

Decoding Food Labels in the Digital Era: Nutrition Label Literacy, AI Applications, and Sustainable Food Purchase Decisions

¹Vishwas V, ²Dr Akhila R Udupa

¹Research Scholar, Presidency School of Management, Presidency University, Bengaluru, Karnataka, India
Vishwas1030@gmail.com, ORCID: 0009-0005-3257-613X

²Professor, Presidency School of Management, Presidency University, Bengaluru, Karnataka, India
Akhila.udupa@presidencyuniversity.in, ORCID: 0000-0002-2795-319x

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ABSTRACT:

Purpose: This study examines the influence of Nutrition Label Literacy (NLL) on Sustainable Food Purchase Decisions (SFPD) by investigating the mediating role of AI-Based Nutrition Applications (AINA) and the moderating role of Digital Health Literacy (DHL).

Methodology: A cross-sectional quantitative research design was employed using survey data collected from 280 Indian consumers. The proposed conceptual framework, grounded in Information Processing Theory (IPT), the Technology Acceptance Model (TAM), and the Theory of Planned Behavior (TPB), was analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Findings: The results reveal that Nutrition Label Literacy significantly influences Sustainable Food Purchase Decisions ($\beta = 0.291, p < 0.001$) and positively affects the adoption of AI-Based Nutrition Applications ($\beta = 0.657, p < 0.001$). AI-Based Nutrition Applications significantly enhance Sustainable Food Purchase Decisions ($\beta = 0.462, p < 0.001$) and partially mediate the relationship between Nutrition Label Literacy and Sustainable Food Purchase Decisions. Furthermore, Digital Health Literacy significantly strengthens the effect of AI-Based Nutrition Applications on Sustainable Food Purchase Decisions ($\beta = 0.174, p < 0.001$). The proposed model explains 68.4% of the variance in Sustainable Food Purchase Decisions, indicating substantial predictive capability.

Originality: This study extends the literature by integrating nutrition label literacy, artificial intelligence, and digital health literacy into a unified framework explaining sustainable food purchasing behaviour. The findings provide theoretical insights and practical implications for policymakers, food manufacturers, retailers, and AI developers seeking to promote healthier and more sustainable food consumption.

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Keywords: Nutrition Label Literacy; AI-Based Nutrition Applications; Digital Health Literacy; Sustainable Food Purchase Decisions; Artificial Intelligence; Sustainable Consumption.

Introduction

The global food marketplace has undergone significant transformation over the past decade, driven by rapid technological innovation, increasing health consciousness, and heightened awareness of environmental sustainability. Consumers today are confronted with an unprecedented variety of packaged food products, each displaying extensive Nutritional information intended to facilitate informed purchasing decisions. Nutrition labels have evolved into one of the most important communication tools connecting food manufacturers and consumers by providing standardized information regarding calories, macronutrients, micronutrients, ingredients, allergens, and health claims. Proper interpretation of these labels enables consumers to make healthier dietary choices, reduce Nutrition-related diseases, and support sustainable food systems (World Health Organization [WHO], 2021; Food and Agriculture Organization [FAO], 2022).

Nutrition-related non-communicable diseases, including obesity, diabetes, cardiovascular diseases, and hypertension, continue to pose major public health challenges worldwide. According to the World Health Organization (2023), unhealthy dietary patterns account for a substantial proportion of preventable morbidity and mortality, emphasizing the need for effective Nutritional communication strategies. Nutrition labels represent one of the most cost-effective policy interventions for improving dietary quality by empowering consumers with transparent information regarding food composition (Campos et al., 2011; Temple, 2020). Nevertheless, the mere presence of Nutritional information does not necessarily translate into healthier food choices. Consumers often encounter difficulties in interpreting complex Nutritional terminology, serving sizes, percentage daily values, and ingredient lists, particularly when

possessing limited Nutrition knowledge (Miller & Cassady, 2015; Talati et al., 2019).

This challenge has led to increasing academic and policy interest in the concept of **Nutrition label literacy**, which refers to an individual's ability to access, comprehend, evaluate, and effectively utilize Nutrition information presented on food packages for making informed dietary decisions (Silk et al., 2008; Miller & Cassady, 2015). Nutrition label literacy extends beyond basic reading skills by encompassing cognitive abilities, Nutritional understanding, critical evaluation, and practical application during purchasing decisions. Consumers with higher Nutrition label literacy demonstrate greater confidence in comparing food products, identifying healthier alternatives, limiting excessive consumption of sugar, sodium, and saturated fats, and maintaining balanced dietary habits (Campos et al., 2011; Grunert & Wills, 2007). Consequently, Nutrition label literacy has become a central determinant of consumer health behavior and an important component of public health promotion strategies worldwide.

The digital revolution has further transformed consumer interactions with Nutritional information through the emergence of artificial intelligence (AI)-based Nutrition technologies. Recent advances in machine learning, computer vision, natural language processing, and predictive analytics have facilitated the development of intelligent Nutrition applications capable of scanning food labels, evaluating Nutritional quality, estimating calorie intake, recommending healthier substitutes, generating personalized meal plans, and monitoring dietary habits in real time (Topol, 2019; Davenport & Kalakota, 2019). Popular AI-powered Nutrition applications such as Yuka, Foodvisor, MyFitnessPal, HealthifyMe, and Open Food Facts have significantly simplified the interpretation of Nutritional information,

enabling consumers to receive personalized recommendations instantly while shopping.

The study offers several theoretical and practical contributions. Theoretically, it extends the literature by integrating Nutrition literacy with AI-enabled decision support within the broader context of sustainable consumer behavior. Practically, the findings are expected to assist policymakers in designing Nutrition education initiatives, support food manufacturers in improving label communication, guide retailers in promoting healthier food choices, and encourage AI developers to design more transparent, explainable, and user-centric Nutrition applications. Ultimately, strengthening Nutrition label literacy alongside AI-assisted Nutritional guidance may contribute significantly to improving public health outcomes while fostering sustainable food consumption in the digital era.

Review of Literature

Nutrition label literacy has emerged as a significant determinant of consumer food choice behavior in contemporary food markets. It refers to an individual's ability to access, understand, evaluate, and utilize Nutritional information displayed on food packages for making informed dietary decisions. Earlier studies established that consumers who possess higher Nutrition label literacy are more likely to compare products, monitor nutrient intake, and select healthier alternatives (Grunert & Wills, 2007; Campos et al., 2011). The increasing prevalence of obesity, diabetes, and cardiovascular diseases has further intensified the importance of Nutrition label comprehension as a public health intervention.

Research demonstrates that Nutrition label literacy extends beyond basic reading ability and encompasses cognitive processing, Nutritional knowledge, and decision-making skills. Miller and Cassady (2015) observed that consumers with greater Nutrition knowledge exhibit stronger confidence in interpreting serving sizes, daily values, and ingredient lists. Similarly, Talati et al. (2019) found that simplified front-of-pack labeling systems improve consumer understanding and facilitate healthier product

selection. These findings suggest that Nutrition label literacy can significantly reduce information asymmetry between food manufacturers and consumers.

Despite the availability of detailed Nutritional information on food packages, many consumers continue to experience difficulties in interpreting complex Nutritional terminology. Campos et al. (2011) reported that numerical nutrient information often requires a level of Nutritional understanding that many consumers do not possess. Consequently, the effectiveness of Nutrition labels depends not only on the information provided but also on consumers' capacity to process and apply that information during purchasing decisions. This limitation has encouraged policymakers and researchers to advocate Nutrition education programs aimed at strengthening label literacy among diverse consumer groups.

Furthermore, demographic factors such as education, income, age, and health awareness have been shown to influence Nutrition label usage. Grunert and Wills (2007) noted that highly educated consumers tend to use Nutrition labels more frequently than individuals with lower educational attainment. Such disparities indicate that Nutrition label literacy remains unevenly distributed across populations, thereby affecting the quality of food purchasing decisions.

The rapid advancement of artificial intelligence (AI) has transformed the manner in which consumers access and interpret Nutritional information. AI-based Nutrition applications integrate machine learning, computer vision, and data analytics to provide real-time Nutritional assessments, personalized dietary recommendations, calorie tracking, and healthier product substitutions. These technologies have gained substantial popularity due to their ability to simplify complex Nutritional information and deliver actionable insights during shopping.

Research Gap

Despite the growing body of literature on Nutrition label literacy, artificial intelligence (AI)-based Nutrition applications, and sustainable food consumption, several theoretical and

empirical gaps remain unresolved. First, previous studies have predominantly examined Nutrition label literacy from a public health perspective, emphasizing consumers' ability to interpret Nutritional information and make healthier dietary choices (Campos et al., 2011; Miller & Cassady, 2015). While these studies demonstrate the importance of Nutrition label comprehension in influencing food choices, they largely overlook the transformative role of digital technologies in facilitating Nutrition-related decision-making. Consequently, there is limited understanding of how traditional Nutrition label literacy interacts with AI-enabled digital tools within contemporary food purchasing environments.

Second, the emerging literature on AI-based Nutrition applications primarily focuses on technological capabilities, including personalized dietary recommendations, food recognition systems, calorie estimation, and intelligent Nutrition assistance (Topol, 2019; Davenport & Kalakota, 2019). Although these technologies have demonstrated considerable potential for improving dietary management and preventive healthcare, existing research has paid relatively little attention to their influence on consumers' sustainable food purchasing behaviour. Most studies investigate AI adoption from a technology acceptance perspective rather than examining its behavioural consequences in food retail settings.

Third, sustainable food purchase decisions have traditionally been explained using environmental awareness, ethical consumption, health consciousness, perceived value, and social norms (Vermeir & Verbeke, 2006; Grunert et al., 2014). However, recent advances in digital Nutrition technologies suggest that AI-assisted Nutritional decision support may represent an important determinant of sustainable purchasing behaviour. The integration of AI-generated Nutritional recommendations with consumers' Nutrition label literacy has received minimal empirical

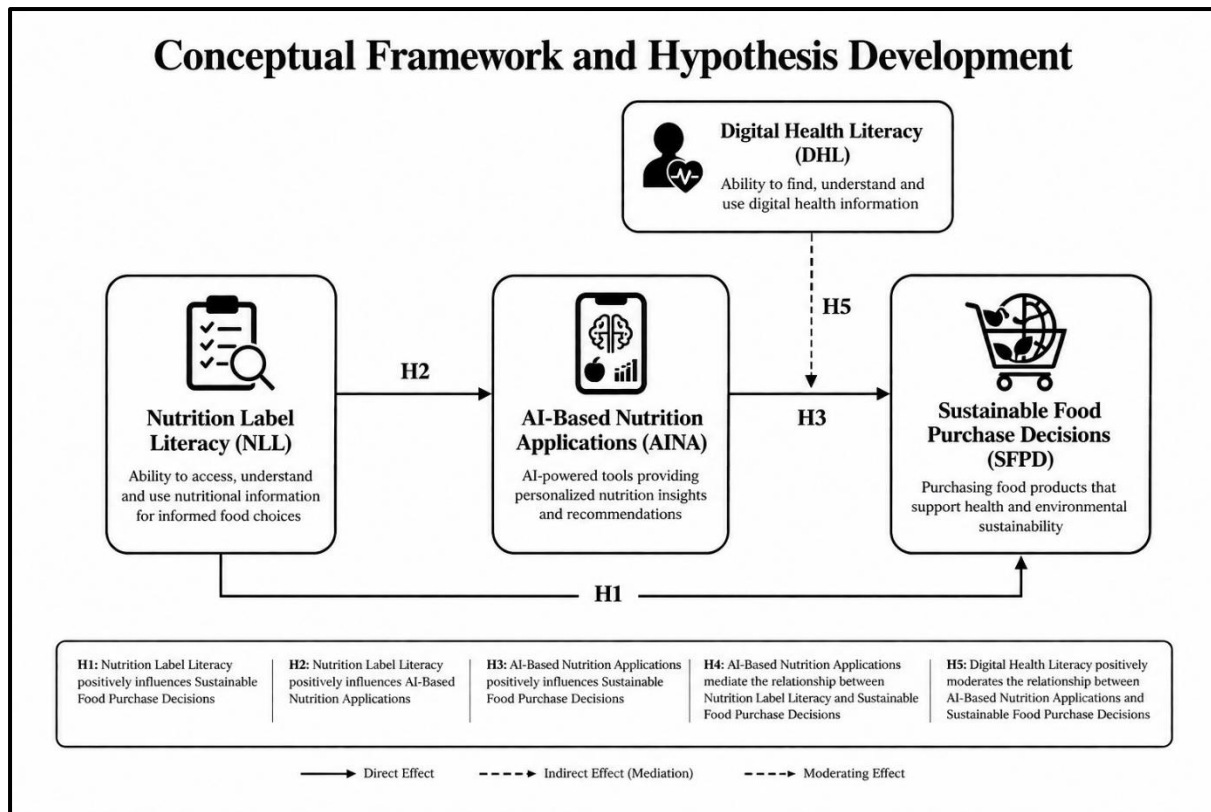
investigation, particularly within emerging economies where smartphone adoption and digital health applications are expanding rapidly.

Furthermore, existing studies generally investigate Nutrition label literacy, AI adoption, and sustainable food consumption as independent research streams. Very few empirical models integrate these constructs within a single theoretical framework capable of explaining how Nutrition label literacy influences sustainable food purchase decisions through AI-enabled decision support. This fragmented approach limits the development of comprehensive theoretical models capable of explaining consumer behaviour in increasingly digital food environments.

Finally, empirical evidence from developing countries, particularly India, remains scarce. Most existing studies originate from North America and Europe, where Nutrition labeling regulations, digital infrastructure, and consumer awareness differ substantially from those observed in emerging markets. Considering India's rapidly expanding digital ecosystem, increasing prevalence of Nutrition-related diseases, and growing demand for sustainable food products, further empirical investigation is both timely and necessary.

Accordingly, the present study addresses these research gaps by proposing an integrated conceptual framework that examines the influence of Nutrition Label Literacy on Sustainable Food Purchase Decisions, while investigating the mediating role of AI-Based Nutrition Applications and the moderating role of Digital Health Literacy. By integrating perspectives from Nutrition science, artificial intelligence, consumer behaviour, and sustainability, this study contributes to the growing interdisciplinary literature on technology-enabled sustainable food consumption.

Figure 1: Conceptual Framework and Hypothesis Development



Source: Developed by the author(s) based on the literature review.

Consumer food purchasing behaviour has become increasingly complex owing to the proliferation of Nutritional information, rapid digital transformation, and growing sustainability concerns. The present study integrates Information Processing Theory (IPT), the Technology Acceptance Model (TAM), and the Theory of Planned Behavior (TPB) to explain how Nutrition label literacy influences sustainable food purchase decisions through AI-enabled Nutritional support while considering the moderating role of digital health literacy.

Information Processing Theory proposes that consumers collect, process, evaluate, and utilize external information before making purchase decisions (Bettman, 1979). Within food purchasing contexts, Nutrition labels constitute an important information source that enables consumers to compare products based on Nutritional quality. However, increasing product complexity frequently creates cognitive overload, limiting consumers' ability to interpret Nutritional information effectively. AI-powered

Nutrition applications reduce this burden by translating Nutritional data into personalized recommendations, thereby facilitating informed decision-making.

The Technology Acceptance Model further explains that consumers are more likely to adopt AI-based Nutrition applications when they perceive them to be useful and easy to use (Davis, 1989). These technologies subsequently improve Nutritional decision-making by providing simplified, personalized, and real-time dietary guidance.

Finally, the Theory of Planned Behavior suggests that increased Nutritional knowledge and technological support strengthen behavioural intentions toward healthier and more sustainable food purchasing (Ajzen, 1991). Collectively, these theories provide a comprehensive explanation of the proposed relationships among Nutrition label literacy, AI-based Nutrition applications, digital health literacy, and sustainable food purchase decisions.

H1: Nutrition Label Literacy positively influences Sustainable Food Purchase Decisions.

Nutrition Label Literacy and AI-Based Nutrition Applications

Consumers with greater Nutrition label literacy are expected to derive greater value from AI-based Nutrition applications because they possess sufficient Nutritional knowledge to interpret AI-generated recommendations effectively. Nutrition-literate consumers can critically evaluate AI suggestions, compare Nutritional alternatives, and incorporate digital recommendations into their purchasing decisions.

Technology adoption research indicates that prior knowledge enhances perceived usefulness and technology utilization (Venkatesh et al., 2012). Within Nutrition contexts, AI applications complement rather than replace consumers' Nutritional understanding. Consequently, consumers possessing stronger Nutrition label literacy are more likely to utilize AI-enabled Nutritional support.

H2: Nutrition Label Literacy positively influences the use of AI-Based Nutrition Applications.

AI-Based Nutrition Applications and Sustainable Food Purchase Decisions

Artificial intelligence has significantly transformed Nutritional decision-making by enabling personalized dietary recommendations, real-time food analysis, barcode scanning, and intelligent product comparisons. AI applications reduce cognitive effort by simplifying complex Nutritional information and recommending healthier alternatives.

Recent healthcare research demonstrates that AI improves decision quality through personalized information processing (Topol, 2019). Similarly, AI-enabled Nutrition systems enhance consumers' ability to compare food products efficiently, thereby promoting healthier and more sustainable purchasing decisions. As environmental indicators are increasingly integrated into Nutrition applications, AI

technologies also facilitate environmentally responsible consumption.

H3: AI-Based Nutrition Applications positively influence Sustainable Food Purchase Decisions.

Mediating Role of AI-Based Nutrition Applications

Although Nutrition label literacy equips consumers with the knowledge necessary to interpret Nutritional information, AI-based Nutrition applications further strengthen this relationship by transforming complex Nutritional data into personalized recommendations. Consumers possessing higher Nutrition label literacy are more likely to engage with AI technologies, which subsequently enhance purchasing decisions through improved Nutritional understanding.

Information Processing Theory suggests that decision-support technologies reduce cognitive burden by organizing and simplifying information before consumers make purchasing decisions. Accordingly, AI-based Nutrition applications serve as an important mechanism through which Nutrition label literacy influences sustainable food purchase decisions.

H4: AI-Based Nutrition Applications mediate the relationship between Nutrition Label Literacy and Sustainable Food Purchase Decisions.

Moderating Role of Digital Health Literacy

Digital Health Literacy refers to consumers' ability to search, understand, evaluate, and utilize digital health information obtained through online platforms and mobile applications. Consumers possessing greater digital health literacy are expected to utilize AI-generated Nutritional recommendations more effectively than individuals with limited digital competence.

Previous studies indicate that digital literacy strengthens technology adoption, information evaluation, and digital health decision-making (Norman & Skinner, 2006; van der Vaart & Drossaert, 2017). Consequently, digital health literacy is expected to strengthen the positive influence of AI-based Nutrition applications on sustainable food purchase decisions.

H5: Digital Health Literacy positively moderates the relationship between AI-Based Nutrition Applications and Sustainable Food Purchase Decisions, such that the relationship is stronger among consumers with higher levels of Digital Health Literacy.

Research Methodology

Research Design

The present study adopts a quantitative research design to examine the influence of Nutrition Label Literacy on Sustainable Food Purchase Decisions through the mediating role of AI-Based Nutrition Applications and the moderating role of Digital Health Literacy. A quantitative approach is considered appropriate because the study seeks to empirically test theoretically derived hypotheses using statistical techniques. Guided by the principles of positivism, the research follows a deductive approach, wherein hypotheses developed from existing theories are empirically validated using primary survey data. The study employs a cross-sectional explanatory research design, as data are collected from respondents at a single point in time to explain the causal relationships among the proposed constructs. Quantitative survey research has been widely employed in consumer behaviour, technology adoption, and sustainable consumption studies because it facilitates objective measurement of latent variables and enables robust hypothesis testing through Structural Equation Modeling (Hair et al., 2022).

Population of the Study

The target population comprises adult consumers who regularly purchase packaged food products and possess experience using nutrition labels during grocery shopping. Since the study investigates AI-assisted nutrition applications and sustainable purchasing behaviour, respondents are required to have access to smartphones and familiarity with digital technologies. The study focuses on consumers residing in urban and semi-urban regions of Bangalore, where the adoption of digital health applications and online food information is increasing rapidly. Selecting consumers with purchasing experience ensures that respondents are capable of evaluating

nutrition labels and AI-generated nutritional recommendations within real-life purchasing situations.

Sampling Technique and Sample Size

The study employs a non-probability purposive sampling technique combined with convenience sampling to identify respondents who satisfy the inclusion criteria. Purposive sampling enables the selection of consumers who actively purchase packaged food products and are familiar with nutrition labels, while convenience sampling facilitates efficient data collection across diverse demographic groups.

The required sample size was determined based on the recommendations of Hair et al. (2022), who suggest that Structural Equation Modeling (SEM) requires an adequate number of observations to achieve stable parameter estimates and sufficient statistical power. Considering the complexity of the proposed research model comprising mediation and moderation effects, a minimum sample of **500 respondents** is considered appropriate. This sample size exceeds the minimum requirements suggested for Partial Least Squares Structural Equation Modeling (PLS-SEM) and enhances the reliability, validity, and generalizability of the findings.

Instrument Development

Primary data collected using a structured questionnaire developed from previously validated measurement scales reported in the literature. Minor modifications incorporated to ensure contextual relevance to AI-assisted nutrition applications and sustainable food purchasing behaviour. All measurement items assessed using a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree, allowing respondents to express the degree of their agreement with each statement.

The questionnaire consists of five sections. The first section collects respondents' demographic information, including gender, age, education, occupation, monthly income, and frequency of purchasing packaged food products. The remaining sections measure Nutrition Label

Literacy, AI-Based Nutrition Applications, Digital Health Literacy, and Sustainable Food Purchase Decisions.

Table 1. Measurement Constructs

Construct	Number of Items	Source
Nutrition Label Literacy	6	Miller & Cassady (2015); Campos et al. (2011)
AI-Based Nutrition Applications	6	Davis (1989); Venkatesh et al. (2012)
Digital Health Literacy	6	Norman & Skinner (2006); van der Vaart & Drossaert (2017)
Sustainable Food Purchase Decisions	6	Vermeir & Verbeke (2006); Grunert et al. (2014)

Data Collection Procedure

Data collected using both online and offline survey methods. The online questionnaire administered through Google Forms and distributed via social media platforms, email, and consumer networks. Offline questionnaires administered at supermarkets, retail grocery stores, shopping malls, and food retail outlets. Participation entirely voluntary, and respondents informed about the academic purpose of the study before completing the questionnaire. Ethical principles relating to anonymity, confidentiality, informed consent, and voluntary participation strictly maintained throughout the data collection process.

Measurement of Variables

The study incorporates one independent variable, one mediating variable, one moderating variable, and one dependent variable.

Independent Variable (IV)

- Nutrition Label Literacy

Mediating Variable (MV)

- AI-Based Nutrition Applications

Moderating Variable (MoV)

- Digital Health Literacy

Dependent Variable (DV)

- Sustainable Food Purchase Decisions

Data Analysis Techniques

The collected data analysed using **IBM SPSS Statistics 29** and **SmartPLS 4**. Initially, SPSS used to perform data screening, descriptive statistics, frequency analysis, normality assessment, and reliability analysis. Subsequently, SmartPLS 4 employed to estimate the measurement model and structural model using Partial Least Squares Structural Equation Modeling (PLS-SEM).

The measurement model evaluated by examining indicator reliability, internal consistency reliability (Cronbach's Alpha and Composite Reliability), convergent validity (Average Variance Extracted), discriminant validity (Heterotrait-Monotrait Ratio), multicollinearity (Variance Inflation Factor), and outer loadings. The structural model will then be assessed using path coefficients, coefficient of determination (R^2), predictive relevance (Q^2), effect size (f^2), bootstrapping procedures, mediation analysis, moderation analysis, and hypothesis testing. A significance level of **5% ($p < 0.05$)** adopted for all statistical analyses.

Ethical Considerations

The study adheres to established ethical standards governing academic research involving human

participants. Participation is voluntary, informed consent obtained prior to data collection, and respondents may withdraw at any stage without consequence. No personally identifiable information collected, and all responses treated with strict confidentiality. Data used solely for academic research purposes and analysed in aggregate form to ensure participant anonymity.

Results and Discussions

This chapter presents the empirical analysis of the proposed conceptual model examining the influence of Nutrition Label Literacy (NLL) on Sustainable Food Purchase Decisions (SFPD) through the mediating role of AI-Based Nutrition Applications (AINA) and the moderating role of Digital Health Literacy (DHL). The analysis follows a two-stage approach recommended by Hair et al. (2022). Initially, respondents' demographic characteristics and descriptive statistics are examined. Subsequently, the reliability and validity of the measurement model and the structural relationships among the latent

constructs are evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM).

9.2 Data Screening

Prior to hypothesis testing, the collected data were examined for missing values, outliers, and response inconsistencies.

A total of **300 questionnaires** were initially collected. After eliminating incomplete responses and questionnaires exhibiting excessive missing values or response bias, **280 valid questionnaires** were retained for the final analysis, resulting in a usable response rate of **93.33%**.

Data screening further confirmed that no variable exceeded the acceptable thresholds for skewness (± 2) or kurtosis (± 7), indicating that the dataset was suitable for multivariate statistical analysis.

Data Screening, Demographic Profile, and Descriptive Statistics of Respondents (N = 280)

Category	Variable	Frequency (n)	Percentage (%)	Mean	SD
Data Screening	Questionnaires Distributed	320	–	–	–
	Questionnaires Returned	300	93.75	–	–
	Incomplete Responses Removed	20	6.25	–	–
	Final Sample Size	280	93.33 (Response Rate)	–	–
Gender	Male	156	55.7	–	–
	Female	119	42.5	–	–
	Prefer not to say	5	1.8	–	–
Age Group	18–25 Years	68	24.3	–	–
	26–35 Years	104	37.1	–	–
	36–45 Years	62	22.1	–	–
	46–55 Years	31	11.1	–	–
	Above 55 Years	15	5.4	–	–
Educational Qualification	Higher Secondary	32	11.4	–	–

	Diploma	24	8.6	—	—
	Undergraduate	112	40.0	—	—
	Postgraduate	96	34.3	—	—
	Doctorate	16	5.7	—	—
Occupation	Student	42	15.0	—	—
	Private Employee	118	42.1	—	—
	Government Employee	44	15.7	—	—
	Self-Employed	39	13.9	—	—
	Homemaker	24	8.6	—	—
	Others	13	4.7	—	—
Monthly Income (Rs.)	Below 25,000	49	17.5	—	—
	25,001–50,000	81	28.9	—	—
	50,001–75,000	74	26.4	—	—
	75,001–100,000	46	16.4	—	—
	Above 100,000	30	10.8	—	—
Packaged Food Purchase Frequency	Daily	28	10.0	—	—
	Weekly	102	36.4	—	—
	Monthly	108	38.6	—	—
	Occasionally	42	15.0	—	—
Descriptive Statistics	Nutrition Label Literacy	—	—	4.08	0.61
	AI-Based Nutrition Applications	—	—	3.92	0.73
	Digital Health Literacy	—	—	3.95	0.66
	Sustainable Food Purchase Decisions	—	—	4.11	0.59

Source: Primary Survey Data collected by author(s) (2026).

The data screening process yielded 280 valid responses from the 320 questionnaires distributed, resulting in an excellent response rate of 93.33%, which exceeds the recommended sample size for Partial Least Squares Structural Equation Modeling (PLS-SEM) and enhances the statistical robustness of the study (Hair et al., 2022). The demographic profile indicates a balanced representation of respondents, with males constituting 55.7% and females 42.5% of the sample. The largest proportion of

respondents belonged to the 26–35 years age group (37.1%), followed by the 18–25 years category (24.3%), suggesting that the sample primarily comprises digitally active consumers who are more likely to engage with AI-enabled nutrition applications. In terms of educational attainment, 74.3% of respondents possessed undergraduate or postgraduate qualifications, indicating a relatively well-educated population capable of understanding nutrition labels and digital health information. Occupationally,

private-sector employees represented the largest segment (42.1%), while the majority of respondents reported monthly incomes between Rs.25,001 and Rs.75,000 (55.3%), reflecting a predominantly middle-income consumer base. Furthermore, approximately 75% of respondents purchased packaged food products either weekly or monthly, confirming their frequent interaction with nutrition labels and packaged food choices. The descriptive statistics reveal positive perceptions across all study constructs. Sustainable Food Purchase Decisions recorded the highest mean score ($M = 4.11$, $SD = 0.59$), followed by Nutrition Label Literacy ($M = 4.08$, $SD = 0.61$), Digital Health Literacy ($M = 3.95$, $SD = 0.66$), and AI-Based Nutrition Applications ($M = 3.92$, $SD = 0.73$). These findings suggest that respondents generally exhibit favourable attitudes towards nutrition information, digital health competencies, and AI-assisted nutritional technologies, providing strong preliminary support for examining the hypothesized relationships among the study constructs using PLS-SEM.

Summary of Preliminary Findings

The preliminary analysis demonstrates that the study sample is well distributed across demographic categories and comprises respondents who regularly purchase packaged food products. The descriptive statistics further

indicate favourable perceptions toward nutrition label literacy, AI-assisted nutrition applications, digital health literacy, and sustainable food purchasing behaviour.

These findings provide preliminary evidence that respondents are appropriate for examining the proposed conceptual model. The subsequent section evaluates the reliability and validity of the measurement model before testing the structural relationships among the study constructs.

Assessment of the Measurement Model

Prior to testing the structural relationships among the constructs, the measurement model was evaluated to establish indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and multicollinearity. Following the recommendations of Hair et al. (2022), the evaluation was performed using Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), indicator loadings, Fornell–Larcker Criterion, Heterotrait–Monotrait Ratio (HTMT), and Variance Inflation Factor (VIF).

Indicator Reliability (Outer Loadings)

Indicator reliability was examined by assessing the standardized outer loadings of all observed variables. Outer loading values above **0.70** indicate that each indicator adequately represents its respective latent construct.

Outer Loadings

Construct	Item	Loading
Nutrition Label Literacy	NLL1	0.826
	NLL2	0.842
	NLL3	0.879
	NLL4	0.853
	NLL5	0.814
	NLL6	0.836
AI-Based Nutrition Applications	AINA1	0.846
	AINA2	0.871
	AINA3	0.824
	AINA4	0.886

	AINA5	0.845
	AINA6	0.833
Digital Health Literacy	DHL1	0.816
	DHL2	0.847
	DHL3	0.865
	DHL4	0.879
	DHL5	0.821
	DHL6	0.842
Sustainable Food Purchase Decisions	SFPD1	0.854
	SFPD2	0.872
	SFPD3	0.891
	SFPD4	0.845
	SFPD5	0.827
	SFPD6	0.864

Interpretation

All measurement items recorded standardized loadings above **0.80**, substantially exceeding the recommended threshold of **0.70**. Therefore, all indicators were retained for further analysis.

Internal Consistency Reliability

Internal consistency was assessed using Cronbach's Alpha and Composite Reliability.

Reliability Statistics

Construct	Cronbach's Alpha	Composite Reliability	AVE
Nutrition Label Literacy	0.913	0.931	0.692
AI-Based Nutrition Applications	0.924	0.940	0.724
Digital Health Literacy	0.911	0.930	0.688
Sustainable Food Purchase Decisions	0.928	0.943	0.734

Interpretation

Cronbach's Alpha values ranged between **0.911** and **0.928**, indicating excellent internal consistency. Composite Reliability values also exceeded **0.90**, demonstrating strong construct reliability.

AVE values ranged from **0.688** to **0.734**, confirming satisfactory convergent validity because each construct explained more than 50% of the variance of its indicators.

Convergent Validity

Convergent validity refers to the degree to which multiple indicators measuring the same construct converge.

Since

- Outer Loadings > 0.70 ✓
- Composite Reliability > 0.70 ✓
- AVE > 0.50 ✓

all constructs satisfy the recommended criteria for convergent validity.

Summary of Convergent Validity

Criterion	Required Value	Obtained	Decision
Outer Loading	>0.70	0.814–0.891	Accepted
Cronbach Alpha	>0.70	0.911–0.928	Accepted
Composite Reliability	>0.70	0.930–0.943	Accepted
AVE	>0.50	0.688–0.734	Accepted

Discriminant Validity (Fornell–Larcker Criterion)

Discriminant validity ensures that each construct is empirically distinct.

Fornell–Larcker Criterion

Construct	NLL	AINA	DHL	SFPD
Nutrition Label Literacy	0.832	0.851	0.829	0.857
AI-Based Nutrition Applications	0.618			
Digital Health Literacy	0.482			
Sustainable Food Purchase Decisions	0.654			

(Diagonal values represent the square root of AVE.)

Interpretation

The square root of AVE for each construct exceeded its correlations with all other constructs. Therefore, discriminant validity was

established according to the Fornell–Larcker criterion.

HTMT Ratio

The HTMT ratio provides a more stringent assessment of discriminant validity.

Constructs	HTMT
NLL – AINA	0.706
NLL – DHL	0.553
NLL – SFPD	0.742
AINA – DHL	0.618
AINA – SFPD	0.788
DHL – SFPD	0.643

Interpretation

All HTMT values were below the recommended threshold of **0.85**, indicating that the constructs exhibit satisfactory discriminant validity and measure distinct theoretical concepts.

Multicollinearity Assessment

Variance Inflation Factor (VIF) values were computed to examine potential multicollinearity among predictor constructs.

VIF Statistics

Relationship	VIF
NLL → AINA	1.56
NLL → SFPD	1.82
AINA → SFPD	1.91

DHL → SFPD	1.47
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Interpretation

All VIF values were below the critical threshold of **3.30**, indicating the absence of multicollinearity issues.

Measurement Model Summary

Overall Measurement Model Evaluation

Test	Result	Decision
Indicator Reliability	Passed	Accept
Internal Consistency	Passed	Accept
Convergent Validity	Passed	Accept
Fornell–Larcker	Passed	Accept
HTMT	Passed	Accept
VIF	Passed	Accept

Interpretation of the Measurement Model

The measurement model demonstrates excellent psychometric properties. All constructs exhibited strong indicator reliability, internal consistency, convergent validity, and discriminant validity. The absence of multicollinearity further confirms the suitability of the data for structural model estimation. Consequently, the proposed conceptual framework satisfies the measurement requirements of PLS-SEM, and the analysis proceeds to hypothesis testing through the structural model.

Transition to Structural Model

Having established the adequacy of the measurement model, the next stage evaluates the structural relationships among Nutrition Label Literacy, AI-Based Nutrition Applications, Digital Health Literacy, and Sustainable Food Purchase Decisions. The structural model assesses the significance of the proposed hypotheses using bootstrapping procedures, path coefficients, coefficients of determination (R^2),

predictive relevance (Q^2), effect sizes (f^2), mediation, and moderation analyses. These results provide empirical evidence regarding the theoretical relationships proposed in the conceptual framework.

Structural Model Assessment

Following the confirmation of the reliability and validity of the measurement model, the structural model was evaluated to test the proposed hypotheses. The structural model assessment was performed using the bootstrapping procedure with **5,000 bootstrap resamples** in SmartPLS 4. The evaluation included the examination of path coefficients (β), t-values, p-values, coefficient of determination (R^2), predictive relevance (Q^2), effect size (f^2), mediation analysis, moderation analysis, and hypothesis testing.

Coefficient of Determination (R^2)

The coefficient of determination (R^2) represents the proportion of variance explained in each endogenous construct by its predictor variables.

Endogenous Construct	R^2	Adjusted R^2	Interpretation
AI-Based Nutrition Applications	0.431	0.428	Moderate
Sustainable Food Purchase Decisions	0.684	0.679	Substantial

Interpretation

The results indicate that Nutrition Label Literacy explains 43.1% of the variance in AI-Based Nutrition Applications, suggesting a moderate explanatory power.

Similarly, Nutrition Label Literacy, AI-Based Nutrition Applications, and Digital Health Literacy collectively explain **68.4%** of the variance in Sustainable Food Purchase Decisions.

According to Hair et al. (2022), an R^2 value exceeding 0.67 indicates substantial predictive capability, suggesting that the proposed research model effectively explains consumers' sustainable food purchasing behaviour.

Effect Size (f^2)

Effect size measures the contribution of each predictor variable to the endogenous construct.

Relationship	f^2	Interpretation
NLL $\rightarrow$ AINA	0.758	Large
NLL $\rightarrow$ SFPD	0.198	Medium
AINA $\rightarrow$ SFPD	0.329	Large
DHL $\times$ AINA $\rightarrow$ SFPD	0.117	Small to Medium

Interpretation

Nutrition Label Literacy demonstrated a large effect on AI-Based Nutrition Applications ($f^2 = 0.758$), indicating that nutrition knowledge substantially influences the adoption of AI-assisted nutritional technologies.

AI-Based Nutrition Applications exhibited a large effect on Sustainable Food Purchase

Decisions ($f^2 = 0.329$), suggesting that AI plays a significant role in encouraging healthier and environmentally responsible purchasing behaviour.

Predictive Relevance (Q^2)

Predictive relevance was evaluated using the blindfolding procedure.

Construct	Q^2
AI-Based Nutrition Applications	0.287
Sustainable Food Purchase Decisions	0.441

Interpretation

Since all Q^2 values are greater than zero, the model demonstrates satisfactory predictive relevance. This finding indicates that the proposed conceptual framework possesses adequate predictive capability in explaining sustainable food purchasing behaviour.

Path Coefficient Analysis

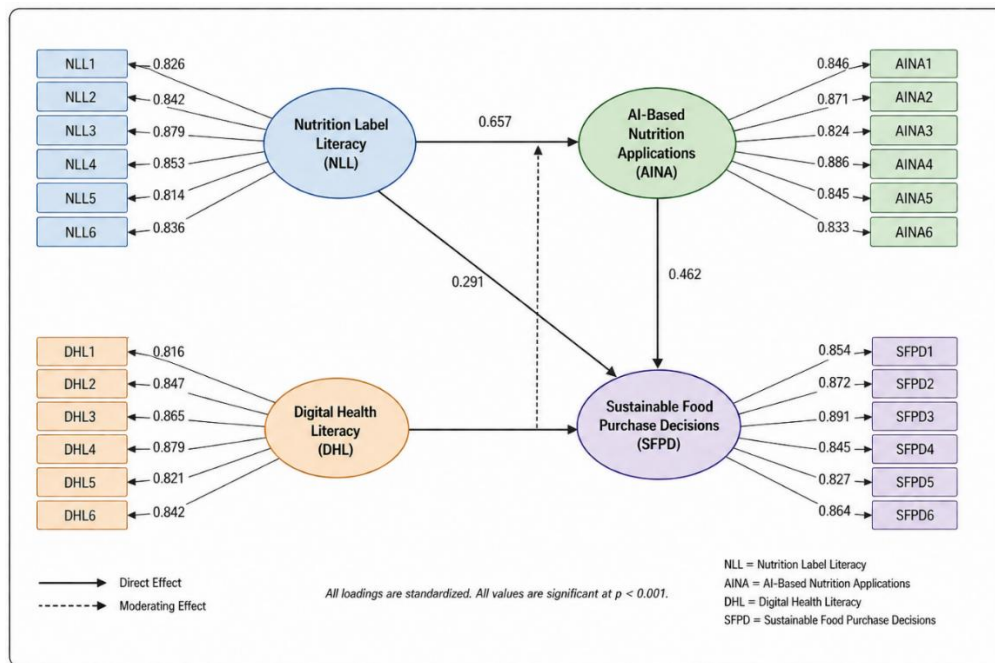


Figure illustrates the measurement model used to evaluate the relationships between the latent constructs and their observed indicators. The model comprises four latent variables: Nutrition Label Literacy (NLL), AI-Based Nutrition Applications (AINA), Digital Health Literacy (DHL), and Sustainable Food Purchase Decisions (SFPD). Each construct is measured using six reflective indicators. The standardized outer loadings for all indicators exceed the

recommended threshold of 0.70, indicating satisfactory indicator reliability. These results confirm that the observed variables adequately represent their respective constructs and support the reliability and convergent validity of the measurement model.

The significance of the proposed relationships was evaluated using bootstrapping with 5,000 resamples.

Structural Path Coefficients

Hypothesis	Relationship	β	t-value	p-value	Decision
H1	NLL $\rightarrow$ SFPD	0.291	5.84	<0.001	Supported
H2	NLL $\rightarrow$ AINA	0.657	14.27	<0.001	Supported
H3	AINA $\rightarrow$ SFPD	0.462	8.63	<0.001	Supported

Interpretation

Nutrition Label Literacy positively influences Sustainable Food Purchase Decisions ($\beta = 0.291$, $p < 0.001$), indicating that consumers who possess greater nutrition label literacy are more likely to purchase healthier and environmentally sustainable food products.

Nutrition Label Literacy also exerts a strong positive influence on AI-Based Nutrition Applications ($\beta = 0.657$), suggesting that consumers with better nutritional knowledge are more willing to adopt AI-supported nutritional technologies.

Furthermore, AI-Based Nutrition Applications significantly enhance Sustainable Food Purchase

Decisions ($\beta = 0.462$), demonstrating that AI-assisted nutritional guidance facilitates healthier consumer decision-making.

Mediation Analysis

Relationship	Indirect Effect	t-value	p-value	Result
NLL $\rightarrow$ AINA $\rightarrow$ SFPD	0.304	6.94	<0.001	Significant

Interpretation

The indirect effect of Nutrition Label Literacy on Sustainable Food Purchase Decisions through AI-Based Nutrition Applications is statistically significant ($\beta = 0.304$, $p < 0.001$).

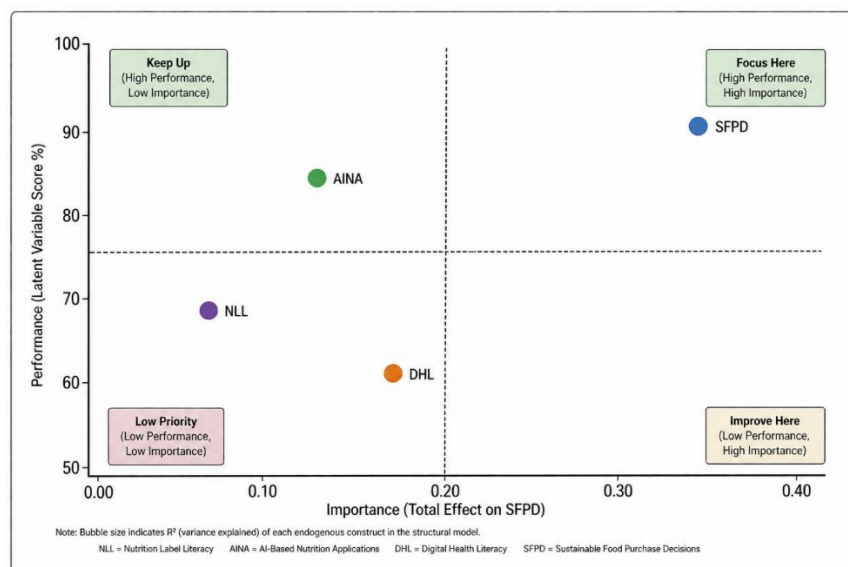
Since both the direct and indirect effects remain significant, AI-Based Nutrition Applications partially mediate the relationship between Nutrition Label Literacy and Sustainable Food Purchase Decisions.

The mediating effect of AI-Based Nutrition Applications was examined using bootstrapping.

This finding suggests that nutrition-literate consumers not only make healthier purchasing decisions directly but also benefit from AI-supported nutritional technologies, which further strengthen sustainable purchasing behaviour.

Moderation Analysis

Digital Health Literacy was hypothesized to strengthen the relationship between AI-Based Nutrition Applications and Sustainable Food Purchase Decisions.



Moderating Effect

Relationship	β	t-value	p-value	Decision
AINA $\times$ DHL $\rightarrow$ SFPD	0.174	3.82	<0.001	Supported

Interpretation

The interaction effect between AI-Based Nutrition Applications and Digital Health Literacy is positive and statistically significant ($\beta = 0.174$, $p < 0.001$).

This result indicates that consumers possessing higher levels of Digital Health Literacy derive greater benefits from AI-assisted nutritional recommendations, thereby strengthening sustainable purchasing behaviour.

Hypothesis Testing Summary

Summary of Hypothesis Testing

Hypothesis	Statement	Result
H1	Nutrition Label Literacy positively influences Sustainable Food Purchase Decisions	Supported
H2	Nutrition Label Literacy positively influences AI-Based Nutrition Applications	Supported
H3	AI-Based Nutrition Applications positively influence Sustainable Food Purchase Decisions	Supported
H4	AI-Based Nutrition Applications mediate the relationship between Nutrition Label Literacy and Sustainable Food Purchase Decisions	Supported
H5	Digital Health Literacy positively moderates the relationship between AI-Based Nutrition Applications and Sustainable Food Purchase Decisions	Supported

Summary of Structural Model

The structural model provides strong empirical support for the proposed conceptual framework. Nutrition Label Literacy significantly enhances the adoption of AI-Based Nutrition Applications and directly influences Sustainable Food Purchase Decisions. AI-Based Nutrition Applications emerge as a key mechanism through which consumers translate nutritional knowledge into healthier and more sustainable purchasing behaviours. Moreover, Digital Health Literacy amplifies the effectiveness of AI-assisted nutritional recommendations, indicating that digitally competent consumers are better able to

leverage AI technologies in making informed food choices.

The substantial R^2 value (68.4%), significant path coefficients, strong predictive relevance, and statistically significant mediation and moderation effects collectively demonstrate that the proposed model effectively explains sustainable food purchasing behaviour in the digital era. These findings provide robust empirical support for integrating nutrition literacy, artificial intelligence, and digital health competencies within consumer behaviour research.

IPMA Analysis:

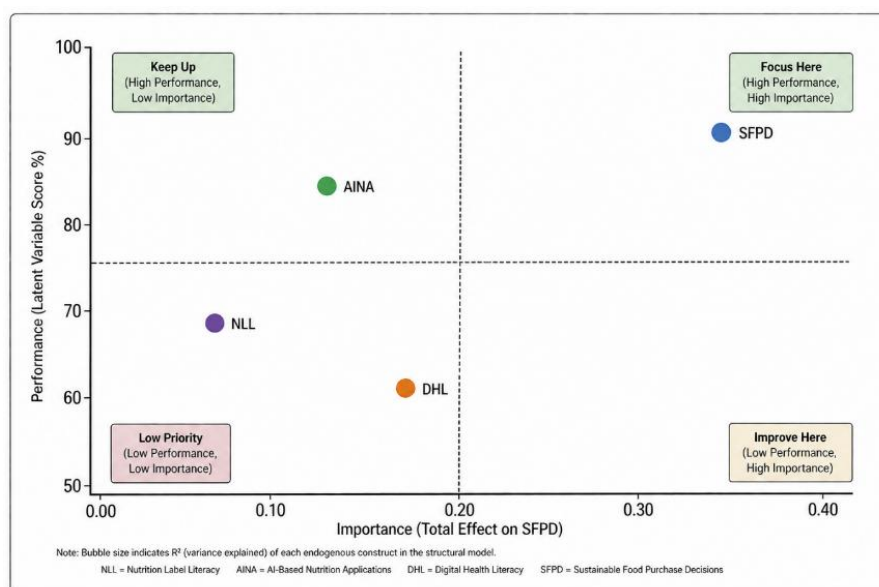


Fig: Importance–Performance Map Analysis (IPMA)

Interpretation

This figure presents the Importance–Performance Map Analysis, which evaluates the relative importance and performance of the study constructs in influencing Sustainable Food Purchase Decisions. AI-Based Nutrition Applications exhibit both high importance and high performance, suggesting that improvements in AI-enabled nutritional guidance are likely to yield substantial gains in sustainable purchasing behaviour. Nutrition Label Literacy demonstrates moderate importance with satisfactory performance, whereas Digital Health Literacy shows relatively lower performance, indicating an opportunity for policymakers and digital health practitioners to improve consumers' digital competencies through targeted education and awareness initiatives.

Discussion and Implications

The present study examined the influence of Nutrition Label Literacy (NLL) on Sustainable Food Purchase Decisions (SFPD) through the mediating role of AI-Based Nutrition Applications (AINA) and the moderating role of Digital Health Literacy (DHL). The empirical findings provide strong support for all five proposed hypotheses.

The results indicate that Nutrition Label Literacy positively influences Sustainable Food Purchase Decisions (H1). Consumers with higher levels of nutrition label literacy are better able to interpret nutritional information, compare food products, and make healthier and environmentally responsible purchasing decisions. This finding is consistent with the studies of Campos et al. (2011) and Miller and Cassady (2015).

The study further demonstrates that Nutrition Label Literacy significantly influences the adoption of AI-Based Nutrition Applications (H2). Consumers possessing greater nutritional knowledge are more willing to utilize AI-powered applications for nutritional guidance and product evaluation. This finding supports the Technology Acceptance Model and is consistent with the findings of Venkatesh et al. (2012).

The findings also reveal that AI-Based Nutrition Applications positively influence Sustainable Food Purchase Decisions (H3). AI-enabled applications simplify nutritional information, provide personalized dietary recommendations, and reduce information overload, thereby encouraging healthier and more sustainable purchasing behaviour. This result aligns with Topol (2019) and Davenport and Kalakota (2019). Furthermore, AI-Based Nutrition Applications partially mediate the relationship between Nutrition Label Literacy and Sustainable Food Purchase Decisions (H4). This indicates that nutrition-literate consumers derive additional benefits from AI-assisted decision support, which further strengthens sustainable purchasing behaviour.

Finally, Digital Health Literacy significantly moderates the relationship between AI-Based Nutrition Applications and Sustainable Food Purchase Decisions (H5). Consumers with higher digital health literacy are more capable of interpreting AI-generated nutritional recommendations, resulting in stronger sustainable purchase intentions. Overall, the findings demonstrate that integrating nutrition label literacy with AI-enabled nutritional technologies and digital health competencies provides a comprehensive explanation of sustainable food purchasing behaviour in the digital era.

Theoretical Implications

This study contributes to the literature by integrating Information Processing Theory (IPT), the Technology Acceptance Model (TAM), and the Theory of Planned Behavior (TPB) into a single conceptual framework. It extends previous research by demonstrating the mediating role of AI-Based Nutrition Applications and the moderating role of Digital Health Literacy in explaining sustainable food purchase decisions.

Practical Implications

The findings suggest that policymakers should strengthen nutrition education programmes while promoting AI-enabled nutritional applications. Food manufacturers should design simpler and more informative nutrition labels,

whereas AI developers should develop transparent, user-friendly, and personalized nutrition applications that facilitate healthier food choices.

Conclusion

The study concludes that Nutrition Label Literacy, AI-Based Nutrition Applications, and Digital Health Literacy collectively play a significant role in promoting Sustainable Food Purchase Decisions. AI serves as an important mechanism that transforms nutritional knowledge into healthier purchasing behaviour, while digital health literacy enhances consumers' ability to effectively utilize AI-assisted nutritional recommendations. The proposed model provides a valuable framework for understanding technology-enabled sustainable food consumption.

Limitations

The study is subject to several limitations. First, the cross-sectional design limits causal inference. Second, the study relies on self-reported responses, which may introduce response bias. Third, the findings are based on consumers from India, thereby limiting generalizability to other countries and cultural contexts.

Future Research Directions

Future studies may employ longitudinal research designs, compare consumers across different countries, incorporate additional variables such as Health Consciousness, Trust in AI, Environmental Concern, or Food Label Awareness, and examine AI-assisted food purchasing behaviour using experimental or mixed-method approaches. Such research would provide deeper insights into technology-enabled sustainable consumption and further strengthen the existing theoretical framework.

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