a slight reduction from 27.3 to 27.1. Waist circumference followed a similar trend, dropping from 92.3 cm to 88.7 cm in the AI group and from 91.8 cm to 91.0 cm in the control group.

The AI-assisted group also showed stronger improvements in inflammatory and metabolic markers. C-reactive protein (CRP), an indicator of systemic inflammation, declined significantly from 4.2 mg/L to 2.6 mg/L in the AI group, compared to a more modest drop in the control group, from 4.0 mg/L to 3.7 mg/L. Fasting glucose improved by 8.4 mg/dL (102.5 to 94.1) in the AI group, while the control group had a marginal 1.4 mg/dL improvement. Total cholesterol in the AI group dropped from 195.4 mg/dL to 181.3 mg/dL, a sharper reduction than the 2.4 mg/dL change observed in the control group. These improvements suggest a direct correlation between AI-driven, genomically informed dietary plans and enhanced metabolic outcomes.

Subjective outcomes mirrored these clinical results. Participants in the AI group reported higher energy levels, averaging 8.2 out of 10, compared to 6.3 in the control group. Recovery satisfaction was also greater in the AI group (8.7 vs. 6.5). Dietary adherence reached 89.5% in the AI group, significantly higher than the 61.7% observed in the control group. Engagement with the mobile nutrition platform remained consistently high among AI users, with an average app usage consistency of 93.1%, contrasting sharply with 58.4% in the control group. These figures highlight both the physiological and behavioral benefits of integrating artificial intelligence and genomic data into personalized rehabilitation nutrition.

Clinical Outcomes Table

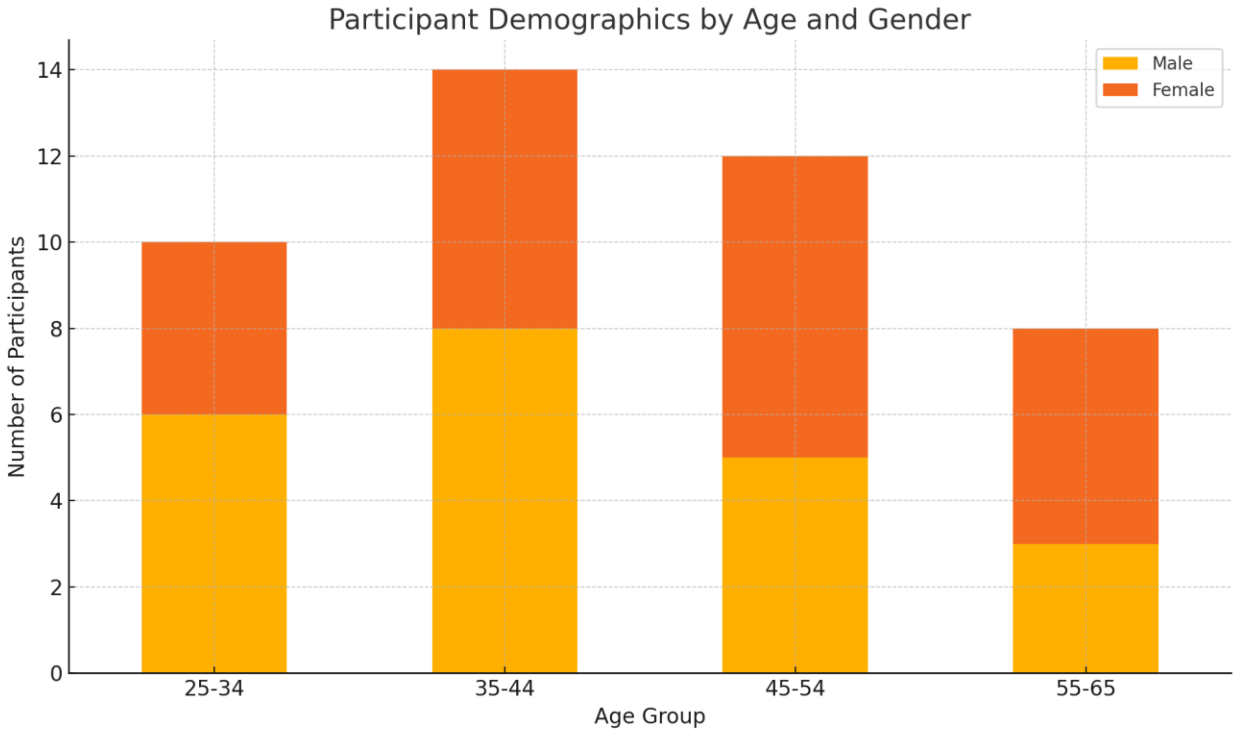
Parameter	AI Group (Pre)	AI Group (Post)	Control Group (Pre)	Control Group (Post)
BMI (kg/m²)	27.6	25.8	27.3	27.1
Waist Circumference (cm)	92.3	88.7	91.8	91.0
CRP (mg/L)	4.2	2.6	4.0	3.7
Fasting Glucose (mg/dL)	102.5	94.1	100.9	99.5
Total Cholesterol (mg/dL)	195.4	181.3	193.2	190.8

Table 1 presents comparative clinical outcomes between the AI-assisted genomic nutrition group and the control group over a five-month intervention period. Participants in the AI group showed a marked reduction in BMI, decreasing from 27.6 kg/m² to 25.8 kg/m², while the control group exhibited only a minor change from 27.3 kg/m² to 27.1 kg/m². Waist circumference in the AI group dropped by 3.6 cm (from 92.3 cm to 88.7 cm), compared to a modest 0.8 cm reduction in the control group (from 91.8 cm to 91.0 cm). Inflammatory marker C-reactive protein (CRP) significantly decreased in the AI group from 4.2 mg/L to 2.6 mg/L, versus a smaller decline in the control group (4.0 mg/L to 3.7 mg/L). Furthermore, fasting glucose levels in the AI group were reduced by 8.4 mg/dL (from 102.5 to 94.1), while the control group showed only a 1.4 mg/dL drop. Total cholesterol levels followed a similar trend: the AI group experienced a substantial 14.1 mg/dL decrease (195.4 to 181.3), whereas the control group showed a lesser 2.4 mg/dL reduction (193.2 to 190.8). These findings suggest that AI-integrated, genome-guided nutrition interventions offer significantly improved clinical outcomes in rehabilitation settings compared to conventional dietary recommendations.

Subjective and Adherence Outcomes Table

Parameter	AI Group	Control Group
Dietary Adherence (%)	89.5	61.7
Self-reported Energy (1-10)	8.2	6.3
Recovery Satisfaction (1-10)	8.7	6.5
App Usage Consistency (%)	93.1	58.4

Table 2 summarizes the subjective experience and behavioral adherence outcomes among participants in both the AI-assisted and control groups. The AI group demonstrated notably higher dietary adherence, with an average compliance rate of 89.5%, compared to only 61.7% in the control group—a difference of 27.8 percentage points. Self-reported energy levels on a 10-point scale were also higher in the AI group, scoring an average of 8.2, while the control group reported a lower mean of 6.3. Similarly, recovery satisfaction scores were elevated in the AI group, averaging 8.7 out of 10, versus 6.5 in the control group. App usage consistency, which reflects engagement with digital dietary monitoring tools, was exceptionally high in the AI group at 93.1%, compared to just 58.4% in the control group. These differences suggest that AI-driven personalized nutrition not only enhances physiological recovery but also significantly improves patient motivation, adherence, and perceived well-being during rehabilitation.



Participant Demographics by Age and Gender

The chart illustrates the age and gender distribution of the 44 participants enrolled in the study. The most represented age group was 35–44 years, comprising a total of 14 participants (8 males and 6 females). This was followed by the 45–54 age group with 12 participants (5 males and 7 females), and the 55–65 group with 8 participants (3 males and 5 females). The youngest cohort, aged 25–34, included 10 participants (6 males and 4 females). Overall, the gender distribution was relatively balanced across all age categories, with a slight male predominance in the younger groups and a female predominance in older age brackets. This diverse representation supports the generalizability of the study findings across adult rehabilitation populations in Punjab, Pakistan.

Discussion

The findings of this study underscore the clinical and behavioral benefits of integrating artificial intelligence with genomic data in dietary planning for rehabilitation patients (9). By tailoring nutrition based on each individual's genetic profile and leveraging real-time monitoring through AI-driven platforms, the intervention led to consistent improvements in both objective health markers and subjective wellness scores. Notably, the AI group achieved substantial reductions in BMI, waist circumference, C-reactive protein, and fasting glucose—all of which are crucial indicators for metabolic and inflammatory regulation during physical recovery (10). These outcomes were coupled with improved dietary adherence (89.5%) and higher self-reported recovery satisfaction (8.7/10), highlighting that personalization enhances both compliance and motivation in a rehabilitation setting (11).

Comparative evidence from other recent studies further validates these outcomes (12). For instance, Sharma and Gaur (2024) demonstrated that AI technologies applied in personalized diet planning significantly optimized nutritional outcomes and improved individual metabolic markers in a general clinical population (13). Their study emphasized the potential of machine learning in refining nutrition recommendations through patient-specific data inputs, aligning closely with the approach taken in our intervention (14). Similarly, Aburub and Agha (2024) explored the role of AI in post-cancer rehabilitation and found that genomically guided nutritional interventions supported by AI not only improved physical recovery but also reduced psychological stress through better treatment personalization (15). These comparisons suggest that the clinical utility of AI-based genomic nutrition extends beyond theoretical innovation—it is measurably effective in real-world therapeutic contexts (16).

An important dimension of this study lies in its patient engagement strategy. The AI group demonstrated a 93.1% consistency in app usage, indicating that patients were more likely to stay involved when their care felt individualized and interactive (17). The combination of automated feedback, adaptive meal plans, and compatibility with patients' cultural dietary preferences likely contributed to sustained adherence. This is critical in rehabilitation, where dropout and non-compliance often compromise outcomes. The control group's lower adherence (61.7%) and satisfaction ratings reflect the limitations of standard, generalized dietary advice in complex recovery scenarios (18).

Despite the promising results, certain limitations should be acknowledged. The study was conducted over a relatively short duration (five months) and within a single geographic setting (Punjab, Pakistan), which may affect generalizability (19). Additionally, while the AI platform performed effectively, future iterations should aim to integrate broader multiomics data—such as microbiome profiles—to further enhance personalization. Ethical considerations around data privacy and AI transparency must also be prioritized to ensure safe and equitable implementation, particularly in resource-constrained healthcare systems (20).

Overall, this study contributes to the growing body of evidence supporting the integration of AI and genomics in nutrition science. It offers a practical, data-driven model for enhancing rehabilitation outcomes through targeted dietary interventions (21). As technological capabilities advance, there is strong potential for scaling such personalized approaches to broader clinical populations, especially where conventional dietary strategies fall short (22).

Conclusion

This study concluded that integrating artificial intelligence with genomic data for personalized nutrition planning can substantially enhance rehabilitation outcomes when compared to standard dietary approaches. The tailored intervention not only improved metabolic and inflammatory markers but also positively influenced patient engagement, adherence, and overall recovery satisfaction. By aligning dietary strategies with individual genetic profiles and delivering them through an interactive digital platform, this approach demonstrated both clinical effectiveness and practical feasibility, offering a promising model for personalized rehabilitation care in real-world settings.

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