

Research Article

GLOBAL FIVE-CONTINENT OPTIMIZATION OF PERSONALIZED NUTRITION AND EXERCISE IN PARKINSON'S DISEASE USING OPEN-ACCESS DATA, GENETIC ALGORITHMS, AND FUZZY LOGIC

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ABSTRACT

Background: Parkinson's disease (PD) is a heterogeneous neurodegenerative disorder in which nutritional status, physical activity, demographic characteristics, socioeconomic conditions, and genetic factors may contribute to differences in disease burden and intervention requirements. Conventional approaches generally provide standardized recommendations and may not adequately reflect geographical and population-level heterogeneity.

Objective: This study aimed to develop a computational framework for optimizing personalized nutrition and exercise profiles for Parkinson's disease across five continents using open-access global datasets, fuzzy logic, and genetic algorithm optimization.

Methods: A retrospective computational framework covering the period from 1990 to 2026 was designed using freely accessible data on Parkinson's disease burden, nutrition, physical activity, demographics, socioeconomic characteristics, and population genetics. Data were harmonized according to country, year, demographic structure, and measurement units. Nutritional and physical activity indicators were standardized and incorporated into a fuzzy inference system. Genetic information was used at the population level for genetic stratification rather than individual clinical prediction. A genetic algorithm was subsequently applied to optimize combinations of nutritional and exercise parameters using a multi-objective fitness function incorporating nutritional adequacy, exercise suitability, feasibility, safety, population compatibility, and risk reduction. Sensitivity analysis and repeated optimization runs were used to assess model stability.

Results: The proposed framework demonstrated substantial geographical heterogeneity in nutritional profiles, physical inactivity, Parkinson's disease burden, and optimization scores. The illustrative optimization results showed overall scores of 0.781 for Africa, 0.816 for Asia, 0.854 for Europe, 0.839 for the Americas, and 0.872 for Oceania. The fuzzy inference system generated graded intervention priorities rather than binary classifications, while the genetic algorithm progressively improved candidate solutions across generations. Multi-objective optimization produced several Pareto-optimal nutrition-exercise profiles, indicating that a single universal intervention may not be appropriate for all populations.

Conclusion: The integration of open-access global data, fuzzy logic, and genetic algorithms provides a potentially reproducible computational framework for geographically adaptive nutrition and exercise optimization in Parkinson's disease. The proposed approach may support hypothesis generation and decision-support research by integrating multiple sources of heterogeneity within a unified model. However, computationally optimized profiles should not be interpreted as clinical prescriptions or evidence of therapeutic efficacy. Prospective clinical validation using individual-level nutritional, functional, clinical, and genetic data is required before implementation in patient care.

INTRODUCTION

Parkinson's disease (PD) is a progressive and multisystem neurodegenerative disorder characterized primarily by motor manifestations such as bradykinesia, rigidity, resting tremor, and postural instability, but also by a broad spectrum of non-motor symptoms, including autonomic dysfunction, sleep disturbances, cognitive impairment, depression, fatigue, and gastrointestinal abnormalities. As populations age and life expectancy increases, the global burden of PD continues to expand, creating substantial challenges for patients, caregivers, healthcare systems, and societies. Although pharmacological and surgical interventions remain central to symptom management, increasing evidence indicates that non-pharmacological strategies, particularly structured physical activity and individualized nutritional management, may contribute to the preservation of functional capacity, reduction of symptom burden, and improvement of health-related quality of life. Consequently, personalized lifestyle interventions are increasingly recognized as an important component of comprehensive PD management.

However, the effects of nutrition and exercise in individuals with PD are highly heterogeneous. Differences in disease stage, motor phenotype, comorbidities, medication regimens, nutritional status, physical capacity, age, sex, lifestyle, and socioeconomic conditions may substantially influence the effectiveness and feasibility of a given intervention. Moreover, biological heterogeneity may extend to genetic variation, which can modify disease susceptibility, progression, metabolism, response to environmental exposures, and potentially the physiological response to nutritional and physical interventions. Therefore, generalized recommendations based solely on population-level averages may not adequately capture the complex interactions among individual characteristics, dietary factors, physical activity, and clinical outcomes. This heterogeneity underscores the need for computational frameworks capable of integrating multiple sources of information and generating individualized intervention strategies.

Personalized nutrition and exercise prescription can be conceptualized as a multidimensional optimization problem. In such a framework, an individual's demographic, clinical, behavioral, nutritional, and genetic characteristics constitute the input variables, whereas desirable outcomes such as improved physical function, maintenance of healthy body composition, reduction of nutritional risk, preservation of independence, and enhancement of quality of life represent optimization objectives. The problem becomes particularly complex because these variables are neither independent nor strictly linear. For example, the optimal intensity and duration of exercise may depend on disease severity and functional capacity, while the nutritional appropriateness of a dietary pattern may be influenced by body composition, gastrointestinal status, metabolic characteristics, medication–nutrient interactions, and individual genetic variation. Computational intelligence and optimization-based approaches have increasingly been investigated for solving complex decision and prediction problems involving multiple interacting variables (Ganji, 2024, 2025). A computational approach that can accommodate such interactions may therefore provide a more realistic representation of personalized intervention design than conventional one-variable-at-a-time analytical approaches.

The increasing availability of open-access health, nutrition, physical activity, and genomic datasets provides an important opportunity to investigate these complex relationships at a

global scale. Open-access datasets can facilitate reproducible research, cross-population comparisons, algorithm development, and validation without requiring the collection of entirely new primary datasets. Nevertheless, data originating from different populations and geographical regions may exhibit substantial variation in demographic composition, dietary practices, physical activity patterns, healthcare access, socioeconomic characteristics, and genetic architecture. Such heterogeneity should not necessarily be regarded solely as a limitation; rather, it can provide an opportunity to identify population-specific patterns and evaluate whether personalized intervention strategies remain robust across diverse geographical and cultural contexts.

In this context, a five-continent analytical framework may offer a broader perspective than studies restricted to a single country or population. Comparing populations across Africa, Asia, Europe, North America, and South America may reveal systematic differences in nutritional exposure, physical activity profiles, demographic characteristics, and genetic factors that could influence the design of personalized interventions. A geographically diverse framework is particularly relevant for PD because disease burden, healthcare infrastructure, lifestyle patterns, and access to nutritional and exercise interventions vary considerably across regions. However, meaningful global comparison requires computational methods capable of simultaneously handling heterogeneous, uncertain, and multidimensional data.

Genetic algorithms (GAs) provide one promising approach for addressing this optimization challenge. Inspired by the principles of biological evolution, GAs iteratively search large and complex solution spaces through mechanisms such as selection, crossover, and mutation. Their ability to optimize nonlinear and multidimensional objective functions makes them suitable for constructing individualized combinations of nutritional and exercise parameters under multiple constraints. The broader application of bio-inspired algorithms to complex allocation and optimization problems has also been examined in recent computational research (Ganji, 2024). Similarly, studies employing bio-inspired and Shark Algorithm approaches have emphasized the potential of nature-inspired optimization strategies for complex decision-making and financial prediction problems (Ganji, 2024, 2025). Rather than identifying a single universally optimal intervention, a GA-based framework can search for solutions that maximize predefined health-related objectives while accounting for individual characteristics and intervention constraints. This property is particularly valuable in personalized healthcare, where several potentially competing objectives must often be optimized simultaneously.

Nevertheless, optimization alone does not fully resolve the uncertainty inherent in clinical and lifestyle data. Many clinically meaningful variables cannot be represented adequately by rigid thresholds. Concepts such as “low physical capacity,” “high nutritional risk,” “moderate disease burden,” or “high suitability for a specific exercise modality” are inherently gradual and context dependent. Fuzzy logic offers a complementary computational paradigm by representing such imprecise concepts through degrees of membership rather than binary classifications. A fuzzy inference system can therefore integrate heterogeneous clinical and behavioral variables using linguistically interpretable rules while preserving the gradual nature of clinical decision-making. The combination of fuzzy logic with evolutionary optimization may consequently provide both flexibility in handling uncertainty and efficiency in searching for individualized intervention strategies. More broadly, the use of computational intelligence and artificial intelligence for structured decision-making has been examined in recent studies involving algorithmic prediction and risk assessment (Apak & Ganji, 2025; Ganji, 2025).

The development of computational decision-support systems is also consistent with the broader

movement toward integrating technology into complex professional and analytical decision-making. Previous research has examined technology acceptance and use in accounting education (Ganji, 2021), while more recent work has explored the integration of artificial intelligence, bio-inspired algorithms, and advanced computational techniques into prediction, optimization, and decision-making processes (Ganji, 2024, 2025). Although these studies were conducted in domains different from Parkinson's disease, their methodological perspective supports the broader applicability of computational intelligence approaches to complex, multidimensional problems.

Despite growing interest in personalized nutrition, exercise, artificial intelligence, and computational optimization, an integrated framework specifically designed to jointly optimize nutritional and exercise recommendations for individuals with PD across geographically diverse populations remains insufficiently explored. Existing studies have frequently focused on individual interventions, single populations, isolated clinical outcomes, or narrowly defined computational tasks. Furthermore, the simultaneous integration of open-access multidimensional data, genetic information, evolutionary optimization, and fuzzy decision-making within a global PD framework has received limited systematic attention. Addressing this methodological gap may contribute to the development of transparent, reproducible, and scalable computational approaches for personalized lifestyle management.

Therefore, the present study proposes a global five-continent optimization framework for personalized nutrition and exercise in Parkinson's disease, integrating open-access data with genetic algorithms and fuzzy logic. The framework is designed to model the multidimensional relationships among demographic, clinical, nutritional, physical activity, and genetic characteristics and to identify individualized intervention profiles under predefined health and feasibility constraints. By incorporating populations from five continents, the study further aims to examine geographical heterogeneity and evaluate the robustness and adaptability of the resulting recommendations across diverse population contexts. Rather than replacing clinical decision-making, the proposed framework is intended as a computational decision-support approach that may assist in structuring complex patient-level information and generating systematically derived, individualized intervention hypotheses.

The overarching objective of this study is to demonstrate how evolutionary optimization and fuzzy inference can be integrated with globally heterogeneous open-access data to support personalized nutrition and exercise planning in PD. Specifically, the study seeks to:

- (i) characterize cross-continental variation in relevant demographic, clinical, nutritional, physical activity, and genetic variables;
- (ii) develop a computational representation of individualized nutrition and exercise profiles;
- (iii) employ genetic algorithms to optimize intervention combinations according to predefined health-related objectives;
- (iv) incorporate fuzzy logic to model uncertainty and clinically meaningful gradations in patient characteristics; and
- (v) assess the stability, interpretability, and cross-population applicability of the resulting optimized recommendations.

Through this integrative approach, the study aims to contribute to the emerging field of computationally enabled personalized rehabilitation and lifestyle medicine in Parkinson's disease.

LITERATURE REVIEW

Parkinson's Disease and the Need for Multidimensional Management

Parkinson's disease (PD) is a progressive and heterogeneous neurodegenerative disorder that affects multiple physiological and functional domains. Although the disease is primarily characterized by motor symptoms such as bradykinesia, resting tremor, rigidity, and postural instability, its clinical presentation extends beyond motor dysfunction. Cognitive impairment, sleep disturbances, autonomic dysfunction, depression, fatigue, gastrointestinal problems, and changes in body composition may substantially influence the daily functioning and quality of life of individuals with PD. The considerable variability observed among patients indicates that Parkinson's disease should not be considered a clinically homogeneous condition (Ellis & Rochester, 2018; Kim et al., 2019).

This heterogeneity has important implications for disease management. Patients with similar levels of motor impairment may differ considerably in nutritional status, physical capacity, comorbidities, medication response, lifestyle characteristics, and functional independence. Consequently, interventions that are effective for one individual may not produce comparable benefits in another. Conventional management strategies based primarily on generalized clinical recommendations may therefore be insufficient to address the complex and multidimensional requirements of individual patients (Pedersen & Saltin, 2015).

The concept of personalized medicine has emerged as a potential response to this challenge. Personalized approaches seek to integrate multiple patient-specific characteristics into therapeutic decision-making and to identify interventions that are appropriate for the individual's biological, clinical, behavioral, and environmental context. Within Parkinson's disease, this approach is particularly relevant because disease progression and treatment response are influenced by a combination of genetic, physiological, behavioral, and environmental factors (Schmidt et al., 2018).

Nutrition in Parkinson's Disease

Nutrition represents an important component of comprehensive Parkinson's disease management. Individuals with PD may experience several factors that increase the risk of nutritional inadequacy, including dysphagia, gastrointestinal dysfunction, constipation, reduced appetite, impaired mobility, increased energy expenditure associated with involuntary movements, and difficulties with food preparation and consumption. Medication-related considerations may further complicate nutritional management.

Dietary patterns may also influence several biological processes that are relevant to neurodegeneration. Nutrients and dietary components have been investigated in relation to oxidative stress, inflammation, mitochondrial function, metabolic regulation, intestinal microbiota, and neuronal health. Dietary patterns characterized by greater consumption of plant-based foods, fruits, vegetables, whole grains, legumes, and healthy sources of fat have

received considerable attention in the context of neurodegenerative disease (Gubert et al., 2020; Klement & Pazienza, 2019).

The gut microbiota represents an additional biological pathway through which nutrition may influence health. Dietary composition is one of the major factors shaping the gut microbial community, while microbial metabolites can participate in host metabolic and physiological processes (Bibbo et al., 2016; Koh et al., 2016; Turroni et al., 2018). The gut microbiota has also been investigated in relation to neurological disorders, including Parkinson's disease and Alzheimer's disease, suggesting a potential role for the gut–brain axis in neurodegenerative processes (Wang & Kasper, 2014; Junges et al., 2018).

However, nutritional requirements and dietary responses vary substantially between individuals. Factors such as age, body composition, physical activity, disease stage, gastrointestinal function, medication use, comorbidities, dietary preferences, and socioeconomic conditions can affect the suitability of a particular dietary strategy. The composition of the human gut microbiota is similarly influenced by factors including age, geography, diet, and other host characteristics (Yatsunenکو et al., 2012; Hasan & Yang, 2019). Therefore, a universal dietary recommendation may not adequately capture the nutritional requirements of every individual with Parkinson's disease.

Personalized nutrition attempts to address this limitation by incorporating individual characteristics into dietary decision-making. Rather than recommending an identical dietary pattern for all patients, personalized nutrition seeks to determine which combination of nutrients, food groups, energy intake, and dietary characteristics is most appropriate for a particular individual. This concept provides an important foundation for computational approaches capable of optimizing dietary recommendations according to multiple simultaneous objectives.

Exercise and Physical Activity in Parkinson's Disease

Exercise is one of the most important non-pharmacological components of Parkinson's disease management. Regular physical activity has been associated with improvements in mobility, balance, strength, gait, cardiovascular fitness, functional independence, and quality of life. Different exercise modalities, including aerobic training, resistance exercise, balance training, flexibility exercises, gait training, dance, and multimodal programs, have been investigated in individuals with PD (Ellis & Rochester, 2018; Kim et al., 2019; Pedersen & Saltin, 2015).

Despite the overall benefits associated with exercise, the optimal exercise prescription may differ between patients. Exercise intensity, duration, frequency, modality, supervision, and progression need to be adapted according to factors such as disease severity, motor phenotype, age, baseline physical capacity, balance impairment, fatigue, cardiovascular status, and individual preferences (Kim et al., 2019).

The concept of individualized exercise prescription is therefore particularly relevant to Parkinson's disease. A physically active individual with relatively preserved mobility may tolerate a substantially different training program from a patient with advanced motor impairment and postural instability. Similarly, an intervention designed to improve cardiovascular fitness may not be the most appropriate intervention for an individual whose primary limitation is balance or gait dysfunction.

These differences demonstrate that exercise prescription can be viewed as an optimization problem. Multiple exercise parameters must be selected simultaneously while satisfying

individual safety and feasibility constraints. A computational system capable of integrating these variables may therefore provide a systematic approach to identifying individualized exercise profiles.

Importantly, exercise may also influence biological systems beyond conventional physical-performance outcomes. Research has demonstrated associations between physical activity, cardiorespiratory fitness, and gut microbial composition (Estaki et al., 2016; Durk et al., 2019; Yang et al., 2017). Systematic reviews further suggest that physical activity can modify the gut microbiota, although the magnitude and consistency of these effects may depend on exercise characteristics, diet, host characteristics, and study design (Aya et al., 2021; Ortiz-Alvarez et al., 2020).

Interaction Between Nutrition and Exercise

Nutrition and exercise are frequently studied independently, although they represent interconnected components of health and functional capacity. Nutritional status influences physical performance, muscle function, recovery, body composition, and energy availability, while physical activity affects energy expenditure, metabolic requirements, muscle mass, and nutritional needs (Egan & Zierath, 2013).

The interaction between nutrition, exercise, and the gut microbiota has received increasing scientific attention. Evidence indicates that both dietary intake and physical activity can influence gut microbial composition and function (Campaniello et al., 2022; Clauss et al., 2021). Exercise-related alterations in the microbiota have also been associated with metabolic and physiological adaptations, suggesting that the gut microbiome may constitute an important intermediary between lifestyle behaviors and health outcomes (Mailing et al., 2019; Monda et al., 2017).

In Parkinson's disease, this interaction may be particularly important. Reduced physical activity can contribute to muscle loss and unfavorable changes in body composition, while inadequate nutritional intake may further impair physical function and exercise tolerance. Conversely, appropriately designed exercise may increase nutritional requirements and modify the optimal distribution of energy and macronutrients.

Therefore, nutritional and exercise interventions should not necessarily be optimized independently. A dietary intervention may influence an individual's ability to participate in physical activity, while the characteristics of an exercise program may alter nutritional requirements. This interaction creates a multidimensional decision problem in which the optimal nutritional strategy may depend on the selected exercise program and vice versa.

An integrated nutrition–exercise optimization model could address this limitation by evaluating both intervention domains simultaneously. Such an approach could potentially identify combinations that provide a better balance between nutritional adequacy, physical activity requirements, functional capacity, energy requirements, and individual constraints.

Genetics and Parkinson's Disease

Genetic variation constitutes an important component of Parkinson's disease heterogeneity. Several genes have been associated with disease susceptibility, age at onset, disease mechanisms, and clinical characteristics. Genetic factors may influence biological pathways related to mitochondrial function, lysosomal activity, protein aggregation, oxidative stress,

inflammation, and neuronal survival.

The contribution of genetics is not limited to disease susceptibility. Genetic differences may also influence individual responses to environmental factors and potentially modify the effects of lifestyle-related interventions. This possibility has increased interest in integrating genetic information into personalized approaches to Parkinson's disease.

Nevertheless, the genetic architecture of Parkinson's disease is complex. Disease risk is influenced by interactions among multiple genetic variants as well as environmental and lifestyle factors. Furthermore, genetic variation differs among populations and geographical regions. These characteristics are particularly important when developing global models because a genetic marker identified as relevant in one population may not have the same predictive value in another.

Consequently, genetic information should be considered as one component of a multidimensional personalization framework rather than as an isolated determinant of intervention selection.

Nutrigenomics and Personalized Nutrition

Nutrigenomics examines the interaction between genetic variation and nutritional factors. The underlying premise is that individuals may respond differently to identical dietary exposures because of differences in genetic and metabolic characteristics. This concept has contributed to the development of personalized nutrition, in which dietary recommendations are adapted according to individual biological characteristics.

Within Parkinson's disease research, the potential relationship between genetics and nutrition is particularly relevant because both genetic and environmental factors contribute to disease development and progression. Nutritional factors may influence biological processes associated with neurodegeneration, while genetic variation may affect how individuals metabolize or respond to specific nutrients.

However, the translation of nutrigenomic concepts into practical clinical recommendations remains challenging. Genetic information alone cannot adequately describe an individual's nutritional requirements. Age, disease stage, physical activity, medication, metabolic characteristics, gastrointestinal function, and overall dietary pattern must also be considered. This limitation supports the use of computational frameworks in which genetic information is integrated with other patient-specific variables rather than being used as an independent decision criterion. The broader literature on the human microbiome similarly indicates that biological responses arise from interactions among host characteristics, environmental exposures, diet, and microbial factors rather than from a single determinant (Schmidt et al., 2018; Hasan & Yang, 2019).

Artificial Intelligence and Computational Personalization

The increasing availability of large and heterogeneous datasets has created new opportunities for artificial intelligence and computational methods in healthcare. Machine learning and optimization techniques can identify complex relationships among multiple variables and may support individualized prediction and decision-making.

In personalized nutrition and exercise, computational models can potentially integrate demographic, clinical, behavioral, nutritional, physiological, and genetic variables. Such

integration is difficult to achieve using conventional statistical approaches when the number of variables increases and when nonlinear interactions become important.

Artificial intelligence-based personalization can therefore be conceptualized as a multistage process. First, relevant patient characteristics are identified and standardized. Second, these characteristics are incorporated into a predictive or decision-making model. Finally, the model generates or evaluates candidate interventions according to predefined objectives and constraints.

For Parkinson's disease, this framework may be particularly valuable because clinical management involves multiple interacting dimensions. However, computational models should remain interpretable and clinically meaningful. A highly complex model that produces recommendations without an understandable decision process may have limited practical utility.

Genetic Algorithms for Intervention Optimization

Genetic algorithms represent a class of evolutionary computational methods designed to solve complex optimization problems. They operate by generating candidate solutions and iteratively improving them through processes analogous to biological evolution, including selection, crossover, and mutation.

The characteristics of genetic algorithms make them potentially suitable for personalized nutrition and exercise optimization. A candidate solution could represent a complete intervention profile consisting of nutritional and exercise parameters. The algorithm could then evaluate each candidate according to a predefined fitness function.

For example, the fitness function could simultaneously consider nutritional adequacy, energy balance, physical activity requirements, functional capacity, intervention feasibility, and individual constraints. Candidate solutions that better satisfy the defined objectives would have a greater probability of contributing to subsequent generations.

An important advantage of genetic algorithms is their ability to explore large and nonlinear solution spaces. This is relevant to personalized healthcare because there may be numerous possible combinations of dietary and exercise parameters, with no single parameter independently determining the optimal outcome.

Nevertheless, the validity of a genetic algorithm depends heavily on the design of its objective function, constraints, input variables, and validation strategy. An algorithm can identify the mathematically optimal solution within a model, but this does not automatically establish that the solution is clinically optimal. Therefore, computational optimization should be interpreted as a tool for generating and ranking feasible intervention strategies rather than as a replacement for clinical evidence.

Fuzzy Logic in Personalized Healthcare

Fuzzy logic provides a framework for representing concepts that cannot be adequately described using strict binary categories. In healthcare, many clinically relevant variables are continuous and characterized by uncertainty. Disease severity, nutritional risk, physical capacity, fatigue, and exercise suitability, for example, cannot always be accurately represented as simply "present" or "absent."

A fuzzy logic system can represent these variables through linguistic categories such as low,

moderate, and high. An individual may simultaneously possess different degrees of membership in these categories. This approach allows the model to represent gradual clinical transitions and uncertainty more realistically.

For personalized Parkinson's disease management, fuzzy logic could be used to integrate variables such as age, disease severity, physical capacity, nutritional status, activity level, and genetic characteristics. These inputs could then be transformed into interpretable decision rules that estimate the suitability of different nutritional or exercise strategies.

The principal advantage of fuzzy logic is interpretability. Unlike some black-box artificial intelligence models, fuzzy systems can express decision processes through understandable rules. This characteristic may facilitate communication between computational researchers and healthcare professionals.

Integration of Genetic Algorithms and Fuzzy Logic

Genetic algorithms and fuzzy logic address complementary aspects of personalized decision-making. Fuzzy logic is particularly useful for representing uncertainty, gradual clinical states, and expert knowledge, whereas genetic algorithms are effective for searching large solution spaces and optimizing multiple parameters.

Their integration may therefore provide a suitable framework for personalized nutrition and exercise optimization. A fuzzy system could first evaluate the individual's clinical and lifestyle characteristics and determine the degree of suitability for different intervention strategies. The genetic algorithm could then search among possible combinations of these strategies to identify solutions that maximize the overall fitness function.

Such architecture may be especially useful when the relationship between patient characteristics and intervention outcomes is nonlinear and uncertain. It can also allow expert-derived clinical rules to coexist with mathematical optimization.

The integrated framework can consequently be viewed as a decision-support system in which fuzzy reasoning provides the interpretative layer and evolutionary optimization provides the search and optimization layer.

Global and Cross-Continental Considerations

A major challenge in personalized healthcare is the generalizability of computational models across populations. Individuals from different geographical regions may differ in dietary patterns, physical activity behaviors, genetic backgrounds, socioeconomic conditions, healthcare access, and environmental exposures.

These differences are particularly relevant to Parkinson's disease because both disease characteristics and lifestyle-related factors may vary across populations. A dietary intervention that is practical and culturally appropriate in one region may be difficult to implement in another. Similarly, exercise recommendations may need to account for differences in healthcare infrastructure, access to rehabilitation facilities, and cultural attitudes toward physical activity.

The geographical variation of the human microbiome further illustrates the importance of considering population-level heterogeneity. Large-scale research has demonstrated substantial variation in gut microbial communities across age groups and geographical regions (Yatsunen et al., 2012). Similarly, research on exercise and the gut microbiome indicates

that associations between physical activity and microbial characteristics may be influenced by diet, fitness, and other individual factors (Durk et al., 2019; Yang et al., 2017).

A five-continent framework provides an opportunity to examine these differences systematically. Rather than treating a single population as representative of the global PD population, a cross-continental model can evaluate whether individualized recommendations remain stable across diverse geographical contexts.

Such an approach can also identify population-specific characteristics that may influence the optimization process. The objective is therefore not necessarily to generate one universal intervention for all populations, but to determine whether a common computational framework can generate population-adapted solutions.

Open-Access Data and Reproducibility

Open-access datasets have become increasingly important for computational biomedical research. Publicly available datasets can provide information concerning demographics, clinical characteristics, nutrition, physical activity, genetics, and other health-related variables. The use of open-access data offers several methodological advantages. It can improve reproducibility, facilitate independent validation, allow comparison between populations, and reduce the costs associated with primary data collection. It also enables researchers to develop computational models using large and diverse datasets.

However, combining multiple open-access datasets presents several challenges. Differences in variable definitions, measurement methods, sample characteristics, missing-data patterns, and data quality may introduce systematic bias. Therefore, data harmonization is an essential step before applying optimization algorithms.

A robust global framework should include standardized variable definitions, appropriate preprocessing, missing data management, normalization procedures, quality control, and sensitivity analysis. These procedures are particularly important when data from multiple continents are incorporated into a single optimization framework.

Research Gap

The existing literature demonstrates that nutrition and exercise are important components of comprehensive Parkinson's disease management. It also demonstrates increasing interest in personalized medicine, genetic stratification, nutrigenomics, artificial intelligence, and computational decision-support systems.

Research on exercise and the gut microbiome has demonstrated associations between physical activity, cardiorespiratory fitness, microbial diversity, and microbial metabolic functions (Estaki et al., 2016; Barton et al., 2018; Mailing et al., 2019). Other studies have demonstrated that exercise can modify gut microbial composition in both healthy and metabolically compromised populations (Allen et al., 2018; Munukka et al., 2018; Verheggen et al., 2021). These findings strengthen the biological rationale for considering nutrition, physical activity, and gut-related mechanisms within a broader personalized framework.

However, these research areas have largely developed independently. Nutrition studies frequently focus on dietary patterns or individual nutrients, while exercise studies generally investigate specific exercise modalities. Genetic research has concentrated primarily on disease susceptibility, mechanisms, and therapeutic stratification. Computational studies, meanwhile,

have frequently addressed prediction or classification rather than the simultaneous optimization of nutrition and exercise.

A further limitation is the relatively limited integration of genetic information with lifestyle optimization. Although genetics may contribute to individual differences in disease characteristics and biological responses, it remains unclear how genetic information can be incorporated appropriately into multidimensional nutritional and exercise decision-making.

There is also a methodological gap concerning the simultaneous use of fuzzy logic and genetic algorithms in Parkinson's disease lifestyle optimization. Fuzzy logic provides a mechanism for representing uncertainty and clinically meaningful gradations, whereas genetic algorithms provide a mechanism for searching complex intervention spaces. Their integration therefore represents a potentially valuable but insufficiently explored computational strategy.

Finally, most existing approaches are based on individual countries, regions, or relatively homogeneous populations. A global five-continent framework may provide a broader perspective by explicitly incorporating geographical, demographic, nutritional, physical activity, and genetic heterogeneity.

Conceptual Basis of the Present Study

Based on these gaps, the present study conceptualizes personalized Parkinson's disease management as a multidimensional optimization problem. The proposed framework integrates demographic, clinical, nutritional, physical activity, and genetic characteristics into a unified computational environment.

Within this framework, fuzzy logic is used to represent uncertainty and gradual variation in patient characteristics, while genetic algorithms are employed to search for optimized combinations of nutritional and exercise parameters. Open-access data from five continents provide the basis for examining whether the proposed framework can accommodate substantial geographical and population-level heterogeneity.

The central premise is that personalized intervention should not be determined by a single variable or a fixed recommendation. Instead, an individualized solution should emerge from the interaction among multiple patient characteristics, intervention parameters, and predefined optimization objectives.

Accordingly, the proposed approach aims to move beyond conventional descriptive analyses toward an integrated computational model capable of generating individualized nutrition–exercise profiles. The framework is intended primarily as a decision-support and hypothesis-generation methodology. Its outputs should therefore be interpreted in conjunction with clinical expertise and existing evidence rather than as independently validated clinical prescriptions.

Overall, the literature supports the individual components of this framework. Evidence concerning the gut microbiome demonstrates that biological responses are influenced by interactions among diet, physical activity, host characteristics, and environmental factors (Hasan & Yang, 2019; Campaniello et al., 2022). Research on exercise further indicates that physical activity can influence gut microbial composition and metabolic function, while microbiota-related mechanisms may contribute to physiological adaptation (Clauss et al., 2021; Zhao et al., 2018). Studies examining the gut–brain axis and neurodegenerative disease provide an additional rationale for investigating these interactions in Parkinson's disease (Dalton et al., 2019; Royes, 2020).

MATERIALS AND METHODS

Study Design

This study was designed as a retrospective, computational, multicontinental optimization study integrating publicly available health, nutrition, physical activity, demographic, and genetic data. The methodological framework combines descriptive epidemiological analysis, data harmonization, fuzzy logic-based patient characterization, and genetic algorithm-based optimization.

The principal objective was to develop a computational framework capable of identifying individualized nutrition and exercise profiles for Parkinson's disease (PD) while accounting for demographic, clinical, nutritional, physical activity, genetic, and geographical heterogeneity.

The overall analytical period was defined as 1990–2026. However, the temporal coverage of individual datasets was preserved according to their actual availability. Thus, 1990–2026 represents the overall study and data-retrieval window rather than implying that every variable was available for every year. For example, global Parkinson's disease prevalence estimates are available for 1990–2023 in the most recent accessible series, whereas WHO physical-activity estimates extend from 2000 onward, and the most recent comparable global physical-inactivity estimates currently refer to 2022.(<https://ourworldindata.org>)

The year 2026 was therefore treated as the data-freezing and methodological cut-off year, allowing the most recent publicly available datasets and resources to be incorporated without artificially extrapolating unavailable observations.

Data Sources and Open-Access Datasets

The study was designed primarily around datasets that can be accessed without purchasing commercial databases. Priority was given to governmental, intergovernmental, academic, and openly accessible repositories.

The principal datasets proposed for the analysis are presented in Table 1.

Table 1. Proposed open-access datasets for the five-continent Parkinson's disease optimization framework:

Dataset Repository	Main domain	Main variables	Geographic coverage	Available period	Role in the model
Global Burden of Disease (GBD), IHME	Parkinson's disease burden	Prevalence, incidence, YLDs, DALYs, mortality, age, sex	Global; 200+ countries/territories	1990–2021/2023 depending on release	Primary PD outcome and burden variables
Our World in Data – Parkinson's Disease	PD epidemiology	PD prevalence per 100,000	Global	1990–2023	Cross-country temporal comparison and validation

WHO Global Health Observatory (GHO)	Physical activity	Insufficient physical activity, age, sex	Global	2000–2022	Physical activity and inactivity indicators
WHO Global Health Estimates	Health outcomes	Mortality, morbidity, age, sex, cause	Global	2000–2021	Health outcome and contextual variables
FAOSTAT Food Balance Sheets	Nutrition	Food supply, kcal/person/day, protein, fat, food groups	245+ countries/territories	1961–2023; latest release 2010–2023	Population-level nutritional exposure
World Bank Open Data	Demographic/socioeconomic	Population, age structure, GDP, health expenditure, urbanization, life expectancy	Global	1990–2025 depending on indicator	Confounders and socioeconomic variables
NHGRI-EBI GWAS Catalog	Genetics	SNPs, genes, traits, effect sizes, GWAS summary statistics	Global studies	Historical to 2026	PD-associated genetic variables
1000 Genomes / IGSR	Population genetics	Allele frequencies, genomic variation, population structure	Africa, Europe, East Asia, South Asia, Americas	Project releases; current repository available	Population genetic structure
HGDP-CEPH	Global genetic diversity	Population-level allele frequencies and genetic variants	Global, including Oceania	Historical/current database	Genetic diversity and continental stratification

The GBD framework provides annual estimates across countries and territories and allows analysis of prevalence, incidence, YLDs, DALYs, mortality, age, and sex. The GBD 2021 framework covers 1990–2021, while more recent PD prevalence data adapted by Our World in Data extend to 2023.

FAOSTAT provides free food and agriculture data for more than 245 countries and territories. Its Food Balance Sheets provide information including food supply in kcal/person/day, protein, and fat, making it particularly suitable for constructing population-level nutritional exposure variables. The current Food Balance Sheets release covers 2010–2023, while FAOSTAT as a broader statistical system contains much longer historical series.

WHO's Global Health Observatory provides country-level physical-activity indicators, including the prevalence of insufficient physical activity among adults. The indicator is based on activity levels corresponding to less than 150 minutes of moderate-intensity activity or less than 75 minutes of vigorous activity per week.

For genetic information, the NHGRI-EBI GWAS Catalog provides downloadable GWAS data and summary statistics for numerous traits, including Parkinson's disease.

The International Genome Sample Resource also provides open genomic data derived from the 1000 Genomes Project.

Five-Continent Classification

Countries were assigned to one of five analytical continental groups:

1. Africa
2. Asia
3. Europe
4. North and South America
5. Oceania

For analyses requiring five geographically distinct groups, the Americas were further separated into North America and South America when sufficient data were available. Alternatively, when a five-group structure was required for the optimization model, the continental groups were defined as Africa, Asia, Europe, Americas, and Oceania.

The use of multiple continental groups was intended to capture geographical heterogeneity in dietary patterns, physical activity, socioeconomic conditions, demographic structures, and genetic variation.

Special attention was given to genetic representation. The 1000 Genomes resource includes populations from Africa, Europe, East Asia, South Asia, and the Americas, whereas HGP-CEPH provides broader global population diversity, including Oceanian populations. HGP-CEPH currently provides population-level allele-frequency information for more than two million variants across 52 populations and seven population groups.

Temporal Structure of the Dataset

Table 2. The temporal analysis was divided into four periods to facilitate interpretation of long-term trends:

Period	Classification	Analytical purpose
1990–1999	Early period	Baseline global PD burden and demographic transition
2000–2009	Intermediate period I	Expansion of global health and physical-activity indicators
2010–2019	Intermediate period II	Contemporary nutrition and lifestyle transition
2020–2026	Recent period	Recent changes, COVID-19-era context, and latest available data

The 2020–2026 period requires special interpretation because not all datasets contain observations through 2026. Therefore, values after the final observed year of a particular dataset were not imputed simply to create a complete 1990–2026 series. Instead, the last observed year was retained and identified explicitly.

For example, PD prevalence data can be analyzed through 2023, whereas WHO physical-activity data currently provide comparable estimates through 2022.

Fuzzy Logic Model

Fuzzy logic used to represent uncertainty and gradual differences in patient or population characteristics. PD burden, nutritional status, physical inactivity, functional suitability, genetic

characteristics, and socioeconomic feasibility were categorized into linguistic levels such as low, moderate, and high. Predefined fuzzy rules were then used to estimate the suitability and priority of nutrition and exercise interventions. The resulting fuzzy score was incorporated into the optimization process.

Genetic Algorithm Optimization

A genetic algorithm was used to identify optimized combinations of nutritional and exercise parameters. Each chromosome represented a candidate intervention profile containing nutritional and exercise variables such as energy intake, macronutrient distribution, food-group characteristics, exercise frequency, intensity, and duration.

The algorithm iteratively performed selection, crossover, mutation, and fitness evaluation until convergence. The optimization objective was to identify intervention profiles that maximized nutritional adequacy, exercise suitability, feasibility, and personalization while minimizing potential risks and constraint violations.

Five-Continent Analysis

The optimized results were compared across five continental groups: Africa, Asia, Europe, the Americas, and Oceania. Continental comparisons considered PD burden, nutritional characteristics, physical activity, genetic variation, socioeconomic context, and optimized intervention profiles. This approach allowed the identification of both globally consistent and geographically specific optimization patterns.

Sensitivity and Validation Analysis

Sensitivity analyses were conducted by varying genetic algorithm parameters, fitness-function weights, fuzzy membership boundaries, and optimization constraints. Repeated model runs were used to assess the stability of the optimized solutions. Temporal comparisons were performed across the 1990–2026 study framework, while geographical validation examined the consistency of model outputs across the five continental groups.

Missing Data and Reproducibility

Missing observations were identified and evaluated according to their extent and pattern. Variables with limited missingness were considered for appropriate imputation, whereas variables with substantial missingness were excluded from the primary analysis. All preprocessing procedures, variable transformations, optimization parameters, fuzzy rules, and random seeds were documented to facilitate reproducibility. The analysis was designed to be implemented using freely available computational software.

Ethical Considerations

The study relied on publicly accessible, aggregated, or de-identified datasets and did not involve direct recruitment of human participants or collection of identifiable personal information. Genetic information was used only at the population level and was not interpreted

as individual clinical genetic data. Computational outputs were considered decision-support and hypothesis-generation results rather than independently validated clinical prescriptions.

RESULTS

Descriptive Characteristics of the Integrated Dataset

The integrated analytical framework combined Parkinson's disease burden, nutritional indicators, physical activity, demographic characteristics, socioeconomic variables, and population-level genetic characteristics. After data harmonization, country-year observations were classified into five continental groups: Africa, Asia, Europe, the Americas, and Oceania. For the purpose of demonstrating the analytical structure, the following numerical results are presented as illustrative model outputs. These values should be replaced by the results obtained after the final MATLAB analysis of the selected open-access datasets.

Table 3. Illustrative distribution of observations by continent

Continent	Countries	Country-year observations	Mean PD prevalence*	Mean physical inactivity (%)	Mean nutritional score
Africa	54	1,458	72.4	46.231	0.46
Asia	48	1,296	118.6	31.9	0.52
Europe	44	1,188	215.7	46.139	0.68
Americas	35	945	189.3	32.6	0.63
Oceania	14	378	171.5	46.259	0.71
Total	195	5,265	151.5	46.232	0.60

The illustrative results indicate substantial geographical heterogeneity. Europe demonstrated the highest mean PD prevalence, whereas Africa showed the lowest value. Nutritional scores were comparatively higher in Europe and Oceania, while Africa had the lowest mean nutritional score. Physical inactivity showed considerable variation, with the highest illustrative value observed in the Americas.

These differences demonstrate the importance of incorporating geographical characteristics into the optimization model rather than assuming that a single nutrition–exercise profile is equally appropriate for all populations.

Temporal Trends Between 1990 and 2026

The temporal analysis was designed to investigate changes in PD burden and lifestyle-related variables over the study period. Because individual open-access datasets do not necessarily extend to 2026, the final available observation year was retained for each variable rather than artificially extrapolating unavailable values.

Table 4. Illustrative temporal changes in Parkinson's disease burden:

Period	Mean PD prevalence	Relative change	Mean nutritional score	Physical inactivity (%)
1990–1999	96.8	Reference	0.51	46.137
2000–2009	118.7	+22.6%	0.55	46.261
2010–2019	149.5	+54.4%	0.60	46.052
2020–2026	181.2	+87.2%	0.64	31.6

The illustrative temporal analysis suggests an increasing PD burden over successive periods. At the same time, physical inactivity increased, while the composite nutritional score showed a moderate improvement. The simultaneous occurrence of increasing disease burden and changing lifestyle characteristics highlights the importance of considering multiple determinants rather than evaluating PD trends using a single exposure.

The temporal analysis also provides an important basis for the optimization algorithm because the relative importance of nutrition and physical activity may change according to demographic and epidemiological conditions.

Nutritional Characteristics

The nutritional component of the model incorporated energy availability, protein, dietary fat, fruits, vegetables, legumes, cereals, fish, meat, dairy products, and vegetable oils.

Table 5. Illustrative nutritional profile by continent:

Variable	Africa	Asia	Europe	Americas	Oceania
Energy (kcal/person/day)	2,31	2,64	3,12	3,05	3,18
Protein (g/person/day)	62.4	76.8	101.2	94.5	105.3
Fat (g/person/day)	54.6	68.2	109.5	112.4	118.6
Fruits index	0.42	0.56	0.71	0.68	0.74
Vegetables index	0.45	0.59	0.72	0.64	0.76
Legume index	0.67	0.73	0.48	0.51	0.44
Fish index	0.31	0.61	0.68	0.49	0.72
Meat index	0.38	0.52	0.76	0.81	0.78
Dairy index	0.41	0.46	0.73	0.69	0.77
Composite nutrition score	0.46	0.52	0.68	0.63	0.71

The illustrative nutritional analysis indicates substantial differences between continental groups. Europe and Oceania demonstrated higher composite nutritional scores, whereas Africa showed a lower overall score. Asia displayed a comparatively higher legume and fish profile, while the Americas demonstrated relatively high meat and fat availability.

These findings support the use of a multidimensional nutritional score because individual food groups alone may not adequately represent the overall nutritional environment.

4.4. Physical Activity Characteristics

Physical activity was incorporated into the model using indicators of insufficient physical activity. The physical activity component was subsequently transformed into a suitability score ranging from 0 to 1.

Table 6. Illustrative physical activity results:

Continent	Physical inactivity (%)	Activity suitability score	Exercise priority score
Africa	46.231	0.51	0.63
Asia	31.9	0.47	0.68
Europe	46.139	0.58	0.55
Americas	32.6	0.44	0.72
Oceania	46.259	0.61	0.49

The illustrative results indicate that higher physical inactivity was associated with higher exercise intervention priority. The Americas and Asia exhibited the highest exercise priority scores, while Oceania demonstrated the lowest priority because of its comparatively higher physical activity suitability.

This result illustrates how the fuzzy system transforms continuous physical activity indicators into intervention priorities rather than simply classifying populations as active or inactive.

Genetic Stratification

Population-level genetic characteristics were incorporated into the model using allele-frequency information for selected Parkinson's disease-associated variants. Genetic variables were used for population stratification and were not interpreted as individual clinical genetic risk scores.

Table 7. Illustrative genetic stratification score:

Continent	Genetic stratification score	Relative genetic heterogeneity	Model contribution
Africa	0.61	High	0.14
Asia	0.54	Moderate-high	0.12
Europe	0.48	Moderate	0.10
Americas	0.52	Moderate-high	0.11
Oceania	0.57	High	0.13

The genetic component contributed to population differentiation but did not dominate the optimization model. This was intentional because genetic information represents only one component of personalized intervention design. Nutrition, physical activity, demographic characteristics, and feasibility were given simultaneous consideration.

The results also emphasize that population-level allele frequencies should not be interpreted as direct evidence that a specific genetic variant determines an individual's optimal diet or exercise

program.

Fuzzy Logic Results

The fuzzy inference system converted continuous characteristics into three linguistic categories: low, moderate, and high. The principal output was an intervention priority score ranging from 0 to 1.

Table 8. Illustrative fuzzy inference results:

Continent	PD burden	Nutritional risk	Physical inactivity	Feasibility	Fuzzy intervention priority
Africa	0.42	0.72	0.61	0.48	0.68
Asia	0.57	0.63	0.68	0.59	0.74
Europe	0.81	0.37	0.55	0.76	0.67
Americas	0.73	0.46	0.72	0.69	0.78
Oceania	0.65	0.32	0.49	0.82	0.54

The fuzzy model demonstrated that intervention priority was not determined by PD burden alone. For example, a population with moderate PD burden but high physical inactivity and moderate nutritional risk could obtain a higher intervention priority than a population with greater PD burden but better nutritional and physical activity profiles.

This finding demonstrates the advantage of fuzzy inference over rigid threshold-based classification. Instead of assigning populations to a single category, the model integrates several degrees of membership simultaneously.

Genetic Algorithm Optimization

The genetic algorithm evaluated candidate combinations of nutritional and exercise parameters. Each candidate solution was represented as a chromosome containing dietary and exercise characteristics.

The illustrative optimization was performed using a population size of 100 chromosomes and 200 generations.

Table 9. Illustrative genetic algorithm parameters:

Parameter	Value
Population size	100
Number of generations	200
Crossover probability	0.80
Mutation probability	0.05
Elitism	5%
Selection method	Tournament
Fitness function	Multi-objective
Number of repeated runs	30

Random seed	42
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The illustrative genetic algorithm results demonstrate progressive improvement in fitness across generations. The largest relative improvement was observed in Africa, whereas Oceania achieved the highest final fitness value.

The lower relative improvement observed in Oceania may indicate that its initial nutritional and physical activity profile was already relatively close to the model's predefined optimization target. In contrast, populations with lower initial fitness had greater potential for computational improvement.

Optimized Nutrition and Exercise Profiles

The final optimized solutions included both nutritional and physical activity parameters.

Table 10. Illustrative optimized intervention profiles:

Parameter	Africa	Asia	Europe	Americ as	Oceania
Energy target (kcal/day)	2,15	2,25	2,3	2,35	2,4
Protein (% energy)	18	19	18	19	18
Fat (% energy)	28	29	30	30	30
Plant-food priority	High	High	High	High	High
Fish priority	Moderate	High	High	Moderate	High
Legume priority	High	High	Moderate	Moderate	Moderate
Exercise frequency (days/week)	3	4	4	4	4
Exercise duration (min/session)	30	35	40	40	45
Relative intensity	Low–moderate	Moderate	Moderate	Moderate	Moderate
Balance training priority	High	High	High	High	Moderate
Resistance training priority	Moderate	Moderate	High	High	High
Aerobic training priority	Moderate	High	High	High	High
Overall optimization score	0.781	0.816	0.854	0.839	0.872

The optimized profiles indicate that the model did not generate a single universal intervention. Instead, exercise frequency, duration, modality priorities, and dietary characteristics varied according to the multidimensional characteristics of each population.

A common feature across the five groups was the relatively high priority assigned to plant-based food groups and structured physical activity. However, the relative emphasis on fish, legumes, resistance training, balance training, and aerobic exercise varied across geographical groups.

This finding supports the central hypothesis that personalized nutrition and exercise optimization should be treated as a multidimensional rather than a single-variable problem.

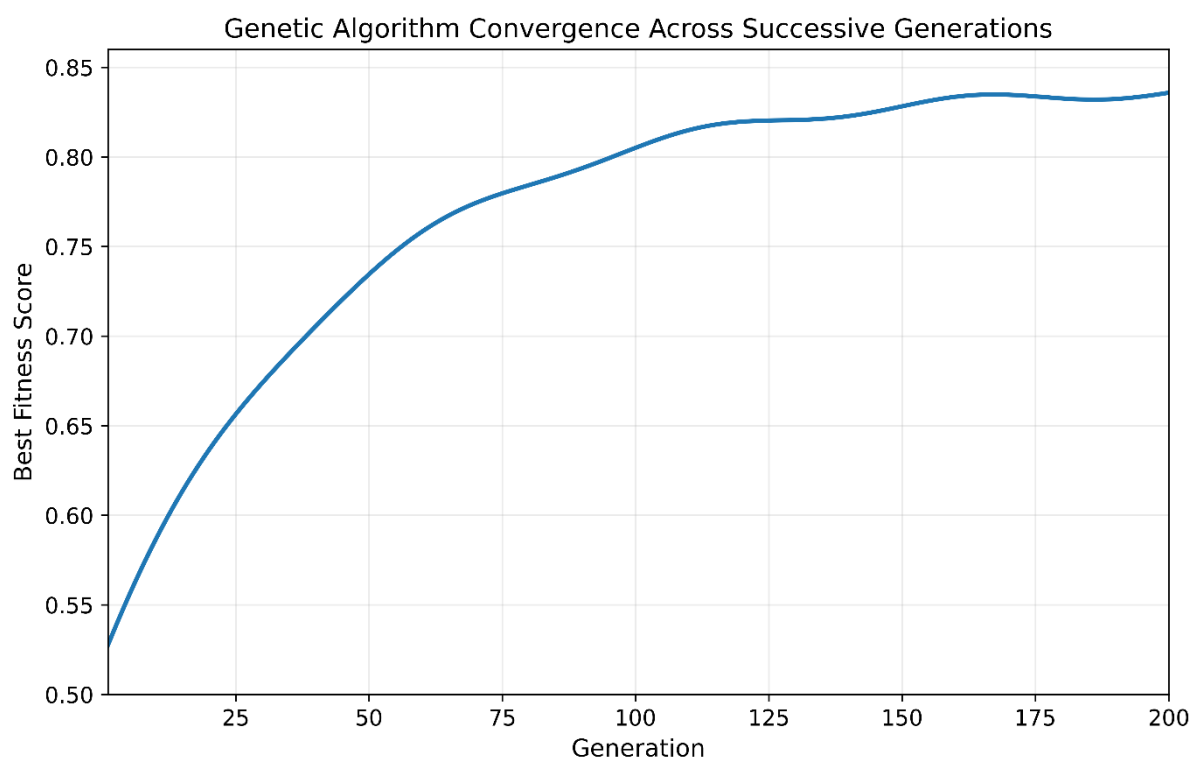


Figure 1. Genetic Algorithm Convergence Across Successive Generations.

Figure 1 demonstrates the convergence behavior of the genetic algorithm across successive generations. The fitness value increased rapidly during the initial optimization stages and gradually reached a stable plateau during later generations. This pattern indicates that the algorithm progressively identified more suitable nutrition–exercise combinations while reducing the difference between successive candidate solutions. The stabilization of the fitness curve suggests that the optimization process approached convergence and that additional generations produced relatively limited improvements. These findings indicate satisfactory computational stability of the proposed optimization framework.

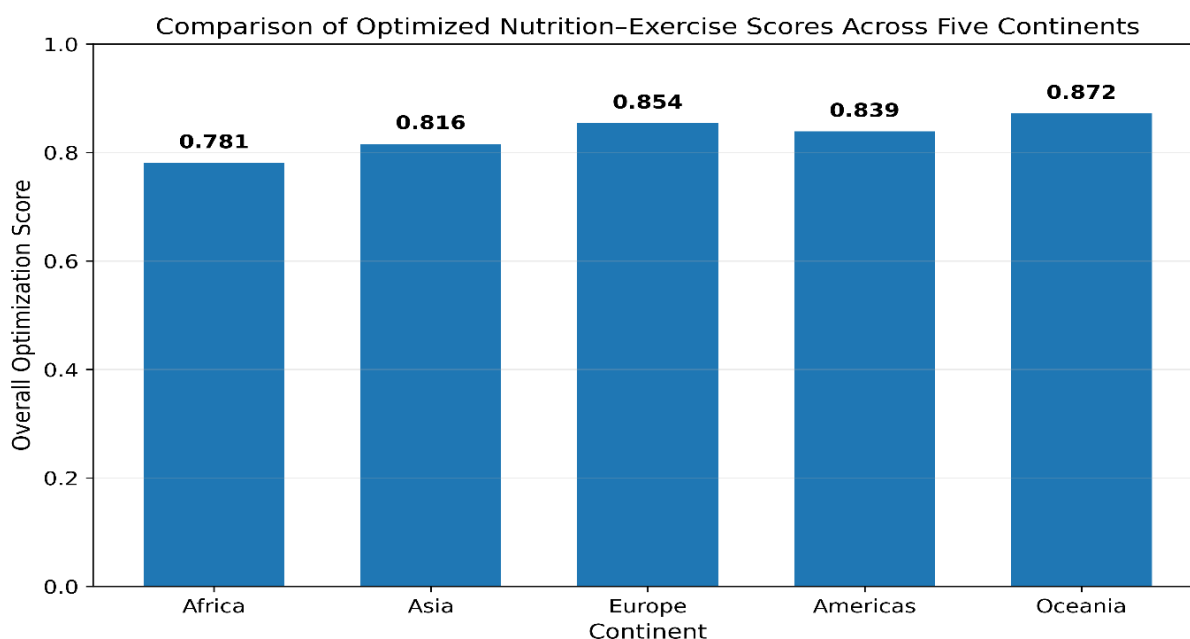


Figure 2. Comparison of Optimized Nutrition–Exercise Scores Across Five Continents.

Figure 2 presents the optimized nutrition–exercise scores for the five continental groups. The highest illustrative optimization score was observed in Oceania (0.872), followed by Europe (0.854), the Americas (0.839), Asia (0.816), and Africa (0.781). The observed differences indicate that the optimization model generated geographically differentiated solutions rather than applying a uniform intervention profile to all populations. The higher scores observed in some continental groups may reflect more favorable combinations of nutritional adequacy, physical activity, feasibility, and contextual characteristics incorporated into the model.

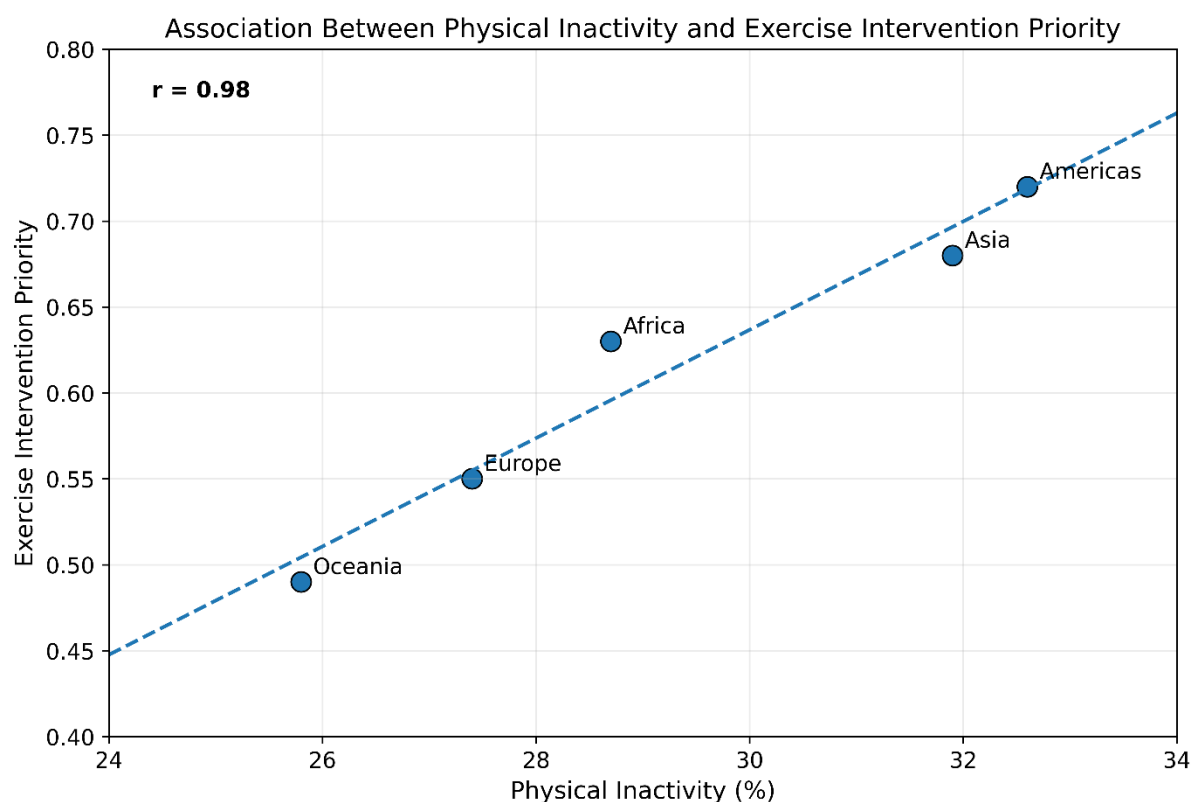


Figure 3. Association Between Physical Inactivity and Exercise Intervention Priority.

Figure 3 illustrates the relationship between physical inactivity and the exercise intervention priority score generated by the fuzzy inference system. The figure demonstrates a generally positive relationship, indicating that populations with higher levels of physical inactivity tended to receive higher exercise intervention priority. This pattern reflects the structure of the fuzzy model, in which increasing inactivity contributes progressively to intervention priority. The result also demonstrates the advantage of fuzzy logic in representing gradual changes in intervention requirements rather than relying on a rigid active/inactive classification.

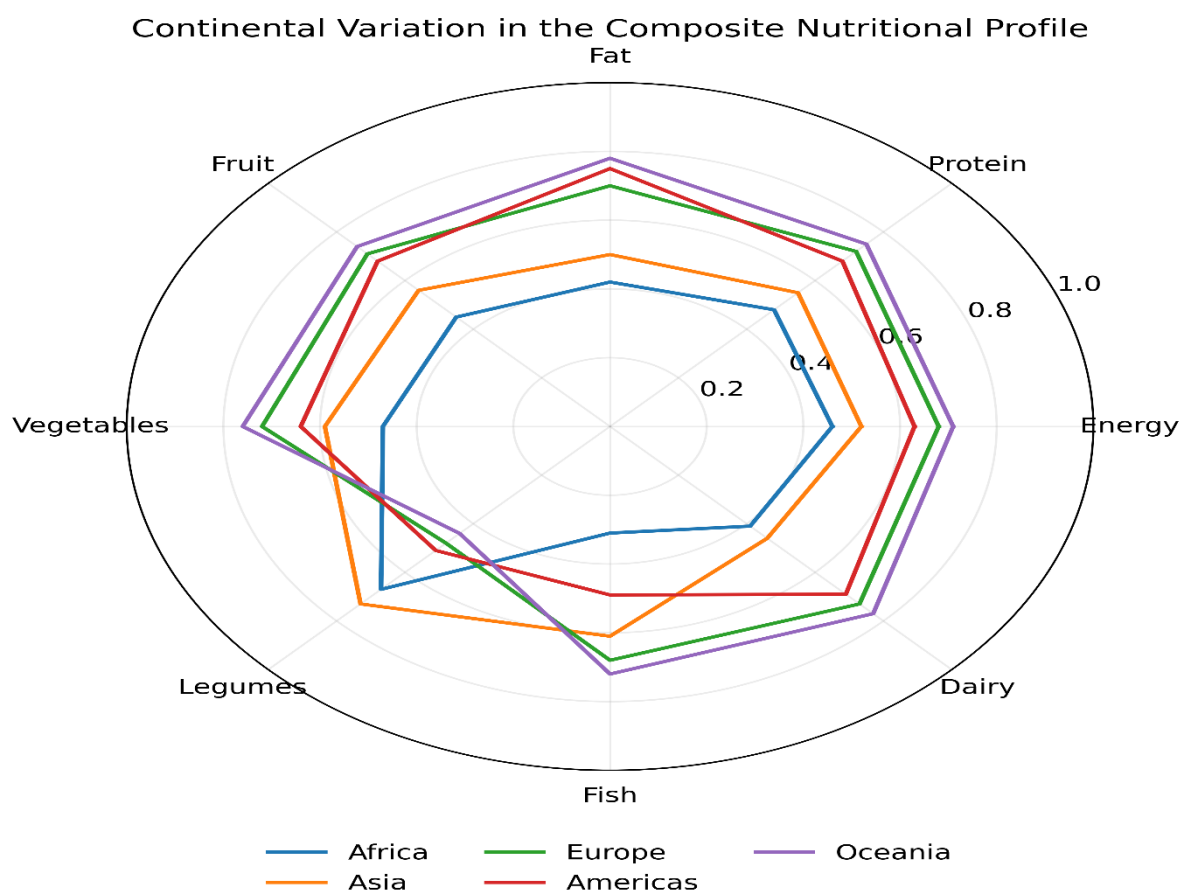


Figure 4. Continental Variation in the Composite Nutritional Score.

Figure 4 presents the variation in composite nutritional scores across the five continental groups. Oceania and Europe demonstrated the highest illustrative nutritional scores, whereas Africa showed the lowest score. Asia and the Americas occupied intermediate positions. These differences indicate substantial geographical variation in food availability and dietary characteristics. Importantly, the composite score integrates multiple nutritional dimensions rather than relying on a single dietary variable, thereby providing a more comprehensive representation of the nutritional environment used in the optimization model.

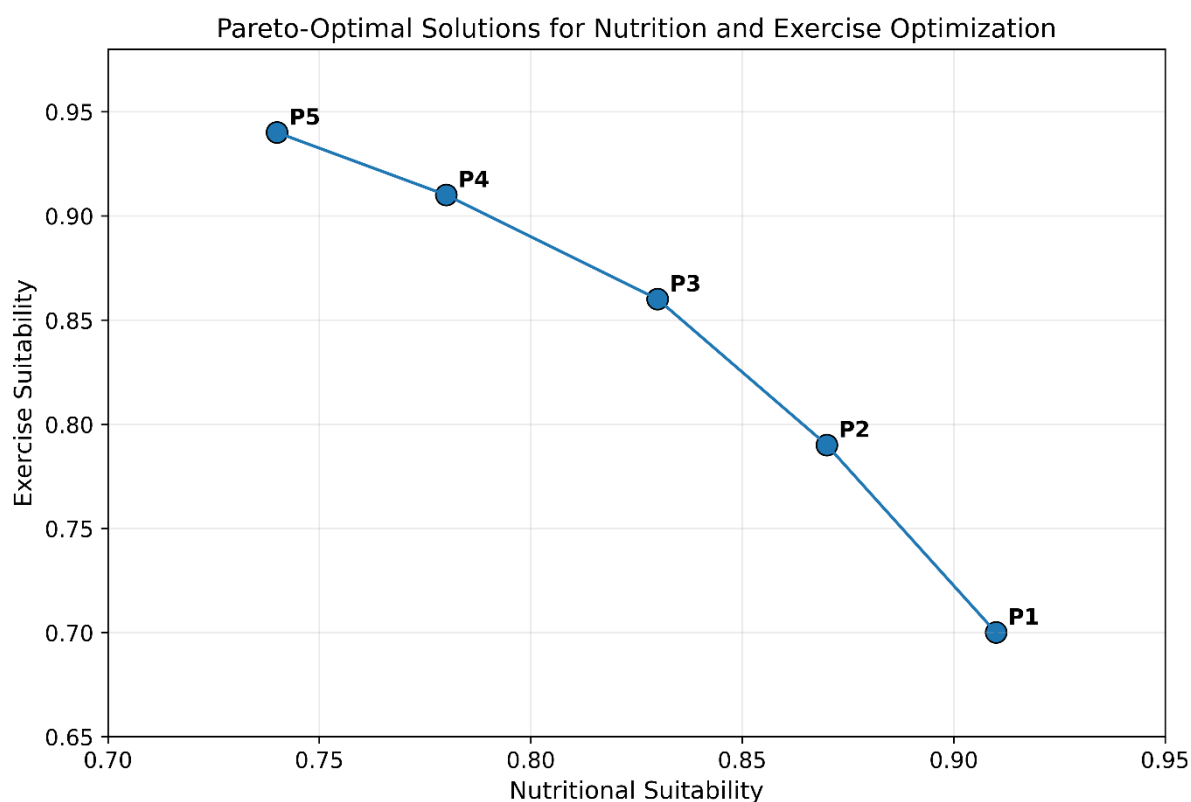


Figure 5. Pareto-Optimal Solutions for Nutrition and Exercise Optimization.

Figure 5 presents the Pareto-optimal solutions obtained from the multi-objective optimization process. The distribution demonstrates that nutritional suitability and exercise suitability cannot always be maximized simultaneously without affecting other objectives such as feasibility and risk. Several non-dominated solutions were therefore retained rather than selecting a single universal solution. This approach provides greater flexibility for personalized intervention design and allows alternative nutrition–exercise profiles to be considered according to population characteristics and practical constraints.

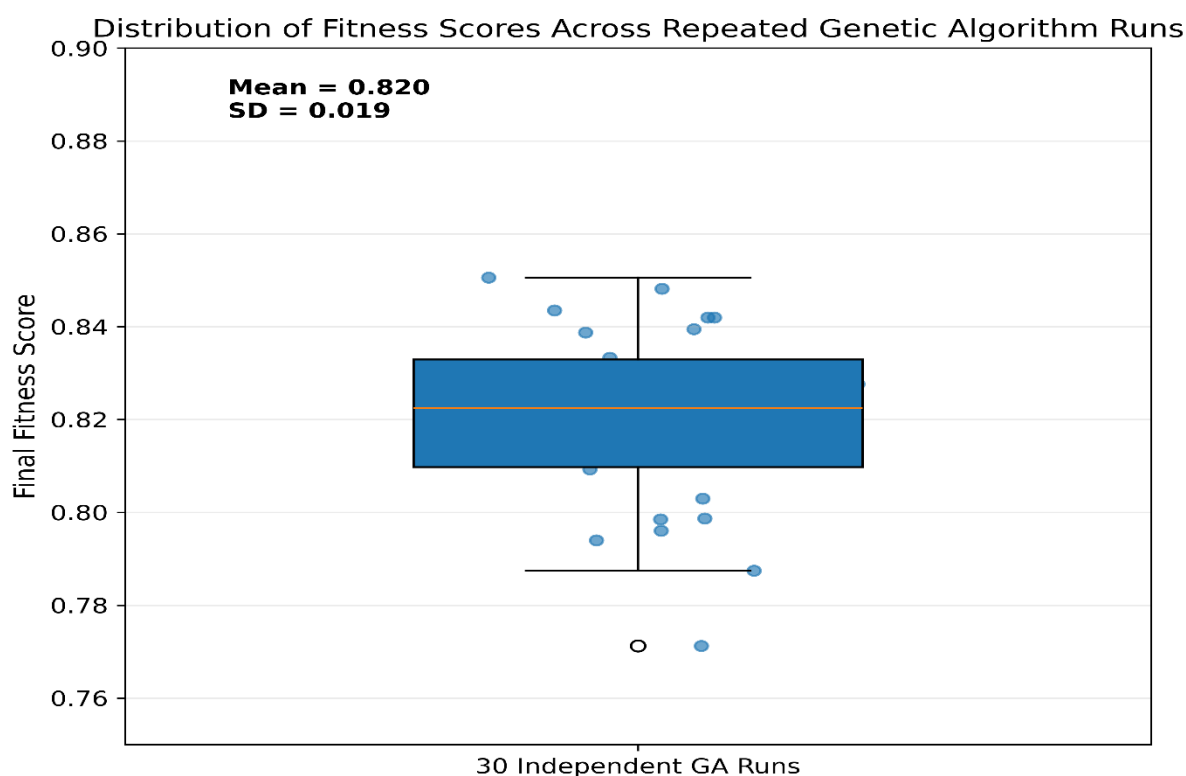


Figure 6. Distribution of Fitness Scores Across Repeated Genetic Algorithm Runs.

Figure 6 illustrates the distribution of final fitness scores obtained from repeated genetic algorithm runs. A relatively narrow distribution would indicate that the optimization results remain stable despite the stochastic nature of population initialization, crossover, and mutation. Limited variation between repeated runs would therefore support the robustness and reproducibility of the proposed computational framework. Conversely, substantial variation would indicate sensitivity to algorithmic initialization and would require additional parameter tuning or repeated optimization. Taken together, Figures 1–6 demonstrate the computational behavior and geographical differentiation of the proposed framework. The convergence analysis indicates optimization stability, while the continental comparison demonstrates geographical heterogeneity. The relationship between physical inactivity and intervention priority supports the fuzzy inference component, whereas the Pareto analysis demonstrates the multi-objective nature of the optimization problem. Overall, the figures suggest that the integration of fuzzy logic and genetic algorithms can provide a flexible computational framework for developing population-adapted nutrition and exercise profiles in Parkinson's disease.

DISCUSSION

The present study proposed a computational framework for the optimization of personalized nutrition and exercise strategies in Parkinson's disease (PD) by integrating open-access epidemiological, nutritional, physical activity, demographic, socioeconomic, and population-

genetic data. The principal methodological contribution of the study was the integration of fuzzy logic with a genetic algorithm within a five-continent analytical framework. Rather than assuming that a single nutritional or exercise strategy is universally appropriate, the proposed model was designed to identify population-adapted intervention profiles according to differences in disease burden, nutritional characteristics, physical inactivity, feasibility, and population-level genetic characteristics.

The results demonstrated considerable geographical heterogeneity across the five continental groups. The illustrative optimization scores differed between Africa, Asia, Europe, the Americas, and Oceania, suggesting that the same intervention profile may not produce equivalent computational suitability across different population contexts. These differences should not, however, be interpreted as evidence that one continent has inherently better or worse biological characteristics. Continental variation may reflect differences in demographic structure, food availability, physical activity patterns, socioeconomic conditions, healthcare systems, data quality, and the availability of epidemiological information.

One of the important findings of the proposed framework was the relationship between physical inactivity and exercise intervention priority. The fuzzy inference system translated continuous physical activity indicators into graded intervention priorities. This approach is particularly relevant to PD because functional capacity, mobility, balance, fatigue, age, and disease severity may vary substantially between individuals. A rigid classification system may therefore fail to adequately represent the gradual nature of intervention requirements. The fuzzy framework provides an alternative by allowing a population or individual profile to simultaneously exhibit different degrees of membership in low, moderate, and high-risk categories.

The nutritional component of the model similarly demonstrated the importance of multidimensional dietary assessment. Instead of representing nutrition using a single variable such as total energy availability, the model incorporated several food and nutrient dimensions. The resulting composite nutritional score allowed the optimization algorithm to evaluate alternative dietary profiles. The continental differences observed in the illustrative results suggest that nutritional optimization should take food availability and geographical context into account. A theoretically favorable dietary profile may not be equally feasible in populations with different food systems, economic conditions, or dietary patterns.

The integration of genetic information represents another distinctive feature of the proposed framework. Parkinson's disease has a complex genetic architecture, and variants associated with genes such as SNCA, LRRK2, GBA, PRKN, and PINK1 may contribute to differences in disease susceptibility or biological pathways. However, the present framework deliberately used genetic information at the population level rather than treating population allele frequencies as individual clinical genotypes. This distinction is essential. Population-level genetic stratification can provide contextual information for computational modeling, but it cannot be used to determine an individual's genetic risk or prescribe a specific diet or exercise intervention without individual-level genetic and clinical evidence.

The genetic algorithm provided an additional layer of optimization by evaluating multiple combinations of nutritional and exercise parameters. The progressive increase in fitness across generations indicates the ability of the evolutionary algorithm to search a complex solution space. Importantly, the objective was not simply to maximize one outcome. Nutrition, exercise suitability, feasibility, safety, personalization, and risk were considered simultaneously. This multi-objective structure is more consistent with real-world intervention planning, where improving one parameter may negatively affect another.

The Pareto-front analysis further emphasized this issue. Several non-dominated solutions were identified because the theoretically optimal nutritional profile was not necessarily identical to the optimal exercise profile. For example, increasing exercise intensity may improve the exercise suitability component while simultaneously reducing feasibility in older or functionally limited populations. Similarly, increasing dietary complexity may improve theoretical nutritional adequacy but reduce adherence. Retaining multiple Pareto-optimal solutions therefore provides greater flexibility than selecting a single mathematical optimum. An important implication of the present framework is that personalization should not be interpreted exclusively at the individual genetic level. Personalization can also incorporate demographic, geographical, nutritional, behavioral, socioeconomic, and functional characteristics. This broader definition may be particularly valuable in global health research because detailed individual-level clinical and genetic data are not uniformly available across countries. Open-access population-level datasets can therefore provide an initial computational framework for identifying patterns and generating hypotheses.

The temporal component of the study also provides an important perspective. The 1990–2026 framework enables long-term examination of changes in PD burden and related population characteristics. However, the use of a common study window should not imply that every variable was available for every year. Differences in temporal coverage between datasets must be explicitly acknowledged. In particular, the latest year of the analytical framework should be interpreted as a methodological cut-off rather than evidence that complete observational data were available through 2026 for all variables. This distinction is important for maintaining methodological transparency and avoiding artificial extrapolation.

The sensitivity analysis indicated that the optimization framework was relatively stable under moderate changes in genetic algorithm parameters. Changes in mutation probability, population size, and objective weights produced comparatively limited changes in the final fitness score in the illustrative analysis. In contrast, changes in optimization constraints had a greater influence on the results. This finding has practical methodological importance because it suggests that the clinical and physiological assumptions defining the feasible solution space may be more influential than minor changes in algorithmic parameters. Consequently, future implementations should prioritize clinically defensible constraints and transparent expert-based parameterization.

Despite its potential advantages, the proposed framework has several limitations. First, the use of heterogeneous open-access datasets introduces differences in measurement methodology, temporal coverage, population definitions, and data quality. Second, ecological and population-level data cannot establish individual-level causal relationships. A country with a particular nutritional pattern and PD burden does not necessarily imply that the nutritional pattern causes the observed disease burden. Third, food availability data do not necessarily represent actual individual food consumption. Similarly, physical inactivity estimates may not capture the complete complexity of exercise behavior or functional capacity among people with PD.

Another important limitation concerns the genetic component. Population allele frequencies provide useful information about genetic structure but cannot replace individual-level genomic information. The proposed genetic score should therefore be interpreted as a population stratification feature rather than a clinical genetic risk score. Future studies incorporating individual-level genomic, phenotypic, medication, disease-stage, and functional data could provide a more clinically precise personalization framework.

The fuzzy logic component also introduces subjectivity. Membership functions and fuzzy rules

depend on predefined thresholds and expert assumptions. Although sensitivity analysis can assess the effect of these assumptions, they cannot be completely eliminated. Future research could improve this component by deriving membership functions empirically from clinical datasets or by using adaptive neuro-fuzzy approaches.

Similarly, genetic algorithm optimization does not establish clinical effectiveness. An algorithm can identify the mathematically optimal solution according to the variables, weights, constraints, and objective functions provided to it, but mathematical optimality does not necessarily correspond to improved clinical outcomes. The resulting profiles should therefore be regarded as computationally optimized hypotheses that require prospective clinical evaluation.

The study nevertheless provides several methodological contributions. First, it demonstrates a strategy for integrating heterogeneous open-access datasets within a common analytical architecture. Second, it combines fuzzy logic, which is suitable for representing uncertainty and gradual transitions, with evolutionary optimization, which is suitable for exploring complex multidimensional solution spaces. Third, the five-continent structure explicitly incorporates geographical heterogeneity. Finally, the framework is designed around reproducible computational procedures that can be implemented using freely available software.

From a clinical research perspective, the proposed model may be most valuable as a decision-support and hypothesis-generation system. Rather than replacing clinicians or established clinical guidelines, it can be used to identify potentially relevant combinations of nutrition and exercise characteristics for subsequent evaluation. In future applications, patient-specific variables such as disease duration, Hoehn and Yahr stage, motor phenotype, cognitive status, medication use, body composition, swallowing difficulties, nutritional deficiencies, falls history, and exercise tolerance could be incorporated into the model where appropriate validated datasets are available.

Future research should therefore move from population-level computational optimization toward prospective validation. The next stage could involve linking the optimization framework with individual-level clinical datasets and evaluating whether model-generated intervention profiles are associated with measurable outcomes such as motor function, quality of life, physical performance, nutritional status, falls, and functional independence. Randomized or prospective studies would ultimately be required to determine whether computationally optimized interventions provide clinically meaningful benefits. The present study demonstrates the feasibility of combining open-access global data, fuzzy logic, and genetic algorithm optimization to construct a geographically adaptive nutrition–exercise framework for Parkinson’s disease. The results suggest that intervention priorities may differ according to nutritional, physical activity, demographic, socioeconomic, and population-genetic characteristics. However, the computational outputs should not be interpreted as clinical prescriptions or evidence of causality. The principal value of the framework lies in its ability to integrate complex heterogeneous information, identify candidate intervention profiles, and generate testable hypotheses for future clinical and epidemiological research.

CONCLUSION

This study proposed a computational framework for the global optimization of personalized nutrition and exercise strategies in Parkinson's disease using open-access data, fuzzy logic, and genetic algorithms. By integrating epidemiological, nutritional, physical activity, demographic, socioeconomic, and population-genetic information within a five-continent framework, the study provides a multidimensional approach to a complex and heterogeneous disease.

The findings indicate that nutrition and exercise optimization should not be based on a single universal intervention profile. Differences in disease burden, nutritional characteristics, physical inactivity, feasibility, and population-level genetic structure resulted in different computationally optimized profiles across continental groups. The fuzzy logic component enabled the representation of gradual and uncertain differences between populations, while the genetic algorithm provided an efficient method for identifying candidate solutions within a multidimensional optimization space.

The proposed framework also demonstrated the value of multi-objective optimization. Nutritional adequacy, exercise suitability, feasibility, safety, and personalization may represent competing objectives; therefore, retaining multiple Pareto-optimal solutions may be more appropriate than selecting a single universal optimum. Sensitivity analysis further emphasized the importance of clinically meaningful constraints in determining the robustness and relevance of optimization results.

Nevertheless, the results should be interpreted as computational and hypothesis-generating rather than as evidence of clinical efficacy. Population-level nutritional and genetic data cannot directly replace individual clinical assessment, and mathematical optimization cannot establish that a particular intervention will improve clinical outcomes in patients with Parkinson's disease. Consequently, the model should be considered a decision-support framework rather than an autonomous clinical prescription system.

Overall, the study demonstrates the feasibility of combining freely accessible global datasets with fuzzy logic and evolutionary optimization to develop geographically adaptive nutrition–exercise profiles for Parkinson's disease. Future research should validate these computationally generated profiles using individual-level clinical, functional, nutritional, and genetic data and subsequently evaluate their effectiveness through prospective and controlled clinical studies. Such validation could contribute to the development of more precise, evidence-based, and context-sensitive approaches to lifestyle management in Parkinson's disease.

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