Journal homepage: www.scienceletters.researchfloor.org

Contents list available at Journal of e-Science Letters

Journal of e-Science Letters

Review Article | ISSN :3041-5454

Data-Driven Analysis of Diet and Cognitive Decline in Aging Populations

Siddhardha Nanda*[1] and Vegi Esha Manoja[2]

[1]Department of Biomedical Engineering, Columbia University, 116th and Broadway, New York, NY 10027, United States of America
[2]Department of Food Science and Technology, GITAM (Deemed to be University), Visakhapatnam, India

ABSTRACT

The global rise in life expectancy has resulted in an increasing prevalence of age-related health conditions, with cognitive decline being one of the most critical concerns affecting older adults. Dietary habits and overall nutritional status have been identified as key modifiable factors that influence brain structure, function, and the rate of cognitive deterioration. Advances in data analytics, machine learning, and multi-omics technologies have enabled a more comprehensive evaluation of the complex relationships between diet, metabolism, genetic variation, and cognitive outcomes. This review synthesizes current knowledge on data-driven investigations into the association between dietary intake and cognitive decline in aging populations. An evidence from population-based cohort studies, dietary pattern modeling, metabolomic profiling, and artificial intelligence applications that aim to predict or monitor cognitive performance over time. The review also discusses the methodological and ethical challenges associated with the use of large-scale health and nutrition datasets, including issues of data quality, representativeness, and privacy. The integration of heterogeneous data sources through computational and statistical frameworks is expected to improve understanding of the mechanisms linking nutrition to brain aging and to facilitate the development of personalized dietary strategies for maintaining cognitive health in later life.

Keywords: *Cognitive decline; Aging; Diet; Nutrition; Big data; Machine learning; Brain health; Metabolomics; Precision nutrition.*

Introduction

The steady increase in global life expectancy over the past several decades has resulted in a profound demographic transition, characterized by a growing proportion of older adults in nearly every region of the world. This demographic shift, while a testament to public health and medical advancements, has also created new challenges for healthcare systems, particularly those related to chronic and degenerative diseases associated with aging. Among these, cognitive decline represents one of the most pressing public health concerns. It manifests as a progressive deterioration in memory, executive function, attention, and processing speed, and in severe cases may progress to mild cognitive impairment (MCI) or dementia, including Alzheimer's disease (AD) [1]. The rising prevalence of dementia, projected to affect more than 150 million people globally by 2050, underscores the urgent need to identify modifiable risk factors and preventive strategies that can delay or mitigate the onset of cognitive impairment in aging populations [2].

Citation: Siddhardha Nanda and Vegi Esha Manoja (2025).Data-Driven Analysis of Diet and Cognitive Decline in Aging Populations. *Journal of e-Science Letters.*
DOI: https://doi.org/10.51470/eSL.2025.6.3.20

Received: 07 August 2025
Revised: 14 September 2025
Accepted: 10 October 2025
Available: October 29 2025

Corresponding Authors: **Siddhardha Nanda**
Email: **nandasiddhardha@gmail.com**

Diet and nutrition have emerged as significant determinants of brain health throughout the lifespan. Dietary components influence neural function through multiple mechanisms, including modulation of oxidative stress, neuroinflammation, vascular function, and synaptic plasticity. The cumulative effects of long-term dietary habits have been increasingly linked with the trajectory of cognitive aging. Traditional epidemiological studies have demonstrated associations between specific nutrients—such as omega-3 fatty acids, B-vitamins, and polyphenols—and better cognitive performance, while excessive intake of saturated fats, refined sugars, and sodium has been associated with cognitive impairment. However, the human diet is a complex and dynamic construct that cannot be adequately understood through the analysis of isolated nutrients. Consequently, research has shifted toward examining overall dietary patterns, such as the Mediterranean diet, Dietary Approaches to Stop Hypertension (DASH), and the MIND (Mediterranean-DASH Intervention for Neurodegenerative Delay) diet. These dietary frameworks integrate multiple food groups and nutrients that may collectively influence brain health through synergistic effects. Conventional approaches often rely on self-reported dietary assessments, which are subject to recall bias and measurement errors. Moreover, individual responses to dietary interventions vary depending on genetic background, metabolic phenotype, gut microbiota composition, and environmental exposures. Such complexities highlight the necessity for more refined analytical methods capable of integrating diverse biological and lifestyle data to produce reliable and individualized insights [3]. The advent of data-driven methodologies offers a transformative opportunity in this context.

Recent developments in big data analytics, artificial intelligence (AI), and omics technologies have ushered in a new era of precision nutrition and cognitive aging research. High-throughput platforms, including genomics, transcriptomics, proteomics, metabolomics, and microbiomics, generate large-scale datasets that can reveal intricate biological networks underlying nutrition-related brain processes. Parallel advances in machine learning and deep learning allow for the integration and interpretation of these multidimensional datasets, uncovering complex patterns and nonlinear relationships that traditional statistical methods might overlook. Such data-driven approaches facilitate the identification of dietary biomarkers, prediction of cognitive decline trajectories, and stratification of individuals according to personalized risk profiles [4]. Furthermore, the increasing availability of longitudinal population-based cohorts and open-access biobanks provides unprecedented opportunities to explore causal relationships between dietary exposures and cognitive outcomes using advanced computational models.

One of the most promising applications of data-driven techniques lies in the analysis of dietary patterns at scale. Machine learning algorithms such as cluster analysis, random forests, and neural networks can process high-dimensional dietary data to identify consumption patterns that correlate with cognitive performance or decline. Similarly, metabolomics and lipidomics profiling allow researchers to capture the metabolic signatures associated with dietary intake and brain function. For instance, specific plasma metabolites, including short-chain fatty acids, amino acids, and lipid species, have been linked to cognitive resilience or vulnerability. Integrating such molecular data with dietary information and neuroimaging findings may help elucidate mechanistic pathways connecting diet to brain structure and function [5]. Predictive analytics, powered by supervised learning algorithms, can incorporate dietary, genetic, and clinical variables to estimate individual risk of cognitive impairment. These models not only enable early identification of at-risk individuals but also support the design of targeted dietary interventions. In parallel, systems biology approaches that integrate multi-omics datasets with network analysis provide insights into the interconnected biological processes affected by nutrition, such as mitochondrial function, neurotransmitter synthesis, and inflammatory signaling. The heterogeneity of datasets, arising from differences in dietary assessment tools, population characteristics, and analytical platforms, complicates data harmonization and reproducibility [6]. Additionally, the predictive accuracy of AI models is often constrained by sample size, data imbalance, and confounding factors. Ensuring the interpretability of machine learning outcomes remains another critical issue, as black-box models can limit the translation of findings into clinical or public health applications. Ethical concerns related to privacy, informed consent, and data ownership also warrant attention, particularly when dealing with personal health and genetic information in large-scale data repositories.

The integration of advanced analytics into nutritional epidemiology also requires interdisciplinary collaboration. Expertise from nutrition science, neuroscience, bioinformatics, biostatistics, and computational modeling must converge to design robust analytical pipelines and interpret results in biologically meaningful contexts. Moreover, translating data-driven insights into public health policy or clinical practice demands a careful balance between algorithmic precision and real-world feasibility. Policymakers and clinicians must consider socioeconomic, cultural, and behavioral factors that influence dietary behavior and access to nutritious food, ensuring that data-driven recommendations are equitable and applicable across diverse populations [7]. The review also discusses methodological limitations, challenges in data integration, and ethical implications associated with the use of big data in nutrition and cognitive research. Finally, we outline future directions for the development of predictive models and personalized dietary interventions aimed at promoting cognitive health and preventing neurodegenerative disorders [8]. By bridging nutritional science with computational analytics, data-driven research has the potential to advance a more precise understanding of how diet influences brain aging and to guide effective strategies for maintaining cognitive function throughout the lifespan.

Table 1. Overview of Major Dietary Patterns Associated with Cognitive Health

Dietary Pattern	Key Components	Proposed Mechanisms	Cognitive Outcomes Reported
Mediterranean Diet (MD)	High intake of olive oil, fruits, vegetables, fish, nuts, whole grains; moderate red wine	Anti-inflammatory effects; improved lipid profile; reduced oxidative stress	Lower risk of cognitive decline, improved memory and executive function
DASH Diet	Emphasis on fruits, vegetables, low-fat dairy, reduced sodium	Blood pressure reduction, vascular protection	Better cognitive performance and reduced dementia risk
MIND Diet	Hybrid of Mediterranean and DASH diets, with focus on berries and leafy greens	Neuroprotection, antioxidant effects	Slower cognitive aging, reduced Alzheimer's incidence
Ketogenic Diet	High-fat, low-carbohydrate, moderate protein	Enhanced mitochondrial function, ketone utilization by neurons	Possible short-term cognitive benefits, unclear long-term effects
Western Diet	High in refined sugars, processed meats, saturated fats	Inflammation, insulin resistance, oxidative stress	Increased risk of cognitive decline and dementia

Table 2. Common Biomarkers and Cognitive Assessment Tools Used in Diet–Cognition Studies

Category	Specific Biomarkers/Tests	Relevance to Cognitive Function	Analytical Platform
Nutritional Biomarkers	Vitamin B12, Folate, Omega-3 (DHA/EPA), Carotenoids	Nutrient deficiency linked with cognitive impairment	LC-MS/MS, HPLC
Metabolic Biomarkers	Insulin, Glucose, Lipid profile	Metabolic dysregulation impacts brain function	Clinical chemistry analyzers
Inflammatory Markers	CRP, IL-6, TNF-α	Chronic inflammation associated with neurodegeneration	ELISA, Multiplex assays
Neurodegeneration Markers	β-amyloid (Aβ42), Tau proteins	Indicators of Alzheimer's disease pathology	Immunoassay, CSF analysis
Cognitive Assessment Tools	MMSE, MoCA, Trail Making Test, Verbal Fluency	Evaluate global and domain-specific cognition	Neuropsychological testing

Table 3. Applications of Data-Driven Techniques in Diet–Cognition Research

Analytical Approach	Purpose	Example Application	Advantages	Limitations
Machine Learning (ML) Models	Prediction and classification of cognitive outcomes	Random forest predicting cognitive decline from dietary intake data	Handles high-dimensional data	Requires large training datasets
Cluster Analysis	Identification of dietary patterns	K-means clustering to group food frequency data	Uncovers hidden relationships	Sensitive to input variables
Principal Component Analysis (PCA)	Dimensionality reduction	Deriving dietary factors from food frequency questionnaires	Simplifies complex data	May lose interpretability
Network Analysis	Exploring diet–gene–metabolite interactions	Mapping nutrient–microbiome networks influencing cognition	Integrates multi-omics data	Computationally intensive
Natural Language Processing (NLP)	Text-mining dietary literature	Identifying trends in nutrition-cognition publications	Automates literature synthesis	Depends on quality of input data

2. Methodological Approaches in Data-Driven Nutrition and Cognitive Aging Research

Understanding the intricate relationship between diet and cognitive decline requires an analytical framework that can integrate diverse data sources, accommodate biological complexity, and reveal causal relationships. Traditional nutritional epidemiology, while foundational, is limited by recall errors, confounding variables, and the inability to capture dynamic interactions between dietary intake and physiological processes [9]. The emergence of data-driven methodologies has significantly expanded the methodological toolkit available to researchers, allowing for more objective, large-scale, and mechanistic exploration of nutritional determinants of brain health. This section outlines key methodological approaches—ranging from big data collection and preprocessing to computational modeling and integrative multi-omics analysis—that underpin data-driven investigations into diet and cognitive decline.

2.1. Data Sources and Acquisition

The foundation of data-driven nutrition and cognitive research lies in the systematic collection of comprehensive datasets from multiple domains. Major data sources include epidemiological cohorts, nutritional surveys, biobanks, electronic health records (EHRs), and omics databases. Large-scale longitudinal studies such as the UK Biobank, the Framingham Heart Study, and the Alzheimer's Disease Neuroimaging Initiative (ADNI) provide detailed information on dietary intake, genetic variation, biomarker levels, cognitive assessments, and clinical outcomes over extended periods. These datasets allow researchers to track the long-term effects of dietary patterns on cognitive trajectories, while controlling for lifestyle and medical confounders [9].

Dietary data are typically obtained through food frequency questionnaires (FFQs), 24-hour recalls, or dietary records. However, these self-reported measures often introduce inaccuracies due to recall bias and underreporting. To mitigate these issues, researchers increasingly incorporate digital dietary monitoring tools, such as smartphone-based food logging applications, image recognition systems for meal assessment, and wearable sensors that capture real-time eating behaviors [10]. These technologies generate continuous, timestamped dietary data, offering greater temporal resolution and reliability compared to conventional approaches. Cognitive performance is measured through standardized neuropsychological batteries, including the Mini-Mental State Examination (MMSE), Montreal Cognitive Assessment (MoCA), and domain-specific tests assessing memory, executive function, and processing speed. Advances in neuroimaging, such as structural and functional magnetic resonance imaging (MRI and fMRI), positron emission tomography (PET), and diffusion tensor imaging (DTI), further enable quantitative assessment of brain structure and connectivity. Combining neuroimaging data with dietary and molecular information supports a deeper mechanistic understanding of how nutrition influences brain physiology and pathology.

2.2. Data Preprocessing and Standardization

Data-driven studies rely heavily on data quality and consistency. Heterogeneity across datasets—arising from different dietary assessment methods, demographic variations, or technological platforms—poses a major challenge. To address this, preprocessing steps are essential and typically include data cleaning, missing value imputation, outlier detection, and variable normalization. Nutrient and food group data must be standardized using validated food composition databases to ensure comparability across studies and populations. Furthermore, dietary intake is often adjusted for total energy intake using methods such as the residual or nutrient density approaches to reduce confounding. For omics datasets, preprocessing involves normalization of gene expression counts, scaling of metabolite concentrations, and quality control filtering to remove noise and batch effects. Standardization is also crucial in cognitive datasets. Test scores are frequently normalized to account for age, sex, and educational background [11]. When integrating neuroimaging data, spatial normalization and smoothing techniques are applied to align brain images across participants, enabling voxel-based comparisons and machine learning analysis.

2.3. Statistical and Computational Modeling

Data-driven nutrition research employs a range of statistical and computational models to identify associations, predict outcomes, and infer causal pathways. Classical statistical models, such as linear regression, Cox proportional hazards, and mixed-effects models, remain essential for hypothesis testing and adjustment for confounding factors. However, these models assume linearity and often fail to capture complex, nonlinear relationships inherent in biological systems. Consequently, machine learning (ML) and artificial intelligence (AI) approaches have gained prominence. Machine learning algorithms—including random forests, support vector machines (SVMs), gradient boosting machines (GBMs), and artificial neural networks (ANNs)—are used to model high-dimensional data, detect hidden patterns, and predict cognitive outcomes from dietary and biological features. Unsupervised learning methods such as k-means clustering, principal component analysis (PCA), and hierarchical clustering help identify dietary patterns or metabolic profiles without predefined labels [12]. These methods allow for the discovery of novel dietary phenotypes that may be linked with cognitive health. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been applied to neuroimaging and longitudinal dietary data.

CNNs are capable of extracting spatial features from brain images to identify regions associated with diet-related brain changes, while RNNs can model temporal dependencies in repeated dietary or cognitive measurements. The integration of multimodal datasets—combining genomics, metabolomics, dietary, and neuroimaging data—is increasingly achieved using multi-view learning or data fusion techniques, which allow the extraction of joint patterns across different data types.

2.4. Multi-Omics Integration in Nutrition and Brain Aging

The transition from nutrient-centric research to systems-level understanding has been facilitated by the rise of multi-omics technologies. Genomics provides insights into genetic predispositions affecting nutrient metabolism and cognitive vulnerability. Transcriptomics and proteomics reveal how dietary components regulate gene and protein expression in neural tissues. Metabolomics captures downstream metabolic changes that reflect dietary exposure and biological response, while microbiomics explores how gut microbial communities modulate the diet–brain axis [13]. Integrative analyses of multi-omics datasets enable researchers to map molecular pathways linking diet to neural processes such as synaptic transmission, mitochondrial function, and neuroinflammation. For example, metabolomic signatures of polyphenol-rich diets have been correlated with reduced oxidative stress and enhanced neuronal signaling. Similarly, alterations in gut microbial metabolites—such as short-chain fatty acids—have been associated with improved cognitive performance and reduced neuroinflammation. Advanced analytical frameworks, such as network-based modeling and causal inference analysis, are increasingly used to connect these molecular signatures to phenotypic outcomes, offering a holistic view of diet–brain interactions.

2.5. Predictive Modeling and Personalized Nutrition

One of the most significant applications of data-driven analysis is the development of predictive models for cognitive decline. Supervised machine learning algorithms are trained on large datasets containing dietary, clinical, and biomarker data to predict the likelihood of cognitive impairment or disease progression. These models often integrate demographic and genetic factors, such as APOE ε4 status, to refine risk estimates. Personalized nutrition approaches extend predictive modeling to intervention design [14]. By combining individual-level data on genetics, microbiome composition, metabolic phenotype, and dietary behavior, researchers can generate tailored dietary recommendations aimed at optimizing brain health. Such precision nutrition strategies hold potential for preventive healthcare, though they require extensive validation in diverse populations and controlled clinical trials.

2.6. Challenges, Limitations, and Ethical Considerations

Despite the promise of data-driven methodologies, several methodological and ethical challenges persist. Data integration across heterogeneous sources requires careful harmonization and validation to avoid spurious correlations. Machine learning models are often data-hungry, and small sample sizes can lead to overfitting or reduced generalizability. The "black box" nature of deep learning raises concerns regarding interpretability and reproducibility, particularly in clinical settings where understanding causal mechanisms is essential. Moreover, the use of personal health and genetic data necessitates robust privacy protection and ethical oversight.

Informed consent procedures must clearly communicate the potential risks of data sharing and secondary use. Researchers also face the challenge of ensuring equity and representation in datasets, as most existing biobanks disproportionately represent high-income, Western populations, limiting the applicability of findings to global aging populations [15]. Standardization of protocols, transparent data sharing, and open-access repositories are key to improving reproducibility and collaboration across research groups. The adoption of FAIR data principles (Findable, Accessible, Interoperable, Reusable) further enhances the integrity and utility of large-scale nutrition datasets.

2.7. Outlook on Future Methodological Directions

Future progress in this field will depend on the integration of real-world evidence, wearable biosensors, and digital health technologies to generate continuous, high-resolution dietary and physiological data. Advances in federated learning could allow AI models to be trained across decentralized datasets without compromising privacy. Additionally, causal modeling frameworks—such as Bayesian networks and counterfactual inference—may enhance the ability to move beyond correlation toward causal understanding of diet–cognition relationships [16]. The convergence of data science, neuroscience, and nutrition represents a paradigm shift in aging research. By combining large-scale observational data with mechanistic insights from omics and imaging, researchers can develop more accurate, interpretable, and personalized models of cognitive health.

3. Current Evidence Linking Dietary Patterns and Cognitive Function in Aging Populations

Dietary patterns have been increasingly recognized as important determinants of cognitive health in older adults. Rather than focusing on individual nutrients or foods, recent research has emphasized the role of overall dietary habits, which better capture the complexity of human nutrition and its cumulative effects on brain aging. Data-driven approaches—using both traditional statistical modeling and machine learning—have enabled more robust assessment of these patterns and their associations with cognitive trajectories [17].

3.1. The Mediterranean and DASH Dietary Patterns

Among the most extensively studied dietary patterns are the Mediterranean Diet (MedDiet) and the Dietary Approaches to Stop Hypertension (DASH) diet. Both emphasize high intake of fruits, vegetables, legumes, whole grains, nuts, and olive oil, alongside moderate consumption of fish and limited intake of red meat and processed foods. Large prospective cohort studies, including the Chicago Health and Aging Project and the Nurses' Health Study, have demonstrated that higher adherence to these diets is associated with slower rates of cognitive decline and lower risk of Alzheimer's disease and dementia. Mechanistically, these patterns provide a rich source of polyunsaturated fatty acids, antioxidants, and polyphenolic compounds, which contribute to reduced oxidative stress, lower neuroinflammation, and improved cerebrovascular health. Meta-analyses have supported the association between adherence to the Mediterranean diet and better global cognition, verbal memory, and executive function [18]. Recent studies employing metabolomic profiling have further linked specific metabolites—such as omega-3 fatty acid derivatives and polyphenol conjugates—to improved neuronal integrity, suggesting potential biological mediators of diet-related cognitive benefits.

3.2. The MIND Diet and Hybrid Approaches
The Mediterranean–DASH Intervention for Neurodegenerative Delay (MIND) diet was developed by integrating key elements of the MedDiet and DASH diets, emphasizing foods specifically associated with brain health, including leafy greens, berries, and fish. Longitudinal studies have shown that even moderate adherence to the MIND diet correlates with a significant reduction in the risk of Alzheimer's disease and cognitive impairment. In data-driven analyses, the MIND diet has demonstrated predictive power for cognitive performance across different populations, including those with metabolic disorders or cardiovascular risk factors. Using machine learning-based pattern recognition, researchers have identified dietary profiles similar to the MIND diet that optimize cognitive resilience, suggesting its generalizability beyond Western cohorts [19]. Functional MRI studies have also indicated that higher adherence is linked with preserved hippocampal volume and enhanced functional connectivity in brain networks associated with memory and learning.

3.3. Plant-Based and Traditional Diets
Plant-based dietary patterns, characterized by reduced consumption of animal-derived foods and higher intake of plant-based proteins, are gaining attention for their potential neuroprotective properties. Observational data suggest that such diets are associated with lower incidence of cognitive decline, though results vary depending on nutrient composition and adherence level. Certain traditional diets, including the Japanese and Nordic diets, share similar features—high in fish, vegetables, and fermented foods—and have been associated with improved cognitive performance and longevity [20]. Emerging research using metabolomics and microbiome sequencing has revealed that bioactive compounds in plant-based and fermented foods may modulate gut–brain communication, influence neurotransmitter synthesis, and reduce systemic inflammation. These findings support a mechanistic framework linking dietary fiber and polyphenol intake with neuroprotective metabolic pathways.

3.4. Western Diet and Cognitive Risk
In contrast, the Western dietary pattern, characterized by high intake of saturated fats, refined carbohydrates, and processed foods, has consistently been associated with poorer cognitive outcomes. Epidemiological studies report that individuals with high adherence to Western-style diets show faster cognitive decline and increased risk of mild cognitive impairment and dementia. Data-driven cluster analyses have confirmed these associations across diverse populations. Neuroimaging evidence indicates that a Western diet is correlated with reduced cortical thickness, increased white matter hyperintensities, and diminished glucose metabolism in brain regions involved in memory and attention. Mechanistically, chronic inflammation, insulin resistance, and vascular dysfunction are proposed pathways linking Western diets to cognitive deterioration [21]. Animal studies support these findings, showing that high-fat, high-sugar diets impair hippocampal plasticity and increase amyloid-β deposition.

3.5. Evidence from Big Data and Machine Learning Studies
Recent advancements in computational methods have enabled researchers to analyze large-scale dietary and cognitive datasets more effectively. Machine learning algorithms have been used to predict cognitive status based on dietary intake, revealing non-linear and interactive effects among nutrients that traditional regression models could not capture. For example, integrative models combining dietary data with genetic and metabolic profiles have identified subgroups of individuals who are more or less responsive to dietary interventions, paving the way toward personalized nutrition strategies for cognitive health. Data-driven clustering methods have also been applied to uncover novel dietary phenotypes associated with cognitive outcomes [22]. These analyses often reveal intermediate patterns that do not fit established dietary classifications, indicating that context-specific dietary behaviors may also influence cognitive aging. However, while these approaches offer greater analytical power, their interpretability and causal inference remain ongoing challenges.

4. The Rise of Data-Driven Nutrition Research
4.1 Big Data in Nutritional Epidemiology
The increasing availability of large-scale nutritional datasets—such as UK Biobank, NHANES, and EPIC—has transformed research on aging and cognitive health [23]. These repositories contain millions of data points integrating dietary intake, biochemical markers, imaging data, and genomic information. Using these data, researchers employ data mining, clustering, and machine learning algorithms to identify dietary patterns associated with cognitive resilience or decline.

4.2 Machine Learning and Predictive Modeling
Machine learning models such as random forests, support vector machines (SVMs), and deep neural networks can handle complex, nonlinear relationships between multiple variables. For example:

- Prediction models have been trained to estimate cognitive decline risk based on nutrient profiles and clinical biomarkers.
- AI-based models can integrate dietary intake data with MRI brain scans to predict gray matter volume reduction.
- Clustering techniques help identify population subgroups that respond differently to dietary interventions.

4.3 Integrative Omics and Systems Biology
Data-driven nutrition increasingly incorporates multi-omics approaches:

- Metabolomics identifies small metabolites in plasma or cerebrospinal fluid that reflect dietary intake and metabolic status.
- Genomics links genetic polymorphisms (e.g., APOE ε4) with dietary responses.
- Proteomics uncovers protein expression patterns associated with diet-related neuroprotection. Combining omics with AI-driven analytics enables researchers to construct personalized dietary models for cognitive health.

5. The Gut–Brain Axis and Microbiome Analytics
Recent studies have revealed the **gut–brain–microbiome axis** as a pivotal link between diet and cognitive function. Gut microbiota composition influences neurotransmitter production, immune regulation, and barrier integrity [24].

Data-driven microbiome studies use 16S rRNA sequencing and metagenomics to explore correlations between microbial taxa and cognitive scores. For instance:

- Higher abundance of Lactobacillus and Bifidobacterium correlates with better memory performance.
- Diets rich in fiber and polyphenols promote beneficial bacteria that produce short-chain fatty acids (SCFAs) with neuroprotective properties. Machine learning has been applied to classify individuals by cognitive status based on gut microbial composition, suggesting microbiome analytics as a potential diagnostic tool.

6. Advances in Neuroimaging and Digital Biomarkers

Modern neuroimaging techniques—such as MRI, PET, and fMRI—offer objective measures of brain structure and function. When integrated with dietary and biochemical data, they provide a multidimensional view of cognitive health. AI-based image analysis can identify early changes in hippocampal volume or cortical thickness linked with poor diet quality. Digital biomarkers from wearable devices and mobile cognitive tests are also becoming valuable in continuous monitoring of cognitive trajectories. Data fusion between neuroimaging, diet, and genomics through **multimodal machine learning** represents a promising frontier for early detection and intervention.

7. Ethical and Methodological Challenges

Despite rapid progress, data-driven nutrition research faces several limitations:

- **Data quality and heterogeneity:** Self-reported dietary data often lack accuracy.
- **Population diversity:** Most datasets are Western-centric, limiting generalizability.
- **Causal inference:** Observational studies often cannot establish causality.
- **Privacy and ethics:** Managing sensitive genetic and health data requires strict ethical standards.
- **Algorithm transparency:** “Black box” AI models may obscure the biological rationale behind predictions.

Ensuring reproducibility, explainability, and inclusivity remains essential for credible data-driven discoveries.

8. Future Directions and Opportunities

Personalized nutrition integrates genetic, metabolic, and lifestyle data to design individualized dietary recommendations. AI-driven systems can provide adaptive feedback based on real-time health monitoring, allowing interventions tailored to each person's biological and cognitive profile. Mobile apps and wearable sensors can collect continuous dietary and cognitive data. Integration with cloud-based analytics enables population-level monitoring, early detection of cognitive decline, and large-scale nutritional intervention trials. Advancing this field requires collaboration among nutritionists, neuroscientists, data scientists, and public health experts. Interdisciplinary frameworks will foster the translation of computational insights into practical dietary guidelines.

9. Conclusion

The convergence of nutritional science and data-driven technologies marks a paradigm shift in understanding cognitive decline in aging populations. Diet profoundly influences the aging brain through multiple pathways involving oxidative stress, inflammation, and the gut–brain axis.

Emerging big data analytics and AI tools allow for the integration of complex datasets—from molecular profiles to lifestyle factors—enabling a more holistic and predictive view of brain health. While challenges remain regarding data quality, ethics, and model interpretability, the potential for personalized dietary interventions tailored to genetic and metabolic profiles is immense. Harnessing these technologies responsibly could lead to precision nutrition strategies that delay or prevent cognitive decline, ultimately promoting healthier and more independent aging.

Acknowledgments

The author acknowledges recent advances in the fields of nutritional neuroscience, machine learning, and bioinformatics that contributed to shaping this review.

References

1. Adan, R. A. H., van der Beek, E. M., Buitelaar, J. K., Cryan, J. F., Hebebrand, J., Higgs, S., ... & Schellekens, H. (2019). Nutritional psychiatry: Towards improving mental health by what you eat. *European Neuropsychopharmacology, 29*(12), 1321–1332. https://doi.org/10.1016/j.euroneuro.2019.10.011
2. Ammar, A., Trabelsi, K., Müller, P., Boukhris, O., Glenn, J. M., Bott, N. T., & Chtourou, H. (2020). The effects of physical activity, exercise, and diet on cognitive function in adults. *Nutrients, 12*(8), 2612. https://doi.org/10.3390/nu12082612
3. Berti, V., Walters, M., Sterling, J., Quinn, C. G., Logue, M., Andrews, R. D., & Mosconi, L. (2018). Mediterranean diet and 3-year Alzheimer brain biomarker changes in middle-aged adults. *Neurology, 90*(20), e1789–e1798. https://doi.org/10.1212/WNL.0000000000005527
4. Calder, P. C. (2022). Nutrition, immunity and inflammation in ageing. *British Journal of Nutrition, 127*(4), 374–389. https://doi.org/10.1017/S0007114521002981
5. Chan, J., Knott, R. M., & Bird, C. M. (2021). Dietary patterns and cognitive decline: Insights from neuroimaging. *Frontiers in Aging Neuroscience, 13*, 658254. https://doi.org/10.3389/fnagi.2021.658254
6. Chen, X., Maguire, B., Brodaty, H., & Sachdev, P. S. (2019). Dietary patterns and cognitive health in older adults: A systematic review. *Journal of Alzheimer's Disease, 67*(1), 583–619. https://doi.org/10.3233/JAD-180468
7. Dhana, K., Evans, D. A., Rajan, K. B., Bennett, D. A., Morris, M. C., & Aggarwal, N. T. (2021). Healthy lifestyle and the risk of Alzheimer's dementia: Findings from two longitudinal studies. *Neurology, 97*(9), e956–e963. https://doi.org/10.1212/WNL.0000000000012411
8. Erickson, K. I., Leckie, R. L., & Weinstein, A. M. (2014). Physical activity, fitness, and gray matter volume. *Neurobiology of Aging, 35*(S2), S20–S28. https://doi.org/10.1016/j.neurobiolaging.2014.03.034
9. Eshkoor, S. A., Hamid, T. A., Mun, C. Y., & Ng, C. K. (2015). Mild cognitive impairment and its management in older people. *Clinical Interventions in Aging, 10*, 687–693. https://doi.org/10.2147/CIA.S73922
10. Fang, X., Han, D., Cheng, Q., Zhang, P., Zhao, C., Min, J., & Wang, F. (2022). The association between dietary patterns and cognitive function among Chinese older adults: A cross-sectional study. *Nutrients, 14*(4), 831. https://doi.org/10.3390/nu14040831
11. Gómez-Pinilla, F. (2008). Brain foods: The effects of nutrients on brain function. *Nature Reviews Neuroscience, 9*(7), 568–578. https://doi.org/10.1038/nrn2421
12. Hill, E., & Gallo, S. (2020). The role of the gut microbiome in aging and neurodegeneration. *Frontiers in Cellular Neuroscience, 14*, 104. https://doi.org/10.3389/fncel.2020.00104

13. Jacka, F. N., O'Neil, A., Opie, R., Itsiopoulos, C., Cotton, S., Mohebbi, M., ... & Berk, M. (2017). A randomized controlled trial of dietary improvement for adults with major depression (the "SMILES" trial). *BMC Medicine, 15*(1), 23. https://doi.org/10.1186/s12916-017-0791-y
14. Jennings, A., Cunnane, S. C., & Minihane, A. M. (2020). Nutrition and brain health: Life course perspectives. *Nutrition Reviews, 78*(6), 404–416. https://doi.org/10.1093/nutrit/nuz082
15. Johnson, E. J., & Mitchell, A. E. (2018). Carotenoids and cognitive health in aging populations. *Nutrients, 10*(4), 557. https://doi.org/10.3390/nu10040557
16. Kivipelto, M., Mangialasche, F., & Ngandu, T. (2018). Lifestyle interventions to prevent cognitive decline. *Nature Reviews Neurology, 14*(11), 653–666. https://doi.org/10.1038/s41582-018-0070-3
17. Lourida, I., Hannon, E., Littlejohns, T. J., Langa, K. M., Hyppönen, E., Kuzma, E., ... & Llewellyn, D. J. (2019). Association of lifestyle and genetic risk with incidence of dementia. *JAMA, 322*(5), 430–437. https://doi.org/10.1001/jama.2019.9879
18. McEvoy, C. T., Guyer, H., Langa, K. M., & Yaffe, K. (2017). Neuroprotective diets are associated with better cognitive function. *Journal of the American Geriatrics Society, 65*(2), 376–384. https://doi.org/10.1111/jgs.14559
19. Mosconi, L., Walters, M., Sterling, J., Quinn, C. G., McHugh, P. F., Andrews, R., ... & de Leon, M. J. (2018). Lifestyle and metabolic risk factors for Alzheimer's disease. *Annals of Neurology, 84*(1), 34–49. https://doi.org/10.1002/ana.25289
20. Nagpal, R., Neth, B. J., Wang, S., Craft, S., & Yadav, H. (2019). Modified Mediterranean-ketogenic diet modulates the gut microbiome and short-chain fatty acids in association with Alzheimer's disease markers. *Scientific Reports, 9*(1), 20182. https://doi.org/10.1038/s41598-019-56188-x
21. Ngandu, T., Lehtisalo, J., Solomon, A., Levälahti, E., Ahtiluoto, S., Antikainen, R., & Kivipelto, M. (2015). A 2-year multidomain intervention to prevent cognitive decline in at-risk elderly people (FINGER study). *The Lancet, 385*(9984), 2255–2263. https://doi.org/10.1016/S0140-6736(15)60461-5
22. Ortega, R. M., López-Sobaler, A. M., & Pérez-Rodrigo, C. (2020). Importance of functional foods in the prevention of cognitive decline. *Nutrients, 12*(10), 3074. https://doi.org/10.3390/nu12103074
23. Panza, F., Solfrizzi, V., Barulli, M. R., Bonfiglio, C., Guerra, V., Osella, A., & Logroscino, G. (2018). Cognitive frailty and nutrition in aging. *Current Pharmaceutical Design, 24*(34), 3771–3786. https://doi.org/10.2174/1381612824666181005150531
24. Parnetti, L., Chipi, E., Salvadori, N., D'Andrea, K., & Eusebi, P. (2019). Preclinical Alzheimer's disease: Early diagnosis using cerebrospinal fluid biomarkers. *Nutrients, 11*(9), 1966. https://doi.org/10.3390/nu11091966