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Predictive Analytics Framework Using Machine Learning for Personalized Nutrition and Lifestyle Recommendations: A Technical Approach toward Women's Wellness

[1]Sonali R. Patil, [2]Dr. Rupali H. Patil

[1]Research Scholar, S.S.V.P.S's L. K., Dr. P. R. Ghogre Science College, Dhule, Maharashtra, India

[2]Professor, S.S.V.P.S's L. K., Dr. P. R. Ghogre Science College, Dhule, Maharashtra, India

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Abstract

The use of artificial intelligence, machine learning and predictive analytics in nutrition and lifestyle studies has expanded rapidly. However, many of the studies that are currently available are not sufficiently addressing women-specific health issues. The purpose of this study is to examine and compile the most current studies on AI and machine learning-based methods for evaluating women's nutrition and lifestyle. A comprehensive review of published research was carried out, with particular focus on studies that used machine learning methods for nutrition and health analysis, including Random Forest, Decision Tree, Support Vector Machine, K- Nearest Neighbours, and Naive Bayes. Less than 20% of the examined 30 peer-reviewed publications address individualized lifestyle or nutrition guidance systems, specifically for women, whereas more than 70% concentrate on obesity prediction or nutrient deficiency detection. These findings suggest a significant research gap in integrated predictive analytics frameworks that are women-centric. In order to create more individualized and data-driven nutrition and lifestyle solutions for women's health, this review offers recommendations for future research on AI- and ML-based blended framework represents a meaningful step toward personalized wellness recommendations. Tailoring dietary and lifestyle guidance specifically to women is a promising direction that aligns with modern trends in precision health.

Introduction

A lot of factors, including nutrition, exercise, stress, sleep patterns, and general lifestyle choices, affect women's health and fitness. [1].Because each woman's body, surroundings, and routine are unique, it can be challenging to maintain a healthy balance between these factors.[2] Because not everyone responds well to general diet or exercise habits, there is an increasing demand for individualized health advice.[3]

Large volumes of lifestyle and health data can now be analysed to develop personalized nutrition and wellness plans thanks to the quick development of artificial intelligence (AI) and machine learning (ML).[4] In order to recommend what is most effective for each individual, predictive analytics assists in identifying patterns in individual behaviour, food preferences, and bodily parameters.[5]

The goal of this study is to create a predictive analytics framework that can suggest individualized lifestyle and nutrition plans for women.[6] The suggested system includes use of information about body composition, diet, exercise, and metabolic markers.[7] In order predict health outcomes and offer specific recommendations, the framework combines AI and ML algorithms.[8] It seeks to support improved fitness outcomes, minimize the risk of disorders related to nutrition, and encourage women's long-term wellness.[9]

Related Work

Based on a person's genetics, lifestyle, and health information, author Pakapon Rojanaphan investigates how machine learning can enhance individualized dietary recommendations. The author emphasizes that conventional diets are frequently too universal and unsuitable for all people. Precision nutrition, on the other hand, considers the particular requirements of every person. Data for the study came from a variety of sources, including blood tests, fitness equipment, diet tracking apps, and DNA testing. Machine learning models like Random Forest, CNN, and RNN were used to analyze this information and predict what kind of diet would work best for someone. The results were promising—people who followed ML-based recommendations saw improvements in their health, like lower BMI and better glucose control. The study shows that using AI in nutrition can lead to more effective and personalized health plans. The author suggests that future systems could include even more detailed biological data to make diet advice even more specific to each person.[1]

Suchita Arora et al. investigated in 2024 how machine learning could be used to improve employee well-being by creating predictive models for wellness and health initiatives. A customized employee health and wellness dataset that included variables like work-life balance, physical activity, stress levels, sleep, and nutrition was used in the study. Handling missing values, encoding categorical variables, scaling features, and choosing the most pertinent attributes for modeling were all part of the data preprocessing process. To identify workers who may be at risk for health or wellness problems, the authors used Scikit-learn to implement a Random Forest algorithm. The model's ability to precisely identify at-risk workers allowed for focused interventions, according to the results.. The strategy increased organizations' cost effectiveness and wellness outcomes. The model showed good predictive ability with an accuracy of roughly 0.92. This study offers a scalable and data-driven approach for proactive wellness initiatives, demonstrating the potential of machine learning in workplace health management. [2]

Tagne Poupi Theodore Armand et al. carried out a scoping review in 2024 on the use of AI in nutrition research, examining 66 relevant studies that made use of a variety of datasets, such as surveys, cohort studies, food images, clinical data, and dietary records. Each study used a different approach to data preprocessing, which included cleaning, normalization, and text or image preprocessing specific to the AI method used. Natural language processing (NLP), convolutional neural networks (CNN), artificial neural networks (ANN), support vector machines (SVM), decision trees, k-nearest neighbors (KNN), and ensemble learning are just a few of the AI and machine learning techniques used in the reviewed studies.. These methods were used for tasks like health prediction, nutrient analysis, and dietary assessment. Nutrient intake, food classification, dietary patterns, and related health risks were among the important factors that were investigated. Results showed that AI greatly improves accuracy in nutrition prediction, food classification, and customized dietary advice. Depending on the model type and dataset quality, reported accuracies in various studies varied from 78% to 99%. The review emphasizes how AI has the potential to improve dietary health interventions and advance precision nutrition. [3]

In 2023 the author Laura Moreno-González et al. analysed 2255 children and adolescents (aged 6–17 years) from rural Spain involved in extracurricular sports.. Validated field tests were used to measure physical fitness, bioelectrical impedance analysis was used to determine body composition, and the KIDMED questionnaire was used to gauge adherence to the Mediterranean diet. Health indicators were predicted using statistical modeling based on training characteristics, age, sex, and sport modalities. The results show that physical fitness and body composition are strongly influenced by sport modality, training frequency, intensity, sex, age, and maturational stage. Sports participation has a positive impact on anthropometric and health metrics, highlighting the value of consistent physical activity for young people.. However, compared to other modalities, combat sports were linked to lower levels of cardiorespiratory fitness, highlighting the necessity of customized approaches. In light of sex, age, and developmental stage, the study recommends that future strategies concentrate on tracking sports modalities and related health risks, especially in populations participating in combat sports. By encouraging ideal training and balanced development, this strategy seeks to prevent health issues, such as cardiorespiratory deficiencies, in adulthood.[4]

The Author Arash Golibagh Mahyari, Peter Pirolli developed a system to help people make better exercise choices using mobile technology like smartphones and smartwatches.. The goal of the study is to promote healthier behaviors like exercise. The authors presented a dual-recurrent neural network (RNN) model that performs two primary functions: it predicts whether an individual will successfully finish the next workout and suggests the next workout based on the individual's previous activity. The model outperformed previous models in terms of accuracy after being trained and evaluated using data from a four-week mobile health study. The intriguing aspect is that, while the system functions better with more user history, it still functions well for new users without any prior data. The researchers also point out that when data is scarce, relying solely on machine learning may present challenges. They propose using psychological models like ACT-R, which can produce insightful predictions even with little to no training data, in conjunction with machine learning to address this issue. The machine learning component gets more precise with time and can even aid in enhancing the psychological models as more data is gathered. This study demonstrates how integrating various strategies can result in more intelligent, beneficial health recommendation systems that adjust to the needs of specific users. [5]

Vesna Knights, Mirela Kolak, Gordana Markovikj, and Jasenka Gajdoš Kljusurić studied artificial intelligence modeling and optimization in nutrition in 2023, with an emphasis on obesity prediction. Information from 200 participants in a supervised ketogenic weight loss program from Skopje and Priština made up the dataset. Data cleaning, normalization, categorical conversion, outlier removal, and an 80/20 train-test split were among the preprocessing procedures. The authors used Keras to create a neural network model in Python that used L2 regularization, dropout, and ReLU and Sigmoid activation functions. They then compared the model's performance to that of a Random Forest model. Age, gender, BMI, MCHC, ALT, triglycerides, TSH, magnesium levels, platelets, leukocytes, cholesterol, glucose, and triglycerides were among the important characteristics that were used. The neural network performed better than the Random Forest, according to the results, exhibiting high performance metrics, strong generalization, and efficient obesity prediction. The model obtained an F1 score of 0.98, precision of 0.96, recall of 1.0, validation accuracy of 0.98, and training accuracy of 1.0. These results highlight the potential of deep learning methods for managing obesity and ensuring precision nutrition.[6]

The dataset used in this paper, which has 2111 rows and 17 columns that indicate the data's attributes, was examined by authors Jayvee Ryan Banal, Kenneth Dynielle Lawas, and Laurice M. Mariquina (2023). An online platform with a survey was used to collect data for the computation of obesity levels in adults from Mexico, Peru, and Colombia, ages 14 to 61, with a range of dietary patterns and physical conditions. To prevent BMI bias, the dataset contained 15 dietary and lifestyle characteristics, excluding height and weight. A number of characteristics, including age, gender, smoking, alcohol use, physical activity, family history, eating habits, and technology use, were subjected to predictive analysis. To assess classification performance, machine learning methods like Random Forest, K-Nearest Neighbor (KNN), Gradient Boosting, and AdaBoost were used. With the highest accuracy of 83.6%, Random Forest was followed by AdaBoost at 73.7%, Gradient Boosting at 81.4%, and KNN at 80.7%. According to the study's findings, Random Forest is the most accurate method for identifying obesity in behavioral data. Future research will focus on enhancing model performance through parameter tuning and applying the framework to actual health applications in order to anticipate and prevent conditions linked to obesity. [7]

A study on modeling and optimization with artificial intelligence in nutrition, with a focus on predictive modeling for health-related outcomes, was presented in 2023 by Vesna Knights, Mirela Kolak, Gordana Markovikj, and Jasenka Gajdoš Kljusurić. 200 participants from Skopje, North Macedonia, and Priština, Kosovo, made up the dataset. Data normalization, outlier elimination, categorical conversion, and the use of dropout and weight regularization to improve model generalization were all part of the preprocessing process. Age, gender, BMI, height, weight, cholesterol, glucose, platelets, leukocytes, MCHC, ALT, TSH, and magnesium levels were among the important characteristics. The main predictive model was a neural network constructed using Keras, and performance comparison was done using the Random Forest algorithm. The neural network outperformed the Random Forest model in terms of classification metrics, low loss, and high prediction accuracy, according to the results. With an F1-score of 0.98 and 98% validation accuracy, the final neural network demonstrated strong predictive power. This study shows how AI-driven models can help with health management and precision nutrition..[8]

According to research by author Javeria Ali et al., malnutrition is a serious health concern for women in Asia, including Pakistan. To determine whether a woman is likely to experience malnutrition, the researcher has created a model. They trained this prediction model using a variety of machine learning techniques, including K-Nearest Neighbors, Random Forest, Support Vector Machine, Logistic Regression, and Naïve Bayes. The Random Forest model outperformed the others and produced the most accurate findings. Women's nutrition was analyzed in this study using a variety of machine learning techniques, including Decision Trees, Logistic Regression, Random Forest, KNN, and SVM. A program known as Jupyter Notebook was used to complete the task. The study demonstrated that a model's accuracy and quality increase with the amount of data it contains. Additional data and health surveys are required to further enhance the prediction system. Women of all ages can use the model created in this study to identify early indicators of nutrition issues and take appropriate action before the situation worsens. [9]

Using deep learning models, Hyerim Kim, Dong Hoon Lim, and Yoona Kim studied how dietary intake affected overweight/obesity, dyslipidemia, hypertension, and type 2 diabetes mellitus (T2DM) in 2021. Data from the 4th through 7th Korea National Health and Nutrition Examination Survey (KNHANES, 2007–2018) were used in the study. To guarantee model robustness, data preprocessing included removing outliers and missing values, normalizing features, and using five-fold cross- validation. In addition to structural equation modeling (SEM) for further analysis, a Deep Neural Network (DNN) built in Python with Keras and TensorFlow was put into practice and contrasted with logistic regression and decision tree models. Energy intake was found to be the most significant factor, and the DNN continuously outperformed the baseline models in terms of predictive accuracy. Accuracy values for dyslipidemia, hypertension, and type 2 diabetes were reported to be 0.58654, 0.79958, 0.80896, and 0.62496, respectively. These results demonstrate how well deep learning techniques can predict complicated health outcomes. The study also highlights how crucial dietary energy intake is for controlling risks to metabolic health..[10]

Using a hybrid SEM-ANN model, Maryam M. Kheirollahpour, Mahmoud M. Danaee, Amir Faisal A. F. Merican, and Asma Ahmad A. A. Shariff examined the prediction of significant factors on eating behaviors in 2020. 340 randomly chosen University of Malaya students from a variety of faculties participated in the study. The resulting factor scores were utilized as inputs to an Artificial Neural Network (ANN) after linear preprocessing using Partial Least Squares Structural Equation Modeling (PLS-SEM). A 70/15/15 ratio was used to divide the data into training, testing, and validation sets. The Levenberg–Marquardt algorithm was used to optimize the hybrid approach, which combined SEM with a multilayer perceptron (MLP) ANN architecture of 3-17-8. Body Appreciation (BA), Body Shape Concern (BSC), and the Emotional Eating Scale (EES) in connection to Eating Behavior Patterns (EBP) were among the important variables that were investigated. The hybrid model performed better than SEM alone, according to the results, with $R2$ increasing by 27% and MSE falling by 9.6%. Significant psychological predictors of eating behavior were identified by the optimal network, which had an $R2$ of 0.624 and an MSE of 0.559. This study demonstrates how well SEM and ANN work together for intricate behavioral modeling. [11]

Amin Gasmi investigated the use of bioinformatics and machine learning in 2020 for the analysis and diagnosis of obesity spectrum disorders. The study used a variety of data sources, such as genetic profiles, genome-wide association study (GWAS) datasets, electronic medical records (EMRs), and public health datasets. Preprocessing methods included clustering, bootstrapping, dimensionality reduction, K-fold cross-validation, and feature selection using the Minimum Redundancy Maximum Relevance (MRMR) approach. In addition to bioinformatics tools for neural imaging, biomarker identification, and genomic/epigenetic analysis, a variety of machine learning models were used, such as Decision Trees, Support Vector Machines (SVM), Random Forest, Gradient Boosting Machines (GBM), Artificial Neural Networks (ANN), LASSO regression, and Bayesian Networks. BMI, waist circumference (WC), waist-hip ratio (WHR), genetic loci, and environmental or lifestyle factors were among the important variables that were investigated. The results showed that precise obesity risk prediction and classification are possible when machine learning and bioinformatics are combined. Early diagnosis is supported by this integrated approach, which also makes it easier to create individualized intervention plans. The study emphasizes how crucial multidimensional data is to enhancing the accuracy and efficacy of managing obesity.[12]

By identifying various nutritional "phenotypes"—groups of people who react differently to diet and physical activity—Ramyaa Ramyaa, Omid Hosseini, Giri P. Krishnan, and Sridevi Krishnan's 2019 study investigated how machine learning could be used to support personalized nutrition. Based on variables such as food consumption (carbohydrates, fats, proteins, sugars, and fibers) and degrees of physical activity (mild to vigorous), they aimed to forecast body weight. They tested various machine learning techniques, including Support Vector Machine (SVM), neural networks, and k-nearest neighbors (kNN), using data from the Women's Health Initiative Observational Study. These models predicted body weight and BMI categories with a moderate degree of accuracy. The researchers also employed clustering techniques to help group people with similar traits into ten possible phenotype clusters in order to improve predictions and identify patterns. For some individuals, these clusters showed promise in improving prediction accuracy. Despite certain drawbacks, including the use of self-reported data and some prediction errors, the study demonstrates how machine learning can be used to tailor nutrition and determine which diets might be most effective for various populations, particularly postmenopausal women. According to the researchers, this type of method can be helpful in identifying false food reporting and customizing early nutrition warnings in large health studies. They also point out that further research, such as controlled feeding trials, is required to verify the effectiveness of this approach in practical situations. Overall, this research represents an early step toward building personalized diet plans using machine learning.[13]

Talko Dijkhuis et al. (2018) Data from the Het Nieuwe Gezonde Werken (HNGW) program, in which 48 employees received biweekly coaching sessions and used Fitbit Flex devices to track their daily physical activity, was used in the study. Cleaning up incomplete data, aggregating step counts to hourly intervals, and generating features (day, hour, week, and cumulative steps) were all part of the preprocessing process. ADAboost, Decision Tree, Random Forest, and Stochastic Gradient Descent (SGD) were used as machine learning classification models. Customized time-sliced models were created for the entire week, weekends, and weekdays to forecast if participants would meet their daily step targets. When it came to predicting the achievement of daily step goals, individualized machine learning models performed better than group-level models. With F1-scores as high as 0.96, the Random Forest algorithm performed the best. Predictive accuracy was increased through time-sliced modeling (weekday versus weekend). Stronger outcomes were obtained by combining customized models, which supports the incorporation of these techniques into virtual coaching platforms and preventive eHealth systems to facilitate prompt interventions. By adding contextual information like leisure time, regular exercise, and illness, the authors propose improving prediction accuracy. To find the best combinations, they advise building time-sliced weekend and week models for each person. Developing day-specific customized models for every person is an additional approach that could improve adaptive eHealth coaching systems..[14]

[15] Sharon M. Donovan et al.2025 The paper is a comprehensive expert review based on discussions held during a 2023 virtual workshop by the Personalized Nutrition Initiative at the University of Illinois. It explores challenges and strategies in integrating health, behavioral, environmental, and consumer purchasing data for personalized nutrition (PN).The study highlights the need for standardized data architecture, ethical data sharing, and equitable PN programs. It emphasizes using AI and machine learning responsibly for data fusion and personalized health outcomes. Future efforts include developing shared AI-ready data repositories, incentivizing cross-sector data sharing, establishing global standards, and refining algorithms for scalable, inclusive, and effective PN applications.[15]

The author M. Fátima Domingues et al.(2025) This editorial synthesizes findings from six interdisciplinary studies exploring smart devices and AI tools in personalized nutrition and lifestyle behavior change. It highlights AI-driven meal recommendations, mobile health (mHealth) platforms, and neural networks for dietary analysis.

Domingues et al. conclude that smart technologies, particularly AI and mHealth tools, offer promising potential to personalize health interventions, enhance self-management, and support chronic disease prevention. They also stress the value of interdisciplinary approaches combining nutrition, digital health, and behavioural science.Future research should focus on validating digital tools in real-world settings, refining AI models, and improving access in underserved populations.[16]

The author Jakob Linseisen et al.(2025) presented a perspective paper proposing

Adaptive Personalized Nutrition Advice Systems (APNAS), integrating biomedical, psycho-behavioral, and food environment data. They analyzed current limitations of personalized nutrition and suggested a multidimensional, dynamic framework using AI, mobile sensors, and real-time data. Existing PN models are narrow and fail to serve diverse populations. The APNAS model offers a scalable solution by considering individual behaviors, constraints, and environments alongside biological data.Emphasis is placed on refining real-time personalized interventions, enhancing interoperability of devices, ensuring ethical data use, and developing explainable AI-driven PN systems.[17]

The literature review for the article by İdil Alpat Yavaş et al. (2024) in A cross-sectional study was conducted on 3,459 white-collar adults aged 18–65 in Türkiye to assess their nutrition literacy (NL), adherence to the Mediterranean diet, and lifestyle factors. Data were collected using validated instruments: the EINLA for NL, MEDAS for diet adherence, SF-36 for quality of life, and IPAQ for physical activity. Anthropometric data were also measured. Statistical analysis was performed using SPSS with appropriate tests (Chi-square, Kruskal-Wallis, Spearman correlation).The study found that individuals with higher NL had significantly better adherence to the Mediterranean diet, healthier anthropometric measurements (lower BMI and waist circumference), higher physical and mental quality of life scores, and greater physical activity levels. NL was positively associated with income, education, and gender (higher in females). Thus, NL emerged as a key factor in promoting healthier lifestyle choices and preventing noncommunicable diseases.The authors recommend longitudinal studies to establish causality between NL and health outcomes. They also suggest expanding research across diverse occupational and socioeconomic groups to ensure generalizability. Additionally, tailored nutrition education and interventions are advised to raise awareness and improve NL in broader populations.[18]

Janaka Godevithana, Champa J. Wijesinghe, and M. S. D. Wijesinghe (2024) This 2024 cross-sectional study surveyed 518 sedentary office workers in Southern Sri Lanka using dietary recall and questionnaires. Only 4.6% adhered to Sri Lankan dietary guidelines. Group eating and meal skipping were linked to poor diet, though multivariate analysis showed no significant predictors. The study concluded dietary intake was imbalanced, especially lacking fruits, dairy, and nuts. Future research should assess broader worker groups and explore long-term effects of dietary habits to guide effective nutrition interventions.[19]

The author Madhumeeta veeramreddy et.al (2024) propses the study NutriVision, a smart healthcare system using Faster R-CNN for food detection from images, combined with a custom nutrition database to estimate nutritional values. The system applies content-based and collaborative filtering using NLP (TF-IDF and cosine similarity) and SVD for personalized diet recommendations. NutriVision enables accurate food identification, nutritional estimation, and real-time personalized dietary advice using health data like BMI, dietary preferences, and health history. The system achieves 92% classification accuracy and includes an interactive chatbot for improved engagement.Plans include removing the need for a reference object in food quantification, enhancing IoU and precision, expanding food categories, integrating real-time updates, and aligning with national dietary guidelines for broader applicability.[20]

Hitomi Suzuki, Phyu Phyu Tun, Shuxian Liu, Erika Ota, Naoko Arata (2025)

In 2025, the authors conducted a systematic review of four RCTs involving 1965 women planning to conceive, assessing web-based lifestyle interventions. Methods included mobile apps, email-based programs, and conversational agents. Results showed modest improvements in systolic blood pressure, serum folate, and physical activity. However, no significant changes were found for diet, folic acid intake, smoking, alcohol use, BMI, or pregnancy outcomes. The authors concluded that digital interventions have limited but promising effects. Future work should include larger, high-quality trials with standardized outcomes to better inform preconception care strategies.[21]

Ritu Ramakrishnan, Tianxiang Xing, Tianfeng Chen, Ming-Hao Lee, Jinzhu Gao (2023)

In 2023, the authors developed an AI-based personalized nutrition recommendation system using machine learning and deep learning techniques, including BERT and neural networks. The system integrated chatbots, exercise, supplement, and nutritionist recommenders. It utilized user data such as BMI, dietary preferences, and fitness goals to provide tailored suggestions. The results showed effective performance in personalized meal and fitness planning. The study concluded that AI enhances lifestyle interventions. Future work includes real-time data updates, improved user interaction, expanded nutritionist databases, and addressing data privacy and accuracy concerns.[22]

Tanvir Islam, Anika Rahman Joyita, Md. Golam Rabiul Alam, Mohammad Mehedi Hassan, Md. Rafiul Hassan, Raffaele Gravina (2023) In 2023, the authors proposed the AMRP system—an EEG-based personalized meal recommendation and menu planning framework. Using Emotiv Epoc+ EEG signals and self-assessment, they measured affectivity (liking, excitement, feelings) toward food images. Feature extraction (STFT, DWT, HHT) and ensemble classifiers predicted food preferences. TOPSIS was applied for food ranking, and a bin-packing algorithm created nutrition-aware menus. Results showed promising accuracy in affect-based predictions. The study concludes affective computing improves personalization. Future work suggests integrating deep learning methods and expanding neural datasets for broader real-world application and user-specific adaptation.[23]

The author Sangeetha Shyam et al.(2022) This was a systematic review of randomized controlled trials evaluating the effect of personalized nutrition (PN) interventions on dietary intake, physical activity, and health outcomes. The authors reviewed 9 studies with a total of 2322 participants from diverse geographic regions. The review found inconsistent evidence for the effectiveness of PN in improving diet, physical activity, and health outcomes. Salt reduction showed the most consistent benefit. Future research should focus on long-term effects, larger sample sizes, pediatric populations, and standardized intervention reporting for better implementation and replication.[24]

The author Rachael Jinnette et al.(2021) Jinnette et al. conducted a systematic review of 11 randomized controlled trials from 2009–2020 involving healthy adults, comparing the effectiveness of personalized nutrition (PN) advice—based on dietary, phenotypic, or genetic data—against generalized dietary guidance. Studies were assessed using quality checklists and behavior-change frameworks. PN advice led to modest improvements in dietary intake compared to general advice, especially when combined with behavior-change techniques. However, evidence supporting the added value of genetic information was limited. More rigorous RCTs are needed, emphasizing behavior-change models, broader personalization bases, and standardized dietary outcome measures.[25]

The authors conducted a systematic review using the TIDieR (Template for Intervention Description and Replication) checklist to assess the impact of workplace lifestyle programmes on diet, physical activity, and weight-related outcomes specifically for working women. The review included 20 studies (with 26 intervention arms) selected from seven databases, applying strict inclusion criteria and risk of bias tools (RoB 2.0 and ROBINS-I)

The study found that workplace interventions had a positive effect on physical activity and lifestyle behaviors in working women. Group-based delivery, higher session counts, tailored components, and involvement of non-health professionals contributed to better physical activity outcomes. However, the effectiveness of interventions on dietary behavior and weight outcomes was less consistent.

The authors suggest that future research should explore the mechanisms of intervention success using gender-sensitive approaches and real-world workplace implementations. Further trials are recommended to evaluate long-term effects and the specific needs of working women in various occupational environments.[26]

Alicia Gea Cabrera, Pablo Caballero, Carmina Wanden-Berghe, María Sanz-Lorente, Elsa López-Pinto 2021. A systematic review, meta-analysis, and meta-regression of 13 workplace dietary intervention studies targeting metabolic syndrome (MetS) risk factors among workers, using PRISMA guidelines. Multi-component interventions, especially those including coaching and physical activity, had the most positive effects—such as increased HDL and reduced BMI.Improved strategies are needed to enhance the long-term effectiveness of workplace dietary interventions in reducing MetS risks.[27]

The author José L. Peñalvo, et al (2021) conducted a comprehensive systematic review and meta-analysis of 121 studies (82 randomized controlled trials and 39 quasi-experimental designs) published between 1990 and 2020. They followed PRISMA guidelines, extracted data from multiple databases, and assessed the effectiveness of multicomponent workplace wellness programmes on dietary intake, anthropometrics, and cardio metabolic risk factors using inverse-variance random-effects meta-analysis.

The study concluded that workplace wellness programmes significantly improved fruit and vegetable intake, reduced BMI, waist circumference, blood pressure, LDL cholesterol, and other risk markers. However, there was high heterogeneity across studies and small-study effects were noted for some outcomes, suggesting the need for cautious interpretation.

The authors recommended more long-term and large-scale trials in diverse socioeconomic settings. They emphasized evaluating cost-effectiveness, sustainability of interventions, and tailoring strategies to different work environments. More standardized reporting and intervention design is also needed for future research.[28]

The author Iris M. de Hoogh et al. (2021) studied A 10-week single-arm exploratory trial assessed a Personalized Systems Nutrition (PSN) program using genotypic, phenotypic, and behavioral data to customised diet and lifestyle interventions for 82 adults. The PSN program significantly reduced calorie, sugar, and fat intake and improved BMI, body fat, and metabolic markers like LDL cholesterol, particularly in individuals with low phenotypic flexibility. Personalized meals, coaching, and digital tools enhanced adherence and outcomes. Further validation through randomized controlled trials, longer interventions, and inclusion of more diverse populations is needed to confirm effectiveness and scalability of the PSN model.[29]

The authors Alkyoni Glympi, et al (2020)The authors conducted a comprehensive literature review of studies published from 1999 to 2019 that focused on dietary interventions among office workers. They searched multiple databases and selected 25 relevant studies out of 6647 initially identified. The interventions reviewed included web-based, food-based, informational, and multicomponent strategies. The outcomes assessed were dietary intake, dietary behavior, and health-related indicators.

The review found that all included interventions had at least one positive effect on the targeted outcomes. Web-based and informational interventions were the most common due to their low cost, while food-based and multicomponent interventions showed strong results in improving diet and health markers. The study highlighted that workplace dietary interventions are underutilized yet effective tools for promoting healthy eating habits among office workers.

The authors recommend tailoring dietary interventions to specific workplace contexts and call for more research using standardized measures and long-term follow-ups to evaluate sustained impacts. They also emphasize the need for theory-based and multicomponent strategies to enhance effectiveness.[30]

The authors Susanne Brandstetter, Jana Rüter, Janina Curbach, Julika Loss (2015) The authors conducted a systematic review in 2015 using the PRISMA methodology to examine empowerment-based approaches in healthy nutrition promotion. Only eight studies met the criteria, highlighting the scarcity of such interventions. The review concluded that although empowerment is a valuable concept, its practical application in nutrition programs is underreported and inconsistent. Most studies lacked clear descriptions of how empowerment was implemented. The authors recommend future research to explore and clearly document empowerment strategies in non-clinical, nutrition-focused health promotion settings.[31]

Marciele Alves Bolognese, Carina Bertoldi Franco, Ariana Ferrari, Rose Mari Bennemann, Solange M. A. Lopes, Sônia M. M. G. Bertolini, Nelson Nardo Júnior, Braulio H. M. Branco (2020)

In 2020, the authors conducted a clinical trial comparing group nutrition counseling (GNC) and individualized nutrition prescriptions (INP) among 74 overweight women over 12 weeks, including concurrent exercise. Both methods significantly improved BMI, fat mass, dietary intake, anxiety, and body dissatisfaction. No changes were observed in lean mass or metabolic markers. The study concluded both approaches are equally effective, allowing intervention choice based on patient preference. Future work should involve larger samples and longer durations to validate findings and support public health implementation.[32]

Aikaterini Grimani, Emmanuel Aboagye, Lydia Kwak (2019) The authors conducted a systematic review of 39 workplace nutrition and physical activity interventions using randomized and non-randomized controlled studies. Data were drawn from Medline, EMBASE, Cochrane Library, and Scopus, with quality assessment based on Cochrane tools. Interventions targeting workplace environment and organizational structure can improve absenteeism and potentially workability and productivity. Further high-quality studies with long-term follow-up and objective outcome measures are needed to evaluate broader work-related impacts.[33]

Research Gap

The different studies focus on body parameters like BMI, calorie intake and physical activity. research gaps relates to the conceptual formulation of integrated predictive modeling systems involving concepts such as women's wellness combined with lifestyle, physiological, and behavioral patterns related to nutrition.

AI driven Analytics Review for personalized and lifestyle recommendations:

AI and ML have proved to be groundbreaking technologies for the field of personalized health analysis, helping to systematically analyze complex and divergent health data [8]. Specifically, within the field of women's health, AI-powered technology has helped to analyze nutritional inputs, physical activity levels, levels of stress, sleeping habits, and metabolism data to make personalized lifestyle recommendations [9]. AI-powered technology has helped to move beyond the limitations of traditional rule-based systems, where conventional prediction models were restricted to linear relationships and static health trends [10]. Figure 1 shows the overall framework of the diet and fitness recommendation system.

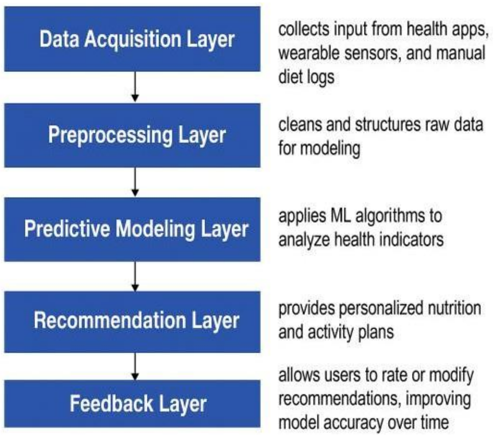


Fig. 1. Conceptual Framework for Predictive Analytics System

Overall, existing research highlights the potential of AI-driven analytics but indicates a clear need for more holistic, women-centric approaches to personalized nutrition and lifestyle management.

Results and Discussion

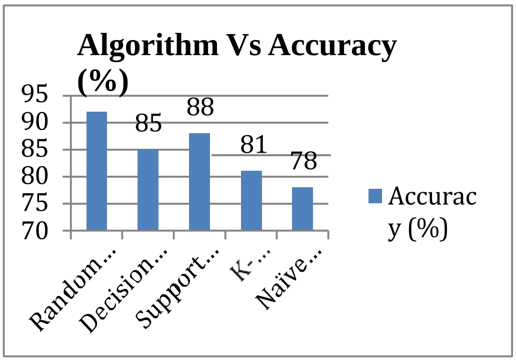
The current research in machine learning (ML) based health, nutrition ,food habits and lifestyle field shows a increasing need for individual , data-driven good health solutions. In general there is a common solutions for all it is not comfortable for every ones body especially in women. ML and predictive analytics help to reduce some limitations by studying similar patterns from various health data , basically for more accurate and personalized recommendations.

Recent studies focused on stress prediction and physical activity recommendations using ML models by showing medium accuracy. Later on improvements in research area by applying advanced methods like connective learning, deep learning and image bae analysis for diet monitoring , weight management and health prediction. Recent studies further increase personalisation by using longitudinal data, feedback of user and intelligent system. Though recent ML models has drawback in some areas while advanced ML models face limitations such as scalability and integration. To overcome these problems need unified predictive framework that combines multiple health problems like diet, physical activity, sleep, stress, and metabolic data. Women-centric wellness management approach can integrate and support for accurate prediction time to time intervention

Table1: Comparison of Machine Learning Model Accuracies Used in Nutrition Prediction

Algorithm	**Dataset Type**	**Application Area**	**Accuracy (%)**
Random Forest (RF) 2025	Lifestyle and health survey data	Obesity prediction, nutrition classification	92.0
Decision Tree (DT) 2024	Anthropometric data	Nutrition deficiency prediction	85.0
Support Vector Machine (SVM) 2019	Biomedical records	Disease and health risk classification	88.0
K-Nearest Neighbours (KNN) 2020	Lifestyle datasets	Obesity level estimation	81.0
Naïve Bayes (NB) 2022	Survey-based nutrition data	Nutrient gap detection	78.0

According to the analysed studies, Random Forest is often described as a strong and dependable model for managing complex nutrition-related datasets, with multiple studies reporting up to 92% classification accuracy. The research frequently focuses on how well ensemble learning techniques handle diverse health and lifestyle data, indicating that they are appropriate for scalable and accurate predictive analytics in customized nutrition and wellness applications.



Conclusion and Future Scope

Existing research work examined to recommend individualized diet and lifestyle plans for women, this study introduces a Blended Predictive Analytics Framework , which combines artificial intelligence, machine learning, and data-driven personalization. By combining physiological , behavioural, and environmental data into a single, adaptive model,

The framework fills in recent gaps and find on insights from current biomedical and computational research. To recommend inclusivity, dependability, and long-term usability, it point a strong focus on explainable AI data driven and continuing feedback mechanism .

The examination of previous research shows that many of the methods used today have drawbacks, including fragmented data integration, a lack of adaptive feedback mechanisms, and a limited consideration of health parameters unique to women. An efficient personalized nutrition and lifestyle system should include a number of interrelated elements, such as data collection, preprocessing, predictive analytics, recommendation generation, and feedback, according to a summary of the reviewed literature. This kind of conceptual framework is in line with international movements that support preventive healthcare and individualized digital health solutions, especially when it comes to women's wellness.

The review studies suggest for further research heighlights the importance of confirming personalise nutrition and lifestyle frameworks using real world datasets particularly that dietary and lifestyle habits of Indian women. In addition the literature shows that there is extended attentiveness in mobile health(mHelath) platforms that support personalised wellness interventions by integrating wearable sensors data dietary tracking and AI driven analytics.

To evaluate how such systems affect overall health outcomes, physical activity, and diet quality, handling and demographically studies are suggested.

For multi-modal data fusion involving text, images, and sensor data, a number of studies recommend investigating sophisticated deep learning architectures, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models. Additionally, federated learning and privacy-preserving methods are emphasized to improve scalability, ethical compliance. Furthermore, the use of securely algorithms and supervised learning will guarantee data security, ethical compliance, and scalability in personalized health analytics.

By advancing predictive analytics in women's health, this research review contributes to the emerging field of AI-enabled personalized wellness, promoting precision healthcare and sustainable lifestyle management through technology-driven solutions.

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