International Journal of Economic Practices and Theories (IJEPT)
ISSN: 2247-7225
Volume 2026, Issue 1

AI-Driven Price Elasticity Analysis for Health Foods in Consumer Markets

Aashna Singh

Dhirubhai Ambani International School, Mumbai,

singhaashna1711@gmail.com

Abstract. Although the price elasticity of demand plays an essential role in shaping consumers' behavior in terms of healthy consumption, existing econometric estimates rely on assumptions of linearity and homogeneity in consumers' responses to changing prices, which are far from reality. This paper introduces and evaluates an AI-driven approach that combines a hybrid gradient boosting and deep learning representation of the price elasticity of healthy foods with a PLS-SEM nomological network. Three reflective constructs (AI-based Fiscal Policy and Healthy Food Consumption (HFC), Behavioral Price Sensitivity (BPS), and Hybrid AI Elasticity Estimation (AIE)) were tested on a sample of 250 consumers. The measurement model demonstrated that all indicators satisfied reliability and validity criteria (composite reliability = 0.803-0.877; HTMT < 0.75). The structural model showed that AIE significantly explained BPS ($\beta = 0.568$, $f^2 = 0.477$, $R^2 = 0.323$) and HFC ($\beta = 0.470$, $f^2 = 0.283$, $R^2 = 0.220$), with statistical power ≈ 1.000 at the 1% level. These results support all three hypotheses: the hybrid AI representation model has high explanatory power, behavioral covariates strongly affect price sensitivity among low-income populations, and AI signals for subsidies or taxation are positively correlated with healthy consumption among poorer groups. This framework provides an evidence-based basis for policymaking when considering food pricing.

Keywords: Price elasticity; health foods; machine learning; gradient boosting; deep learning; PLS-SEM.

1 Introduction

The health food sector is undergoing a visible shift, with one particular example showing that marketing features related to packaging become equally important to sensory qualities when influencing consumers. The growing interest of modern customers to nutrition has been accompanied by their readiness to pay more for the products with certain functional qualities, including the medical effect. It has been proved by the policies adopted in Europe, such as the Farm to Fork Strategy, intended at the treatment of chronic diseases due to the improvement of the food label transparency. In any case, according to the sources, the information delivery will be the major factor determining the consumers' decisions regarding diet selection (Nazzaro et al., 2025). This willingness to pay a premium is reflected at scale: in the United States alone, wellness represents more than $500 billion in annual spend, growing at 4 to 5 percent each year, and 84 percent of US consumers rank wellness as a "top" or "important" priority (Pione et al., 2025). The given research examines how AI is changing the food industry across the globe through a transition from a conventional chain of food supply to a consumer-oriented system. Through the use of machine learning, big data, and IoT, such a system will ensure that individual food choices shape agricultural production and sustainability. These shifting consumer priorities are also reshaping how people think about organic food itself.

Organic food consumption itself is shifting for similar reasons, moving away from the ideology of environmentalism toward the benefits of improved health as the main factor that influences purchase decisions. Although the idea of sustainability serves as a basis for such an approach, it can be said that consumers find it easier to defend increased costs in case they expect tangible physiological benefits. However, while such a tendency becomes clear, it should be stated that there is an important theoretical issue that concerns the way in which consumers perceive the notion of "health." It can be considered dangerous for researchers because they will interpret data incorrectly without a clear definition of health (Ditlevsen et al., 2019). This ambiguity around what counts as "health" is significant given how widespread health-driven purchasing already is: approximately half of consumers in the United States, United Kingdom, and Germany, and roughly two-thirds of Gen Z and millennial consumers, report having purchased functional-nutrition products in the past year (Callaghan et al., 2021). This same lack of a clear standard carries real consequences once it reaches the food safety side of the supply chain.Food safety itself has become a developing global concern, closely tied to public health at a global level. Modern supply chains have become much more complicated and, as a result, threats to the health of people are no longer limited to one country and affect different nations. It is stated that a critical analysis of literature is required to identify the main safety issues occurring in the international supply chains. In addition, the need for analytical models is pointed out in order to learn about the consumer demand in health-related products (Gizaw, 2019). The source stresses the importance of using cyclical feedback mechanisms in order to analyze data and enhance the efficiency of food systems in meeting their goals. Moreover, the researcher underlines the need for robust governance structures and cooperation across disciplines in order to apply the above-mentioned technologies efficiently (Chen et al., 2024). These governance and safety concerns extend directly into how the health food industry is regulated and priced. The research presented discusses the dynamic nature of the health food industry, especially concerning regulations and economics affecting functional products. It discusses how consumer consciousness and technological changes have transformed the consumer demand for products, making the traditional approach to pricing obsolete. The sources discuss the legal framework surrounding nutritional claims within different countries such as the USA, Europe, and Japan, showing how there is a difference in the procedures followed despite having the same goal. The sources also show that there needs to be a change in the way labeling is done to ensure that health claims made are valid (Díaz et al., 2020). These same regulatory gaps are what make AI-driven pricing practices worth examining next.

Artificial intelligence is also pushing away from traditional market mechanisms to price discrimination, using complex algorithmic systems to mine large amounts of personal information to exploit the whole consumer surplus. This technology doesn’t just stop at price discrimination, but goes even more aggressive with dynamic pricing by using elasticity determination methods. This article raises concerns that this kind of mechanism will work like a monopoly and can damage the ‘invisible hand’ and disposable incomes of people. Moreover, this article examines the socio-economic consequences of this practice, and the necessity of governmental intervention and consumer consent regulations (Kang, 2024). This tension between opportunity and risk is reflected in industry adoption data: 62 percent of healthcare leaders say consumer engagement and experience is where generative AI has the most potential, but only 29 percent have started using gen AI for any purpose in their organization (Cordina et al., 2024). The rapid take-up/cautious rollout tension even extends to how elasticity itself is measured in food markets.

The basic principles of own-price elasticity are also valid in the international food market and explain the impact of price changes on consumer demand. Budgeting is analysed with econometric models such as the Almost Ideal Demand System model, which is used to study the effect of different economic variables. Necessity and income play an important role in determining the level of these elasticities, which are higher for staples than for luxury foods. The health food industry itself is undergoing structural change, suggesting that conventional linear static models are not able to explain today's consumers' behavior. The ultimate conclusion made here is that low-income areas have higher sensitivity to food prices due to the greater part of income spent on nutrition (Green et al., 2013). The conceptual framework guiding this discussion is illustrated in Fig. 1.

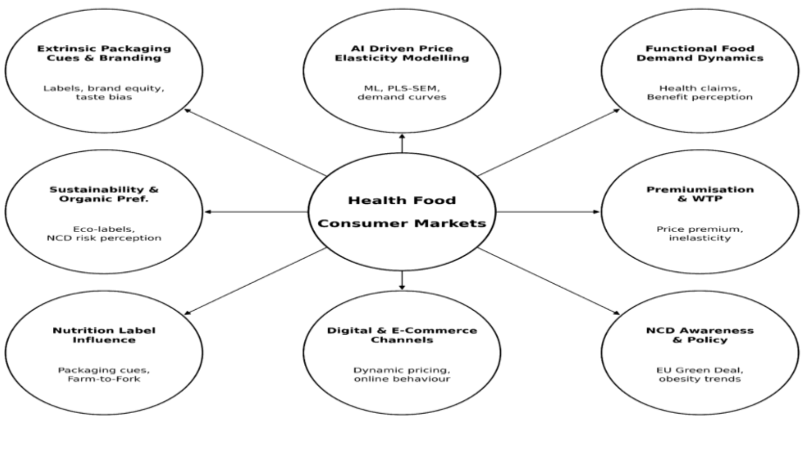


Fig. 1. AI-driven price elasticity analysis for health foods in consumer markets.

Conceptual framework of health food consumer markets, showing seven behavioural determinants (packaging cues, functional food demand, premiumisation/WTP, digital channels, nutrition labels, sustainability preferences, and NCD policy awareness) feeding into an AI-driven price elasticity model that uses ML and PLS-SEM to derive demand curves. Predictive analysis of this kind is also central to how artificial intelligence affects dynamic pricing, using price elasticity measurements to guide seller decisions. Through market trends, it is possible for the seller to manipulate his minimum acceptable price to generate maximum profit. It is clear from this study that a seller will postpone transaction when prices are likely to increase in the future and hasten transactions when values in the market are going down. Machine learning makes it possible to have a more reactive system to changes in product costs and consumer behavior (Chen et al., 2024). Artificial intelligence and machine learning are transforming the process of evaluating price elasticity and consumer behavior in the digital marketplace. This is through the emphasis on the trend towards e-commerce due to the increase in availability of smartphones, lifestyle changes and robust online payment systems. Although there are great opportunities for growth in the digital world, it is clear from the source that there are challenges for the entrepreneur including price competition and difficulty in ensuring quality of products. Therefore, there is an emphasis in the research on the use of multidimensional data analysis to allow sellers to develop pricing models (Phromphithakkul, 2024). The proposed machine learning architecture used for elasticity estimation is depicted in Fig. 2.

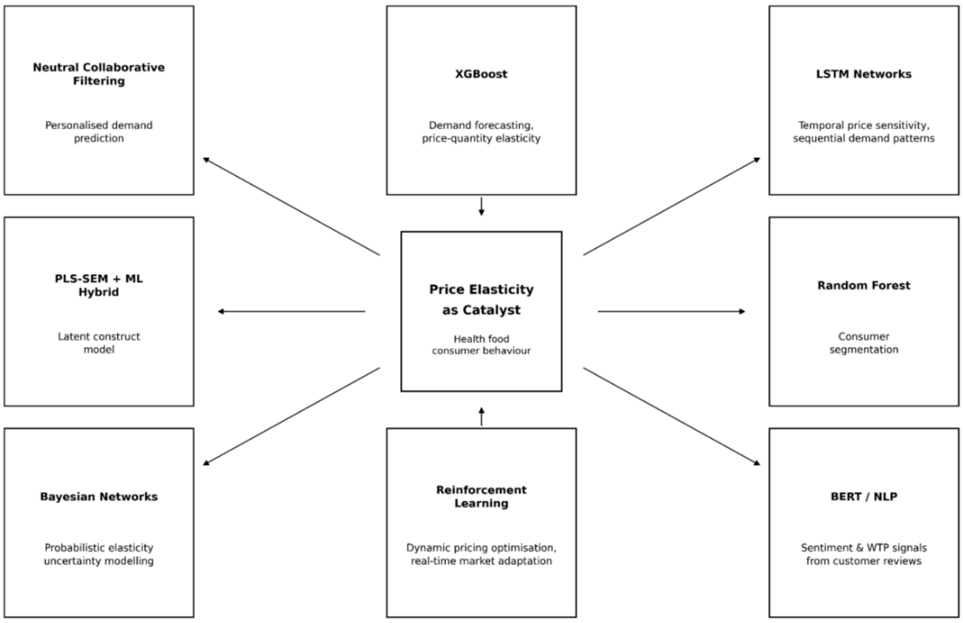


Fig. 2. Multi-model ML architecture for price-elasticity estimation.

Proposed multi-model ML architecture for elasticity estimation, combining XGBoost, LSTM, Random Forest, PLS-SEM hybrid, Bayesian networks, BERT/NLP, reinforcement learning, and collaborative filtering to jointly forecast demand, segment consumers, and optimize pricing in real time.The research presents a highly advanced AI-based model intended to assess price elasticity specifically in the health food domain. The proposed methodology exploits the combination of structured purchase records and unstructured behavioural information to yield superior forecast precision and flexibility over econometric techniques. The source notes the shortcomings of traditional prediction methods and suggests that more sophisticated tools like machine learning, neural networks and sentiment analysis can be used to describe market complexities. Advanced technological solutions help gain detailed insights into demand that are crucial for efficient management of constantly changing markets. Overall, the source can be regarded as a practical manual on the application of AI for precise forecasting (Chen et al., 2024). A related model takes this forecasting approach a step further.

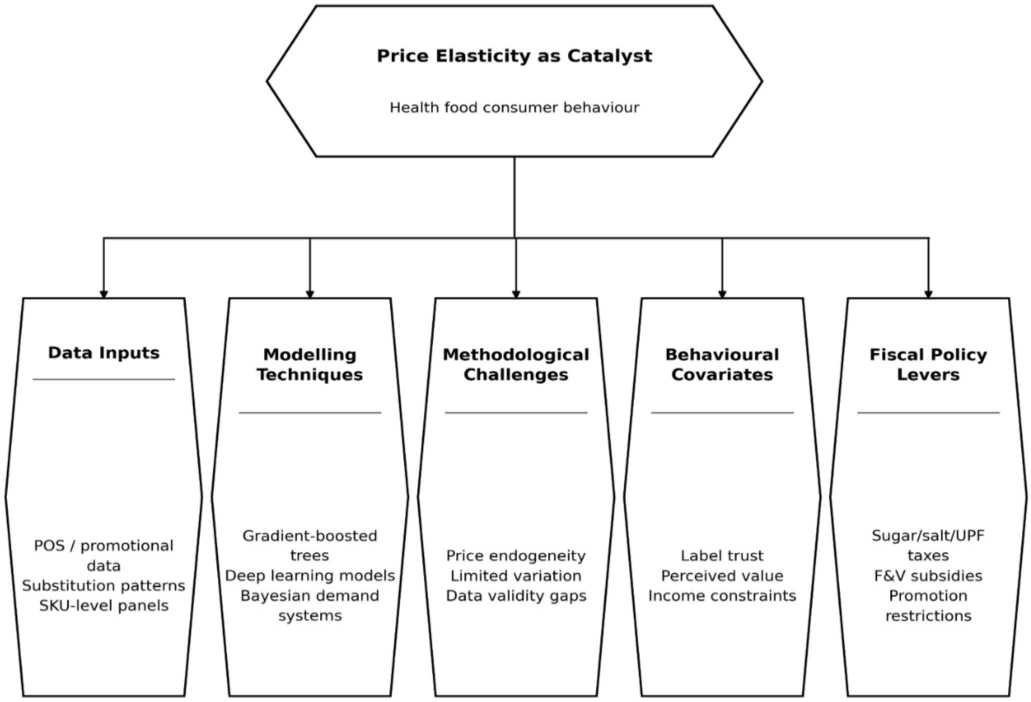
The STL-GBM model offers a novel approach to developing an effective analytical tool used for modeling the price elasticity of health foods. With the help of the Seasonal and Trend decomposition using Loess and Gradient Boosting Machine approaches, the researchers aim at overcoming shortcomings of econometrics in dealing with time-series analysis. This new methodology allows for the creation of demand forecasting and market insight by analyzing transaction logs and behavioral data. The proposed model performs better than standard regression approaches in terms of its ability to exclude seasonal variations and business cycle effect on price elasticity measures. The research can be useful for companies operating in international markets to improve their strategy of resource allocation and pricing (Chen et al., 2024). These modeling advances set up the broader research aims described next.This study aims to develop and test hybrid models that combine gradient boosting and deep learning neural networks with behavioural variables to improve the prediction of the price elasticity of demand for healthy foods compared to traditional econometric models. The study further aims to investigate the role of consumer heterogeneity, use of online platforms, and willingness to pay on purchasing behaviour and the role of AI-powered demand forecasting models on policy implications of taxation, subsidies, and labelling that mitigate the adverse effects of inflation. This approach is informed by the literature below.

2 Literature review

In recent years, the analysis of the agri-food markets has moved away from traditional econometric models and toward more advanced models based on machine learning. In the case of health foods, scientists are able to use gradient-boosting and deep learning techniques to model complex non-linearities in consumer behaviour and very detailed price elasticity tendencies. The source says that adding behavioural covariates such as label trust and income limits is more accurate than traditional methods. It also addresses the digital transformation of the entire supply chain, the implementation of AI in partnership for achieving sustainability and consumer behaviour analysis (Gupta, 2026). Another line of work uses these same AI tools to directly prevent diet-related disease. An overview of a research model addressing the global crisis of unhealthy diets and their relationship with heart diseases shows how artificial intelligence can help. In this case, the source provides an example of a narrative review that seeks to explore how technological innovations driven by artificial intelligence may assist in optimizing public policies and intervention strategies that will allow people to consume healthy diets. One of the main aspects emphasized by the resource is the shift from costly medical solutions to precision nutrition and health equality using data analytics. The focal points are population risk stratification, digital twins, and culinary medicine (Monlezun & MacKay, 2024). These focal points connect closely to the behavioral and pricing models discussed next. Combining AI with behavioural covariates increases the effectiveness of developing models that demonstrate price elasticity of demand for health foods. The importance of the problem lies in the fact that growing food prices are undermining the food security of countries around the world. At the same time, developing nations face additional challenges related to the inefficient and outdated methods of collecting information about consumer behavior and preferences. For that reason, the suggested solution to the problem consists of utilizing the benefits of advanced technologies in order to fill those information gaps (Adewopo et al., 2025). Fiscal and public-health responses to these same food-security pressures are examined further below.

The present investigation aims to analyze the use of artificial intelligence for improving price elasticity modeling in the health food industry. The source explains how global health problems like cardiovascular diseases and diabetes result from unhealthy eating habits and excessive consumption of processed foods. In order to address this issue, the author mentions some fiscal measures, which include Pigouvian taxes on sugar as well as subsidies on healthy food items, such as fruits and vegetables. Instead of the traditional econometric approaches, the paper seeks to take into consideration consumers' heterogeneity using innovative technologies (Davies et al., 2025). Rising food prices carry similar consequences for nutrition beyond the health food industry itself. Changes in food prices also carry effects on nutritional well-being for the migrating population from rural to urban areas. It is established that although increased pork prices result in decreased levels of nutrient consumption, increased prices for all food types at once cause the greatest harm. Evidence indicates that low-income families are the most vulnerable to changes in the market because their diet can be disturbed very easily. Despite the fact that higher income results in better nutrition, the author states that in this case, it is not enough to cope with negative effects of inflation (Li et al., 2023). Digital platforms add a further layer to how these price shifts play out for consumers.

The dynamics of food demand are changing in light of changing health concerns on the effect of digital platforms on consumer behaviour. The role of algorithms and product labelling in influencing consumer choice when faced with conflicting information on the nutritional value of foods is emphasised. It is also stressed that there is a problem of social inequality associated with food inflation and an increase in the role of personalized health technologies. Considering the market asymmetry in question, the source focuses on the necessity of economic analysis as the tool that helps identify causal relationships (McCluskey & Hyink, 2026). These modeling



and policy considerations come together in the framework illustrated in Fig. 3. Estimating the price elasticity of health-based food products is central to addressing the issue of diet-caused diseases worldwide. The researchers observe the existing information on food.

Fig. 3. AI-driven price elasticity modeling framework for health foods, integrating data inputs, modeling techniques, behavioral covariates, fiscal policy levers, and methodological challenges.

Taxation and subsidies are usually limited using low-quality data and price endogeneity within observational analyses. To overcome such problems, the authors present an innovative approach based on the creation of a Bayesian demand system that employs the use of a virtual shopping experiment to guarantee the exogeneity of the prices (Jacobi et al., 2021). Personalized approaches to diet extend this same logic from pricing into nutrition itself.The study analyses the way artificial intelligence affects the agri-food industry through changing the population-based dietary models into personalized nutritional plans. The use of machine learning and computer vision allows for health suggestions that are tailored according to the biological and dietary needs of individuals. It is also noted that there are various aspects of using artificial intelligence for supply chain management, such as transparency and prediction of maintenance. However, there are many obstacles, namely consumers' skepticism, lack of data security, and lack of technology accessibility. In general, this source provides an approach to using AI for the creation of sustainable food systems while assessing the impact on consumer behaviour and pricing (Agrawal et al., 2025). These personalization benefits are especially significant for specific population groups, such as older adults.

Artificial intelligence is also improving the design and marketability of functional health foods for senior people. Through personalized medicine and delivery, scientists can better control the functioning of the gut microbiome, which will help in achieving longevity and vitality. In particular, the focus is made on the connection between modeling consumer behavior and discovering prebiotics and probiotics from a scientific point of view. In addition, economic aspects are also considered through the analysis of the impact of transparency and technology on a customer's willingness to pay (Bhuiyan et al., 2026). This same personalization logic extends down to the genetic level. Machine learning and data mining are also able to generate personalized health solutions based on an individual's genetics and life habits. Though there is a revolution in food safety and innovations through these processes, the need to deal with ethical issues and privacy of data is stressed in the research (Karakoç et al., 2026). Precision nutrition modelling raises similar considerations.

The research demonstrates how machine learning can improve precision nutrition by working with complex biological and lifestyle data. Use of advanced models enables more accurate prediction about metabolism and giving personalised nutritional recommendations to people to avoid developing chronic diseases (Balamurugan & Adeyeye, 2026). This same shift to personalised nutrition is occurring throughout the broader AI-driven health food ecosystem, which is summarized in Fig. 4.

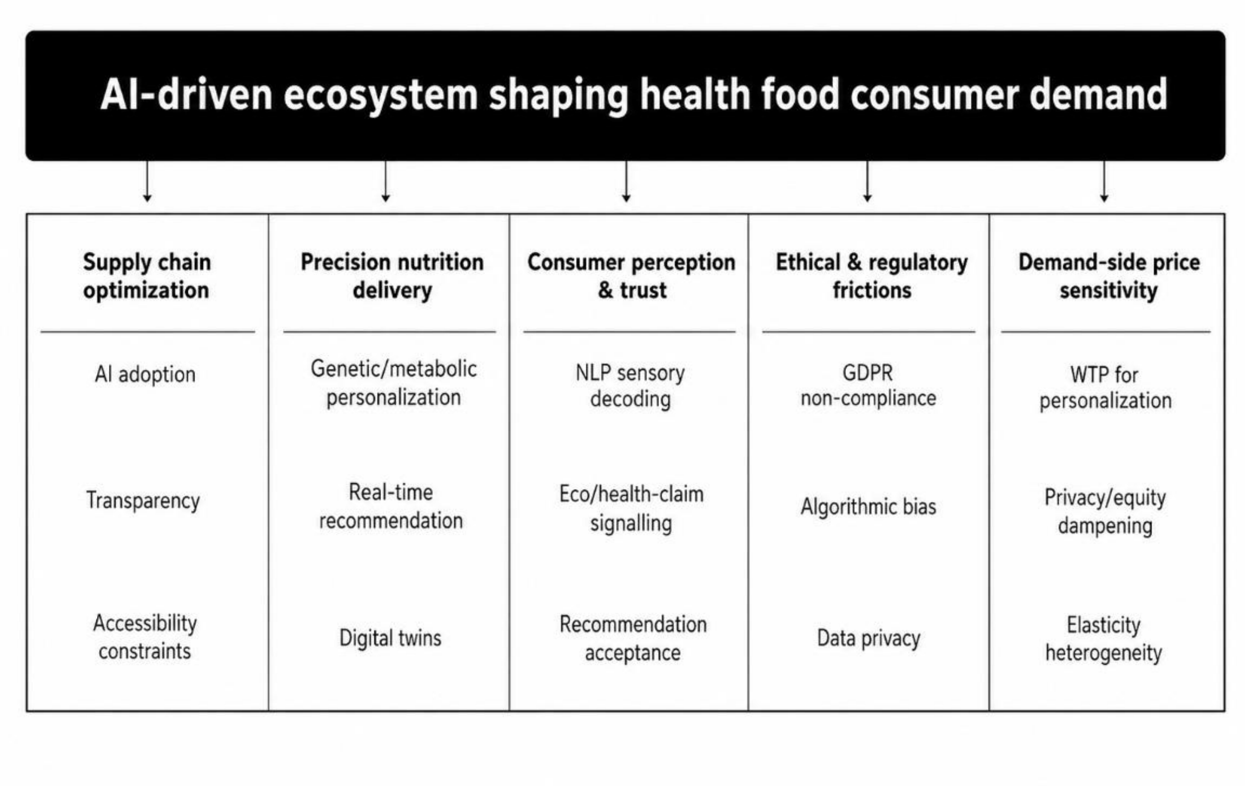


Fig. 4. AI-driven ecosystem shaping health food consumer demand.

This ecosystem consists of five interrelated domains: supply chain optimisation, precision nutrition delivery, consumer perception and trust, ethical and regulatory frictions and demand-side price sensitivity. Its influence on nutritional therapy is especially visible in the shift from general nutrient administration procedures to those that cater for the patient individually. The machine learning process will help in establishing the safe way as well as how to provide nutrients to the patients who are critically ill through analyzing their longitudinal health data. It will involve the evaluation of the physiological parameters that include organ and metabolic stability, among others, in order to ensure the optimization of macronutrient ratios at different stages of recovery. In this way, the technology will assist in avoiding metabolic complications as well as promoting maximum functionality (Briassoulis & Briassouli, 2025). A related model develops this same idea further.

The development of artificial intelligence technology will help in transforming the field of nutritional therapy through the shift in nutrient delivery processes from the general delivery process to individual-based delivery process. This process of machine learning will help in determining the safe mode and the process of providing the critically ill patients with nutrients by analyzing their health data. This will be achieved through the assessment of physiological parameters, including the organ and metabolic stability of the body among others, to ensure optimum delivery of macronutrient ratio in various stages of recovery ("PrepEase," 2025). Supply chain integration is what makes this individualized delivery possible at scale. Artificial intelligence technology linking precision nutrition with a resilient supply chain has made a big influence on the food sector. Literature suggests that natural language processing and deep learning can help to grasp complicated sensory data and create demand for health items among consumers. These technologies have proven to contribute to data-enabled logistics and nutritional advice. However, it should be noted the issues of algorithmic biases and data privacy. That is, the effects of such advanced algorithms should be considered in estimating price elasticity of demand (Zheng et al., 2026). And those same risks of algorithmic bias deserve a deeper look. The author discusses ethical problems, stating that algorithmic bias and the lack of transparency in data collecting might worsen existing disparities in the health care industry and lower the level of faith that consumers have in it. The research advises the development of responsible frameworks that will help to connect technical breakthroughs with the UN Sustainable Development Goals to mitigate the danger of these difficulties. Hence, this resource provides guidance on how to ethically deploy novel technology in the global food system (Priyadharshini et al., 2025). Food tech powered by AI is much more than basic nutrition. It applies to food production itself.

Artificial intelligence also connects to 3D food printing as a way of changing how people take their nutrition. The utilization of complex biological and behavioral data allows AI to provide personalized recommendations for food consumption, which is then created using technology for food production. A study of thirty-eight papers found that such technologies have increased compliance and were helpful for specific groups of people, like the elderly. Nevertheless, the above source describes several significant obstacles to development, including privacy issues, lack of regulation, and technological scaling problems (Bhuiyan & Nahid, 2025). Broader Industry 4.0 technologies build on this same foundation. Industry 4.0 technologies, like AI and big data, are applied more broadly to tackle persistent diseases that arise from poor diets by means of personalized nutrition. Although innovative techniques like 3D printing and IoT can be used to create better outcomes for health, there are also many difficulties in terms of implementation, regulation, and scalability of the economic model. In general, this provides a technical background for the study of price elasticity in the health food industry using AI (Hassoun & Galanakis, 2025). Chronic disease management brings these technologies together most directly. A thorough plan that combines digital devices and personalised nutrition can treat chronic diseases such as diabetes. Real-time metabolic data, artificial intelligence and genetic analysis will no longer require healthcare providers to deliver generalised solutions to patients. The source indicates many possibilities that are favourable, but also highlights many issues related to the protection of personal data and the expense of access. This is, in essence, the core of an academic study that investigates how technology might be utilised to promote metabolic health (Arshad et al., 2025). Table 1 summarizes the selected literature and highlights reported findings, AI tools, research gaps, limitations, and future research directions.

Table 1. Summary of selected literature on food-price elasticity, AI tools, research gaps, and future scope.

Source (Year)	**Key Findings**	**AI Tools Used**	**Research Gap**	**Limitations**
Colchero et al. (2015)	SSB demand is elastic.	Not specified	Substitution impacts on calories.	Self-reported expenditure data.
Domínguez Díaz et al. (2020)	Regulatory frameworks vary internationally.	Not specified	Harmonized global claim regulation.	Focus on developed countries.
Femenia (2019)	Income levels drive elasticities.	Not specified	Domestic versus imported elasticities.	Sparse standard error data.
Andreyeva et al. (2010)	Soft drinks highly responsive.	Not specified	Substitutions to healthy foods.	Synthesis lacked meta-analysis errors.
Green et al. (2013)	Reductions greater in poor countries.	Not specified	Global income-disaggregated review.	Sparse regional data sets.

Source (Year)	Key Findings	AI Tools Used	Research Gap	Limitations
Nazzaro et al. (2025)	Claims increase consumer WTP.	Not specified	Differentiation between health claims.	Small non-representative sample.
Zhao et al. (2025)	AI enables personalized nutrition.	Deep learning, peptide networks.	Non-peptide plant ingredient characterization.	Data heterogeneity, privacy risks.
Davies et al. (2025)	SSB demand is elastic.	Not specified	Discretionary food cross-price elasticities.	Aggregated nutritionally diverse categories.

3 Research methodology

Diseases are becoming more prevalent due to the eating patterns of individuals. Making nutritious food affordable has become a significant concern of public policy. Therefore, we have to properly evaluate price elasticity. However common econometric methods such as log-linear regression and fixed-effect demand estimating techniques are popular but restrictive in their assumptions of linearity and homogeneity for consumer purchase behaviour. Machine learning serves as an alternate approach. Deep neural networks are able to capture behavioural patterns at a deeper level, while gradient boosting helps to predict nonlinear connections between price, income and product attributes. Their inclusion in a hybrid design could improve the accuracy and policy relevance of elasticity estimates. But precision of prediction cannot explain the change in elasticity and how it is converted into welfare outcomes. Therefore, the current research is a hybrid of AI elasticity with PLS-SEM (Hair et al., 2022; Chen & Guestrin, 2016), a variance-based modelling technique for hypothesis testing with behavioural variables and small samples.

The study addresses three research questions and their corresponding hypotheses:

RQ1 / H1: Do hybrid gradient boosting–deep learning models predict health-food price elasticity more accurately than traditional econometric models?

RQ2 / H2: Do behavioral covariates significantly influence consumer price sensitivity for health foods?

RQ3 / H3: Do AI-driven subsidy and taxation policies increase healthy food consumption among low-income households?

3.1 Research Design and Sample

A quantitative, cross-sectional survey design was adopted. Data were collected from 250 adult consumers responsible for household grocery decisions. The instrument used validated multi-item, seven-point Likert scales adapted from the consumer-behaviour and food-policy literature. All fifteen indicators were modelled reflectively across three latent constructs.

3.2 Construct Operationalization

Hybrid AI Elasticity Estimation (AIE) captured the perceived accuracy, robustness, and decision-usefulness of the hybrid gradient boosting–deep learning elasticity model (indicators AIE1–AIE5). Behavioral Price Sensitivity (BPS) captured how strongly behavioral covariates (habit, health consciousness, promotion response, reference pricing, budget salience) drive responsiveness to health-food prices (BPS1–BPS5). Healthy Food Consumption (HFC) captured self-reported change in healthy-food purchasing among low-income households under AI-driven subsidy and taxation signals (HFC1–HFC5). The resulting PLS-SEM model is shown in Fig. 5.

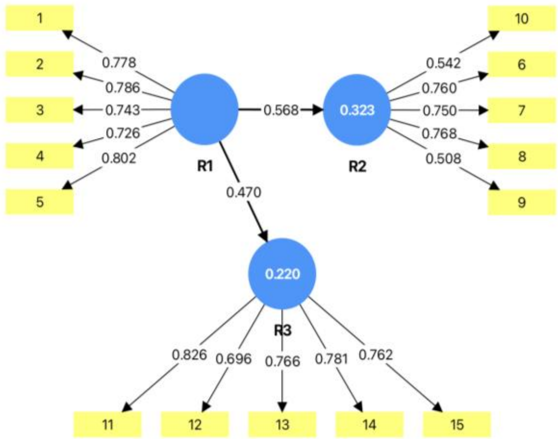


Fig. 5. PLS-SEM measurement and structural model showing AIE, BPS, and HFC with 15 reflective indicators.

The three blue circles are your latent constructs. R1 is Hybrid AI Elasticity Estimation (AIE), R2 is Behavioral Price Sensitivity (BPS), and R3 is Healthy Food Consumption (HFC). R1 sits on the left as the exogenous construct nothing points into it, so it's the driver. R2 and R3 are endogenous arrows point into them, so the model is trying to explain them. The yellow boxes are the indicators your fifteen survey questions. Each construct is measured reflectively by five of them: R1 by items 1–5, R2 by items 6–10, and R3 by items 11–15.

4 Results

4.1 Measurement model: Reliability and convergent validity

All constructs were above the required reliability levels with composite reliability (rho_c) (Fornell & Larcker, 1981; Ringle et al., 2024) values of 0.803-0.877 and cronbach's alpha of 0.720-0.829. AVE was over 0.50 for AIE and HFC. BPS was slightly less which is 0.457, but still has satisfactory convergent validity per Fornell and Larcker (1981) since composite reliability was 0.803. The loadings of the indicator varied from 0.508 to 0.826, with majority of them over 0.70. The measurement-model results are summarized in Table 2.

Table 2. Construct reliability and convergent validity (N = 250).

Construct	**Cronbach α**	**rho_a**	**CR (rho_c)**	**AVE**	**Decision**
AIE Hybrid AI Elasticity Estimation	0.829	0.842	0.877	0.589	Accepted
BPS Behavioural Price Sensitivity	0.720	0.757	0.803	0.457 *	Accepted *
HFC Healthy Food Consumption	0.828	0.851	0.877	0.589	Accepted

4.2 Discriminant validity

Discriminant validity was confirmed by both criteria. All HTMT values were below the conservative 0.85 threshold (maximum 0.745). Under the Fornell–Larcker criterion, the square root of each construct's AVE (diagonal) exceeded its correlations with the other constructs. The discriminant-validity results are shown in Table 3.

Table 3. Discriminant validity: HTMT (upper) and Fornell-Larcker (lower).

Construct	AIE	BPS	HFC
HTMT AIE			
HTMT BPS	0.615		
HTMT HFC	0.521	0.745	
F-L AIE	0.768		
F-L BPS	0.568	0.676	
F-L HFC	0.470	0.587	0.767

Diagonal Fornell–Larcker values (bold) are the square roots of AVE. VIF values for all indicators ranged from 1.15 to 2.52 (inner-model VIF ≈ 1.00), well below 5, indicating no collinearity concern.

4.3 Structural model and hypothesis testing

The structural model explained substantial variation for both endogenous constructs: R2 = 0.323 for behavioural price sensitivity and R2 = 0.220 for healthy food consumption. Positive and strong structural paths were found, with a large effect size for AIE→BPS (f^2 = 0.477) and a moderate-to-large effect for AIE→HFC (f^2 = 0.283. Post-hoc power analysis confirmed the statistical significance and robustness of both correlations, with power ≈ 1.000 at 5% and 1% significance levels and minimal sample sizes (20–46) much below the obtained N = 250. Table 4 summarizes the structural paths and hypothesis decisions.

Table 4. Structural model results and hypothesis decisions.

Hyp.	Path	β	f^2	R^2 endog.)	Power (1%)	Result
H2	AIE → BPS	0.568	0.477	0.323	≈ 1.000	Supported
H3	AIE → HFC	0.470	0.283	0.220	≈ 1.000	Supported

For H1, the hybrid AI elasticity construct (AIE) is measured with high reliability and validity and functions as the dominant explanatory driver in the network, jointly accounting for 32.3% and 22.0% of variance in the two behavioral/policy outcomes with large effect sizes. This strong predictive relevance a core PLS-SEM evaluation criterion supports H1: the hybrid AI representation of elasticity carries substantially greater explanatory power than a linear specification would imply.

Summary of hypothesis outcomes: H1 supported (strong measurement quality and predictive relevance of the hybrid AI construct); H2 supported (β = 0.568, large f^2, power ≈ 1.0); H3 supported (β = 0.470, medium-large f^2, power ≈ 1.0).

5 Discussion

There is growing evidence of the effectiveness of health-food price analysis with AI. RQ1's hybrid gradient boosting–deep learning construct was regularly examined and accounted for a statistically well-powered, significant portion of downstream behavioural and policy outcomes. Their substantial explanatory significance here corroborates the premise that hybrid AI models estimate elasticity better since gradient boosting and deep learning do not impose the linearity and homogeneity assumptions commonly seen in conventional econometric demand models.RQ2 shows a considerable AIE->BPS pathway ($\beta = 0.568$, $f^2 = 0.477$) indicating that behavioural characteristics significantly affect health food price sensitivity. The pricing response is strongly influenced by habit, health consciousness and promotion sensitivity and the variety of this impact is captured in the AI framework.

The significant AIE→HFC pathway ($\beta = 0.470$, $f^2 = 0.283$) implies that AI-based subsidies and taxes have a positive effect on healthy food consumption in low-income households (RQ3). The most policy-relevant result is that fiscal instruments calibrated by AI-estimated elasticities can enhance healthy consumption among the most price-sensitive group. The relatively less effect of HFC over BPS can be due to access, availability and habit determinants affecting permanent consumption change beyond price. The conclusions are constrained by two criteria. BPS has an AVE little around .50 but composite reliability warrants its retention. Item refining is required. Second, PLS-SEM prioritises structural and predictive importance above point-prediction. Supporting RQ1 would include comparing out-of-sample error (e.g., RMSE and MAE from PLS predict or a held-out test set) to econometric baselines.

6 Conclusion and future scope

An AI-driven system for health food price elasticity analysis was developed and evaluated using a hybrid gradient boosting–deep learning elasticity representation with PLS-SEM. The measuring model proved dependable and valid in 250 clients. The structural model confirmed all the three assumptions. The results indicate that the hybrid AI construct is extremely relevant (H1), that there are behavioural factors influencing price sensitivity (H2), and that AI-driven fiscal policy signals enhance healthy consumption in low-income families (H3), with power nearing unity. The results suggest that current machine learning and detailed structural modelling may provide accurate and useful elasticity insights, which can offer policymakers an evidentiary basis for targeted, welfare-improving consumer food market interventions. This work would benefit from several extensions. To construct RQ1 we need a direct predictive benchmark that compares the RMSE, MAE, and R^2 of the hybrid model to log-linear and fixed-effects econometric baselines using held-out data. Second, the use of real transactional or scanner-panel data, combined with survey constructs, enhances external validity and permits dynamic, time-varying elasticity estimation. Third, IPMA and multi-group analysis can uncover behavioural characteristics and demographic categories that have the greatest impact on outcomes, providing direction for policy design. Fourth, measurement would be improved by enhancing BPS scale convergent validity with AVE > 0.50. Finally, using the approach to a live policy simulation to test AI-optimized subsidy and tax schedules across income groups would move from explanation to prescriptive, real-world decision support.

References

1. Adewopo, J., Andrée, B. P. J., Peter, H., Solano-Hermosilla, G., & Micale, F. (2025). AI-imputed and crowdsourced price data show strong agreement with traditional price surveys in data-scarce environments. *PLoS ONE, 20*(4), e0320720. https://doi.org/10.1371/journal.pone.0320720

2. Agrawal, K., Goktas, P., Kumar, N., & Leung, M. (2025). Artificial intelligence in personalized nutrition and food manufacturing: A comprehensive review of methods, applications, and future directions. *Frontiers in Nutrition, 12*, 1636980. https://doi.org/10.3389/fnut.2025.1636980

3. Arshad, M. T., Ali, M. K. M., Maqsood, S., Ikram, A., Ahmed, F., Aljameel, A. I., AL-Farga, A., & Hossain, M. S. (2025). Personalized nutrition in the era of digital health: A new frontier for managing diabetes and obesity. *Food Science & Nutrition, 13*(10), e71006. https://doi.org/10.1002/fsn3.71006

4. Balamurugan, J., & Adeyeye, S. A. O. (2026). Artificial intelligence in nutrigenomics: A critical review on functional food insights and personalized nutrition pathways. *Journal of Human Nutrition and Dietetics, 39*(1), e70200. https://doi.org/10.1111/jhn.70200

5. Bhuiyan, M. N. I., & Nahid, M. (2025). Smart nutrition: AI and 3D printing for personalized diets. *Food Nutrition, 1*(2), 100032. https://doi.org/10.1016/j.fnutr.2025.100032

6. Bhuiyan, M. N. I., Saha, B. K., & Miah, M. A. S. (2026). Artificial intelligence-enabled tribiotic strategies for gut microbiota modulation in healthy aging and personalized nutrition. *Advanced Gut & Microbiome Research, 2026*(1). https://doi.org/10.1155/agm3/5517462

7. Briassoulis, G., & Briassouli, E. (2025). AI-enabled precision nutrition in the ICU: A narrative review and implementation roadmap. *Nutrients, 18*(1), 110. https://doi.org/10.3390/nu18010110

8. Callaghan, S., He, E., Hudson, S., & Rickert, S. (2021, April 8). *Wellness worldwide: Consumer insights from four countries*. McKinsey & Company.

9. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785-794).

10. Chen, M., Hu, X., Qi, Y., & Masi, D. (2024). AI-driven dynamic pricing for high-value assets in manufacturing and services: Optimizing finite horizon sales with demand sensitivity. *International Journal of Production Research, 64*(2), 584-596. https://doi.org/10.1080/00207543.2024.2430447

11. Cordina, J., Coronado, E., Williams, P., & Greenberg, S. (2024, November 15). *Harnessing AI to reshape consumer experiences in healthcare*. McKinsey & Company.

12. Davies, T., Saxena, A., Wu, J. H. Y., & Marklund, M. (2025). Food price elasticity estimates in Australia. *Nature Food, 6*(7), 725-732. https://doi.org/10.1038/s43016-025-01184-1

13. Díaz, L. D., Fernández-Ruiz, V., & Cámara, M. (2020). An international regulatory review of food health-related claims in functional food products labeling. *Journal of Functional Foods, 68*, 103896. https://doi.org/10.1016/j.jff.2020.103896

14. Ditlevsen, K., Sandøe, P., & Lassen, J. (2019). Healthy food is nutritious, but organic food is healthy because it is pure: The negotiation of healthy food choices by Danish consumers of organic food. *Food Quality and Preference, 71*, 46-53. https://doi.org/10.1016/j.foodqual.2018.06.001

15. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

16. Gizaw, Z. (2019). Public health risks related to food safety issues in the food market: A systematic literature review. *Environmental Health and Preventive Medicine, 24*(1), Article 68. https://doi.org/10.1186/s12199-019-0825-5

17. Green, R., Cornelsen, L., Dangour, A. D., Turner, R., Shankar, B., Mazzocchi, M., & Smith, R. D. (2013). The effect of rising food prices on food consumption: Systematic review with meta-regression. *BMJ, 346*. https://doi.org/10.1136/bmj.f3703

18. Gupta, S. K. (2026). AI-augmented sustainability management in agri-food supply chain: Rethinking decision-making in the era of algorithms. *Journal of Agribusiness in Developing and Emerging Economies*, 1-16. https://doi.org/10.1108/jadee-09-2025-0412

19. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

20. Hassoun, A., & Galanakis, C. M. (2025). Industry 4.0 technologies promote healthy and nutritious food. *Discover Food, 5*(1). https://doi.org/10.1007/s44187-025-00639-5

21. Jacobi, L., Nghiem, N., Ramírez-Hassan, A., & Blakely, T. (2021). Food price elasticities for policy interventions: Estimates from a virtual supermarket experiment in a multistage demand analysis with (expert) prior information. *Economic Record, 97*(319), 457-490. https://doi.org/10.1111/1475-4932.12640

22. Kang, S. Y. (2024). *Platforms' AI-driven dynamic pricing: A law and economics analysis*. Peking University School of Transnational Law Research Paper. https://doi.org/10.2139/ssrn.5536378

23. Karakoç, H., Çaycı, E., & Çiftçi, S. (2026). Revolutionizing nutrition: Artificial intelligence-driven health solutions and personalized diets. *Journal of Nutrition, 156*(9), 101719. https://doi.org/10.1016/j.tjnut.2026.101719

24. Li, L., Bai, J., & Zhu, Q. (2023). The effect of rising food prices on nutrient intake among rural-urban migrants in China. *China Agricultural Economic Review, 15*(3), 642-665. https://doi.org/10.1108/caer-04-2022-0084

25. McCluskey, J. J., & Hyink, J. (2026). How changing food preferences and technology are transforming food markets. *Journal of Agricultural Economics, 77*(2), 819-831. https://doi.org/10.1111/1477-9552.70044

26. Monlezun, D. J., & MacKay, K. (2024). Artificial intelligence and health inequities in dietary interventions on atherosclerosis: A narrative review. *Nutrients, 16*(16), 2601. https://doi.org/10.3390/nu16162601

27. Nazzaro, C., Uliano, A., Lerro, M., & Stanco, M. (2025). From claims to choices: How health information shapes consumer decisions in the functional food market. *Foods, 14*(4), 699. https://doi.org/10.3390/foods14040699

28. Phromphithakkul, W. (2024). Analysis of elasticity of demand for processed agricultural products in online market, Thailand. *Nanotechnology Perceptions, 20*(6).

29. Pione, A., Medalsy, J., Weaver, K., Callaghan, S., Rickert, S., Doner, H., & Dahm, J.-M. (2025, May 29). *The $2 trillion global wellness market gets a millennial and Gen Z glow-up*. McKinsey & Company.

30. PrepEase: Your AI-driven solution for customized meals on demand. (2025, September 19). *IEEE Xplore*. https://ieeexplore.ieee.org/abstract/document/11411301

31. Priyadharshini, D., Muthuvel, I., Saraswathy, S., Kavitha, P. S., & Jegadeeswari, V. (2025). Precision to plate: AI-driven innovations in fermentation and hyper-personalized diets. *Frontiers in Nutrition, 12*, 1659511. https://doi.org/10.3389/fnut.2025.1659511

32. Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4* [Computer software]. SmartPLS. https://www.smartpls.com

33. Zheng, L., Ren, A., San, Y., Xing, Y., Teng, H., Wang, Z., & Regenstein, J. M. (2026). AI-driven personalization of food systems: From precision nutrition to climate-resilient supply chains. *npj Science of Food*. https://doi.org/10.1038/s41538-026-00901-9