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Modeling The Impact and Accelerating The Process Of Transitioning To A Sustainable Healthy Diet Through Decision Support Systems

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Modeling The Impact and Accelerating The Process Of Transitioning To A Sustainable Healthy Diet Through Decision Support Systems

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CHAPTER ONE

1 Problem Background

Diet-related chronic diseases are on the rise in the United States. Today, nearly 117 million people, thus about 50% of American Adults have one or more chronic diseases [1, 2]. Many of these diseases are preventable as they are related to poor quality dietary patterns of consumers [3-6]. Currently, the estimated health care cost of obesity-related illness is at a staggering $190.2 billion annually [7]. Looking forward, researchers stipulate that if consumer dietary patterns continue to go unchecked and the current trends persist, the medical cost of obesity related illness could rise by $48 to $66 billion in the United States by 2030 [8]. Therefore, it is important to take pre-emptive actions to develop levers to reduce and control these conditions.

Currently, there are several technology-based tools to help consumers record or monitor their dietary intake at set intervals. These tools include scanner-and-sensor based technologies [9, 10], web/computer-based technologies such as the Automated Self-Administered 24-hour dietary recall (ASA24) [11] or mobile technologies such as MyPlate [12]; or Lose It! [13]. While these tools allow consumers to track their diet, they require users to record the time and type of food usually after purchase. Besides, these tools do not satisfy the increasing consumer quest of consumers to know the environmental sustainability of their diets.

Therefore, consumers need an easy-to-use tool grounded on the best science to provide decision support for real-time exploration of different food choices to improve health and environmental impact at the time of purchase, because when these tools or the information are deployed at the point of decision making, there is a higher chance of influencing consumer behavior [14].

Many interventions aiming to increase the consumption of healthier foods have been tested and implemented in recent years. Among the existing interventions and strategies, methods targeted at consumers' perception, instead of those that limit consumers' choices, seem to have a greater impact on improving the effectiveness of healthy diet campaigns [15]. These methods are often associated with the term "nudge", which refers to changing people's behavior without the constraint of options [16]. Because the environment in which individuals make choices can be altered and influence the way the decision-making processes occur, nudging focuses on enabling and changing behaviors and decisions that are beneficial for society (e.g., public health) rather than delivering information or changing the society's values system. For example, a school cafeteria in New England (North America) asked their students—before they ordered their meals— whether they would have fruit or juice with their lunch, and the intervention resulted in 70% of students consuming one of those in opposition to 40% in the control group [17]. An intervention in a buffet restaurant in Denmark changed the sequencing design of its service combining and separating fruits and vegetables. The change resulted in an increase of self-served fruits and vegetables while reducing the total calorie intake [18]. Gonçalves, Coelho [14] demonstrated how a social norm nudge, a message conveying fruit and vegetable purchasing norms positioned at strategic places in a Portuguese supermarket, affected the purchasing habits of consumers categorized as less healthy and healthy. The study measured 1,636 customers over three months. The results demonstrate that the nudge intervention positively affected the purchasing habit of consumers categorized as less healthy while those with healthy habits were slightly negatively affected.

With the ongoing sustainability-nutrition dilemma, the information used for implementing food choice nudge is essential. Research shows a poor understanding by consumers on the dynamic relationship between the dietary choice, the food ecosystem, and other interrelated systems [19-21]. This is because information which may be effective in improving consumer food choices, such as nutrition information, is complex and difficult to convey in a clear, actionable manner. Although consumers in the US [22] and Europe are knowledgeable about climate change [23, 24], they remain uninformed about the broader environmental impacts of their food choices [25, 26]. Therefore, simple, graphic, and easily understandable messaging will be critical to delivering a digital platform that promotes healthy and sustainable choice and supports chronic disease prevention.

1.1 Main objective

This project aims to use these identified opportunities to enhance the capacity of policymaker and consumer to make decisions about food production, supply and consumption based on nutritional quality, contribution to health, and environmental sustainability.

1.1.1 Specific objective

The **overall objective** of the project is to enhance the capacity of policymakers and consumers to make decision about food production, supply, and consumption by simultaneously considering nutrition quality, contribution to health and environmental sustainability. This will be achieved through the following specific objectives:

(a) **Specific objective 1**: To assess and articulate sustainable consumer dietary patterns and their correlation with human health, the environment and the socio-economic dimension of sustainability.

(b) **Specific objective 2:** To multi-objectively model the risk to health and environmental impact under stringent mitigation policies**.**

(c) **Specific objective 3**: To develop a sustainable healthy food choice platform that provides consumers numerical and pictorial data on nutritional quality, contribution to healthy living, environmental impact, and cost.

1.2 Justification

Consumers' decisions on their food choices have been implicated in the rise of preventable chronic diseases with significant implication on both consumer health and national cost for treatment [27]. This is further complicated by increasing consumer desire for a sustainable diet [28]. However, current platforms offer one or the other, thus environmental enthusiasts may focus on sustainability at the expense of their health [1]. Providing a digital platform that leverages the benefits of both worlds is a great opportunity to enhance consumer health while meeting their sustainability goals. The current literature sufficiently supports the effectiveness of using informational and nudging techniques to reorient consumer behavior towards sustainable food consumption [29-31]. Therefore, implementing nudges using a novel digital technology based on the assumption that, by guiding people towards small, subtle adjustments in their daily dietary routines, we can cumulatively achieve considerable positive health and environmental impacts. The proposed platform, F-COD will:

(a) Draw practical attention to the nutritional implications of diet choices and how it contributes to healthy living at the point of food choice/decision making.

(b) Provide consumers environmental impact information of chosen foods (ecosystem quality and human health impact)

(c) Provide an interactive avenue for environmental-nutrition trade-off analysis and comparison of different choices to enable consumers make informed decision.

This technology presents an opportunity to integrate the present consumer food data and streams to drive consumer food choices towards sustainability and health. The technology will act as an intelligence hub between data, dynamic models and decision making, unlocking the true potential of consumer food expenditure data, improving

CHAPTER TWO

2 Transitioning to sustainable healthy diets: A model-based and conceptual system thinking approach to optimized sustainable diet concept in the United States

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Abstract

Food production and consumption are essential in human existence, yet they are implicated in the high occurrences of preventable chronic diseases and environmental degradation. Although healthy food may not necessarily be sustainable and vice versa, there is an opportunity to make our food both healthy and sustainable. Attempts have been made to conceptualize how sustainable healthy food may be produced and consumed; however, available data suggest a rise in the prevalence of health-related and negative environmental consequences of our food supply. Thus, the transition from conceptual frameworks to implementing these concepts has not always been effective. This paper explores the relative environmental and health risks associated with highly consumed food groups and develops a methodological workflow for evaluating the sustainability of diet concepts in the context of different health, socio-economic and environmental indicators. In addition, we apply the multi-criteria decision-making techniques (an integrated Analytic Hierarchy Process- Technique for order preference by similarity to ideal solution (AHP-TOPSIS) model) to examine the health and environmental impact of selected sustainable healthy diet concepts implemented in the United States. The principal findings indicate that adopting plant-based diet patterns would benefit the environment and the population's health. However, the up-scale, broad adoption and implementation of these concepts are hindered by critical bottlenecks. Hence we propose potential

modification strategies through a conceptual system thinking approach to deliver optimized sustainable diet concepts to aid in the realization of the anticipated benefits of adoption/implementation.

1 Introduction

In the last 50 years, global diets have been increasingly viewed as not healthy or environmentally sustainable. Instead, they are perceived to contribute to environmental degradation, natural resource depletion (for example climate change, biodiversity loss, increased freshwater consumption), and poor health [1].

Today, in the United States, over 78 million people are estimated to be obese, with the presence of associated chronic diseases such as coronary heart disease, stroke, and type 2 diabetes [2]. These diseases are responsible for seven out of ten deaths in the United States, killing more than 1.7 million Americans each year. In addition, about 18.2 million adults have coronary artery diseases [3], while nearly 37 million Americans have diabetes, with nearly 90-95% of this attributed to type 2 diabetes [4]. The high prevalence of obesity-related chronic diseases has been inexplicably linked with consumers' food choices and diet patterns.

From an environmental sustainability perspective, at the global level, our present diet pattern is responsible for over 70% of global freshwater withdrawals, occupies nearly 40% of arable land on the earth, and contributes over 30% of anthropogenic greenhouse gas emissions (GHGE) [5]. As a result, it is the single greatest cause of eutrophication in water bodies (approximate 78% contribution), loss of biodiversity, and air pollution through increased atmospheric fine particulate matter[6].

Acknowledging the existence of these challenges has led to the development of diverse views and concepts regarding sustainable healthy diets as an approach to tackling the trilemma existing between diets, human health, and environmental degradation. The term sustainable healthy diets encompass two dimensions, namely environmental sustainability and healthiness of the diet. This concept simultaneously integrates the environmental cost of food production and consumption with nutrient requirements in a socio-cultural and economic context within safe planetary boundaries [7]. In other words, a sustainable healthy diet aims to provide a diet that promotes optimal growth and development and supports the physical, mental, and social wellbeing of all people at different life stages for the present, without compromising the capacity of the future generation [8].

Achieving a sustainable healthy diet in conjunction with the Sustainable Development Goals number 3 (Good health and wellbeing) and 12 (Responsible consumption and production) has resulted in the proliferation of several concepts to guide local, regional, and government agencies. Broadly, in the United

States, the U.S Department of Agriculture, in collaboration with other stakeholders and international organizations, has made and continues to make massive investments across varying visions of the future to achieve sustainable and healthy diets for all Americans. Prominent among several concepts proposed are climate-smart agriculture, precision farming, Diet Guidelines for Americans, the Mediterranean diet, and the Eat Lancet Commissions diet recommendation of the Planetary Health Diet framework. Additionally, other diet patterns, sustainable agricultural production schemes, and global food initiatives have been fostered with varying resource consumption while improving human health and minimizing environmental impact [9]. These concepts were formulated on the premise that a simple shift in diet behavior or pattern can lead to potential reductions in environment-health impact.

The research to date has confirmed the ramifications of sustainable diet concepts on either the health of people or one or more environmental indicators. This is exemplified by the work undertaken by Reinhardt, Boehm [10], where the authors expanded on the sustainability outcomes of U.S. diet patterns with a specific focus on environmental indicators such as land use, water consumption, energy use, and fertilizer use. Likewise, Mekonnen and Fulton [11] analyzed the consumptive water reductions for vegetarian, vegan and Healthy U.S diet styles. A cohort study by Orlich, Singh [12] investigated the association of vegetarian diet and mortality, concluding that it is associated with reductions in all causes of mortality. Other studies have also reported on the socio-economic aspects sustainable diet concepts. Springmann, Clark [13], reported that the adoption of flexitarian diets concept with less amount of meat and dairy reduced cost by 14%, while pescatarian diets increased cost by 2% in high income countries such as the US, UK and Australia. In the same study, the authors associate vegan diet concept as the most affordable as it reduced food cast by up to one third, with the vegetarian diet close to second among other diet concepts. In this regard high energy dense foods which can lead to health problems for people tend to be cheaper than highly nutritious foods such as fish and vegetables [14]. Collectively, these studies indicate a relationship between different diet concepts and reduction in either health impact of people or environmental impact. Despite the relative abundance of these sustainability concepts, herein lies a conundrum. The transition from conceptual frameworks to implementing these concepts has not always been effective.

Therefore, in the present work, we apply indicators covering human health, environmental sustainability, and socio-economic dimensions of sustainable food systems to evaluate the implementation pathways of sustainable healthy diet concepts implemented in the United States of America. The result of the evaluation is input into an integrated Analytical Hierarchy Process-Technique for order preference by similarity to ideal solution (AHP-TOPSIS) decision-making framework to determine which: (1) indicator/ criteria is of high priority to consumers (2) diet pattern concept has the highest nutrient adequacy and maximizes the potential of the prevention of diet-related chronic disease such as cardiovascular disease, obesity, and diabetes, and (3) diet pattern concept has the minimum environmental footprint based on different descriptors. Although some regionally oriented healthy diet concepts have different socio-cultural connotations and may not be considered as typical American diets, we leverage on the premise of their successful adoption in different parts of the world and their capacity to address nutritional inadequacy and environmental sustainability issues. In addition, their improved health outcomes reported in many epidemiological, cohort, and life cycle assessment studies address environmental concerns serve as the premise to conduct the AHP-TOPSIS analysis. The entire structure of the paper is as follows: Section two describes a rigorous four-step methodology for selecting a sustainable diet pattern and presents a workflow for implementing the AHP-TOPSIS decision model. The third and fourth sections discuss the study's significant findings by providing a brief overview of the historical diet-health-environment trilemma, highlighting the relative environmental and health risk of taking additional servings per day of 15 highly consumed food groups. The remaining part of the paper identifies barriers to implementing top-ranked diet concepts and provides modification strategies to selected case studies on different diet concepts.

2 Method

2.1 Methodological framework

It is evident that the sustainable (environmental) health diet trilemma that we are currently facing is due to the choice of the population under the influence of diverse factors such as increased income and urbanization. However, critical stakeholders have adopted and recommended many sustainable diet concepts due to the negative impact of people’s choices on their health and the environment. Thus, to assess these diet concepts' efficiency and relative performance, this study adopts a methodological workflow to filter, evaluate, and seemingly predict the optimal effectiveness of implementing diverse sustainable and healthy diet concepts. Figure 1 presents the methodological framework adopted for determining optimal sustainable diets in the United States. In the first stage of the methodological framework, we highlight current diet choices' health and environmental impacts and present a historical trends of different impact categories such as GHGE, and overweight. Next, we identify several sustainable diet concepts and develop rigorous inclusion and exclusion criteria to determine which of them apply to the geographical region of focus. Next, we develop a metric to assess their current performance. The metric covers health, environment and socio-economic dimensions of sustainability. Finally, their performance results are input into an integrated AHP-TOPSIS framework to identify the concepts which could maximize the health, environmental gains and socio-economic gains. The AHP-TOPSIS relies on weights, which was computed taking into consideration expert opinions on the relative importance of the criteria used.

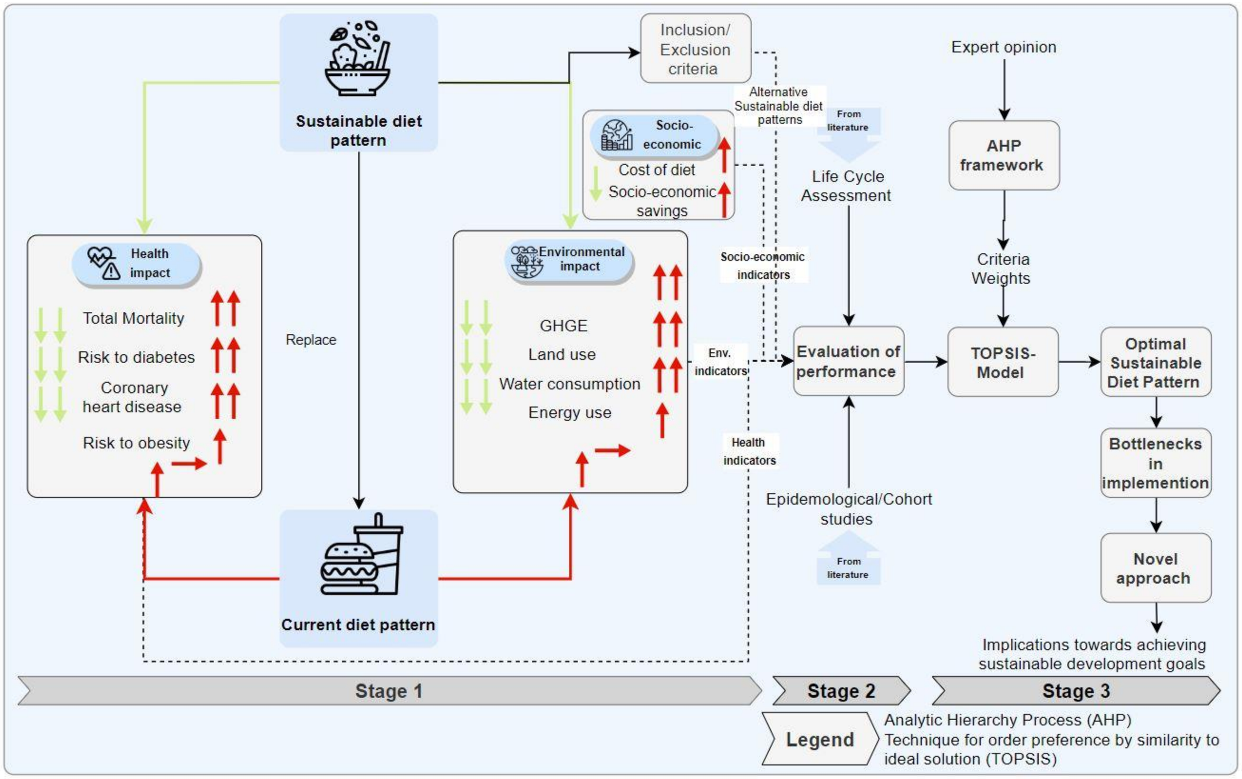

Figure 1: Conceptual framework for determining the performance of sustainable diet concepts in the United States.

2.2 Construction of an evaluation assessment index

According to Lancet Commission on Planetary Health, a shift in diet changes to a more sustainable diet can improve people's health and planetary health. For example, Lancet Commission analyzed healthy diets and determined that a shift towards such that's can prevent approximately 19-24% of total deaths that are diet related. Additionally, a shift to healthy diets was projected to decrease the prevented GHGE from the present baseline impact of 196% to 49-96% [7]. Several other investigations into sustainable diet concepts have identified their correlation with improved health (including reducing mortality, diabetes, hypertension, heart diseases) in large American cohorts. Regarding the environmental impact, the literature shows that changing from a traditional Western diet to alternative diet patterns can reduce environmental footprint [15, 16]. Therefore, to evaluate the impact of sustainable healthy diet concepts, we assembled a set of metrics that captures environmental sustainability, healthy diet benefits and economics. Table 1 presents a summary of the description of the metric and their respective objective in the context of sustainability.

Table 1: Metrics for evaluating sustainable diet concepts

Sustainability Dimenstion	Sustainability Metric	Description	Objective	Ref.
Health	Risk to diabetes	Measures the risk of diet concepts that affect the body's ability to produce insulin in cohort studies.	Minimized	[39]
	Prevention of coronary heart diseases	Measures the diet concept's risk in relation to coronary heart diseases in cohort/epidemiological studies.	Minimized	[40]
	Risk to mortality	Estimates the association of mortality to diet factors	Minimized	[41]
	Risk to obesity	Measures the association of different diet concept intake to the prevalence of obesity	Minimized	
	Total cancer	Measures the risk reduction to cancer from the consumption of different diet patterns	Minimized	[42]
Environment	GHGE reduction, (kg CO_2eq/capita/year)	It is an adjusted indicator that includes CO_2, N_2O, and CH_4	Minimized	[43]
	Agricultural Land use reduction (m^2 /capita/year)	Measures the aggregated land use of the different types of agricultural production e.g. Pasture, cropping	Minimized	[44]
	Water consumption (L/capita/day)	Measures the amount of groundwater evapotranspired by crops or incorporated into the product during growth and processing.	Minimized	[11]
	Energy consumptions	Measures the amount of energy consumed during agricultural product of sustainable diets.	Minimized	[45]

Socioeconomic	Average cost of a healthy diet, €/day	Measures the cost of adherence to diet patterns per day	Minimized	[46]
	Socio-economic savings to society	Measures the savings through health and environmental improvements of consuming sustainable diets	Maximized	

2.3 Criteria for inclusion of implementation case studies

2.3.1 Eligibility criteria

Before evaluating the sustainable diet concepts, we developed rigorous four-step inclusion and exclusion criteria for observational and epidemiological trials that have studied the association between diet patterns on either health or the environment. In the first step, we searched the literature to identify diet patterns and studies on health, and environmental assessment, which focused on U.S. only. Next, we set a minimum threshold of five studies that have reported implementing the initially sampled diet pattern. This step ensured substantial historical evidence of its effectiveness against real environmental and health pressures. Later, a cut-off criterion that considered the sample size, population demography, and duration of the implementation case studies was applied. In each sub-inclusion/exclusion criteria, a threshold of 5000 participants, including women and children was set. A four-year study period and monitoring were used to eliminate studies that did not meet the above requirement. The overall cut-off contribution for each sub-criterion was set at 60%. Aside from this, we checked the availability of data on environmental impact assessment and health risk results associated with each diet.

2.3.2 Data grid

The data used in analyzing the health and environmental burden of American diet shifts and lifestyles was obtained from FAOSTAT, "Our World in Data", and "World bank" [17, 18]. In addition, we constructed a new database using the available literature on health impact and environmental impact assessment of different diet patterns. Data on the literature used, including the publication year, study country, primary health, environmental and socio-economic outcomes, are shown in the supplementary sheet. Where no data was available during the assessment, proxies from high-income countries such as Canada, Sweden, and the United Kingdom were adopted. Additional data for assessing and analysing the effectiveness of the different diet concepts were from the work of Clark, Springmann [19].

2.4 Multi-criteria decision-making method

According to Johnston, Fanzo [20], a sustainable diet promotes environmental and economic stability through low impact and affordable foods while simultaneously improving the population's health by providing adequate nutrition and reducing the risk of diseases. A systematic methodological evaluation of current sustainable healthy diet patterns and their effectiveness in addressing regional and global objectives in the health and environmental context is required to realize these objectives. This is partly because of the complex interactions between health, environment, and socio-economic drivers such as consumer demands. Therefore, sustainable decision-making should integrate Multi-criteria Decision-Making (MCDM) tools to ensure healthy diets delivered from a sustainable food system is achieved for nearly 10 billion people by 2050. Table 2 summarizes MCDM and their respective methods.

Table 2: Categories for classifying Multi-criteria Decision Making methodologies (Extracted from [47])

Categories	Methodology
Multi-Attribute Utility and value theory	Analytic Hierarchy Process (AHP)/ Analytical Network Process (ANP); Fuzzy set methodology; Grey relational method
The multi-objective mathematical programming	Constrain programming; Linear programming; Goal programming
Non-classical method	Fuzzy set methodology
Elementary aggregation method	Weighted sum method; Weighted product method
Complex aggregation method	Analyse and Synthesis Parameters under Information Deficiency (ASPID)
Distance-to-target approach	Technique for order preference by similarity to ideal solution (TOPSIS); Grey Relational Analysis; Data Enveloping Analysis
Direct ranking (High dependence on decision-maker)	Stepwise expert judgment; Delphi; Scoring method
Outranking method	Elimination and choice translating reality (ELECTRE I, I.S., II, III,) ; Preference ranking organization method for enrichment evaluation (PROMETHEE I, II)

2.4.1 Overview of MCDM method employed in this study

MCDM methods have been widely applied to different sectors, including social, economic, industrial, biological systems, and renewable energy systems [21]. Contrary to the single criteria decision-making approach, MCDM employs a multi-attribute/criteria approach to obtain an integrated result for the decision-maker. It is important to mention that not all MCDM methods are the same; while some incorporate certain features, others disregard and are limited in different perspectives. More often than not, the choice of technique is dependent on the availability of data, knowledge of the method, the context of the problem, and the software to implement the method. One of the most well-known, highly adopted, and simplest subjective and objective MCDM methods in food system evaluation include Analytical Hierarchy Process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS). AHP provides a straightforward and flexible model to address problems. When there are multiple conflicting criteria, it becomes expedient to adopt such a method to achieve a consensus.

2.4.2 Relative weight determination using Analytical Hierarchy Process

In general, MCDM requires an evaluation of ***m*** criteria against ***n*** alternatives, as presented in Equation 1.

$$criteria \;\; C_1 \quad C_2 \; \dots\dots C_m$$

$$(weights \; w_1 \quad w_2 \dots\dots\dots w_n)$$

$$X = \begin{array}{c} A_1 \\ \vdots \\ A_n \end{array} \qquad \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}_{m \times n} \qquad (1)$$

Where A_i are the alternative sustainable diet concepts, x_{ij} is the performance of *j-th* criteria of the *i-th* alternative sustainable diet concept and w_j is the weight of criteria. This weight is obtained by employing the A.H.P. method. Saaty and Ramanujam first introduced the A.H.P. method in a seminar work to provide a comprehensive evaluation model of different criteria relevance in problems. The technique uses a pair-wise comparison model that first defines the objective of the decision problem, decomposes to other criteria and sub-criteria, depending on its complexity, and determines unique weights for each criterion [21, 22].

2.4.3 Ranking of sustainable diet concepts using technique for order preference by similarity to ideal solution (TOPSIS).

With an A_i number of alternatives, the ranking to obtain the optimal sustainable diet concept is achieved using the TOPSIS model. TOPSIS is a practical and valuable method for ranking and selecting several possible alternatives through measuring Euclidean distances. It is based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution (P.I.S.) in a geometric sense.

2.4.4 Premises for the AHP-TOPSIS modeling of sustainable diet concepts

As mentioned earlier, not all MCDM methods incorporate certain features. The AHP method cannot capture uncertainties and determine alternative ratings in decision-making. This weakness is complemented by TOPSIS, making the use of an integrated AHP-TOPSIS technique a more robust approach to decision making.

Assuming we have ***m*** number of criteria, the AHP model can be implemented as follows:

Step 1: This involves developing a hierarchy structure that describes the goal, alternatives, criteria, and sub-criteria for the comprehensive evaluation.

Step 2: Here we construct a pair-wise comparison for the criteria and alternatives concerning the decision-making objective. Table 3 shows the relative pair-wise comparison connotations that express each criterion's importance based on the decision makers' discretion.

Table 3: Definition of the intensity of qualitative and quantitative score for criteria weight determination

Intensity of weight	Definition	Explanation
1	Equal importance	This implies that two criteria have equal importance to the objectives.
3	moderate importance of one over another	The judgment slightly favor one over the other
5	strong importance	The judgment strongly favor one over the other
7	Extreme importance	The judgment is very strongly favored one over the other
9	Absolute importance	The judgment is of absolute importance over the other

It is important to mention an instance where intensity adjusted weights such as 2,4,6 and 8 can express intermediate importance between criteria. The matrix was constructed in accordance with the recommendations of [23] to extract a decision matrix.

Step 3: The second step is repeated for each criterion, and then the priority of alternatives is acquired by accumulating the weights. Next, a statistical technique, arithmetic mean method is adopted to construct a vector $W = [W_1, W_2, \dots W_N]$ that represents the weight of each criterion in a pair-wise comparison matrix M presented in Equation 1. Each element in column *j* of matrix *M* is divided by the sum of entries in the j column. This step generates a new matrix called the Normalized matrix ($\mathrm{A_{norm}}$). It is important to highlight other statistical techniques such as the characteristic root method, and the least square method can be employed to estimate the weights.

$$M = \begin{bmatrix} C_1/C_1 & \cdots & C_1/C_N \\ \vdots & \ddots & \vdots \\ C_N/C_1 & \cdots & C_N/C_N \end{bmatrix} \qquad (2)$$

Step 4*:* The comparison matrix (Equation 1) obtained in step 3 is subjected to a consistency check to validate the results' soundness. A consistency ratio of 10% or 0.1 was set. This involves determining the maximum eigenvalues and consistency index by using Equations. (2) and (3), respectively. One advantage of the consistency ratio is that it eliminates the problem of disagreements in individual judgments.

$$\lambda_{max} = 1/n \sum_{i=1}^{n} \frac{i^{th} entry\ in\ AW^T}{i^{th}\ entry\ in\ W^T} \qquad (3)$$

Where: λ_{max} *= maximum Eigen value*

n = number of attributes

A = pair-wise comparison matrix

W = The estimate of the decision-makers weight

Nevertheless, the consistency is checked by comparing the Consistency Index (CI) to the Random Index (R.I.) for the appropriate value of n, used in decision-making [21]. If (CI/RI) < 0.10, the degree of consistency is satisfactory, but if (CI/RI) > 0.10, serious inconsistencies may exist, and the results produced by AHP may not be meaningful.

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (4)$$

Figure 2 presents the hierarchical decomposition of the decision-making problem. It summarizes the overall objective: to determine an optimal sustainable diet pattern, the criteria, and sub-criteria used to evaluate the sustainable diet concepts.

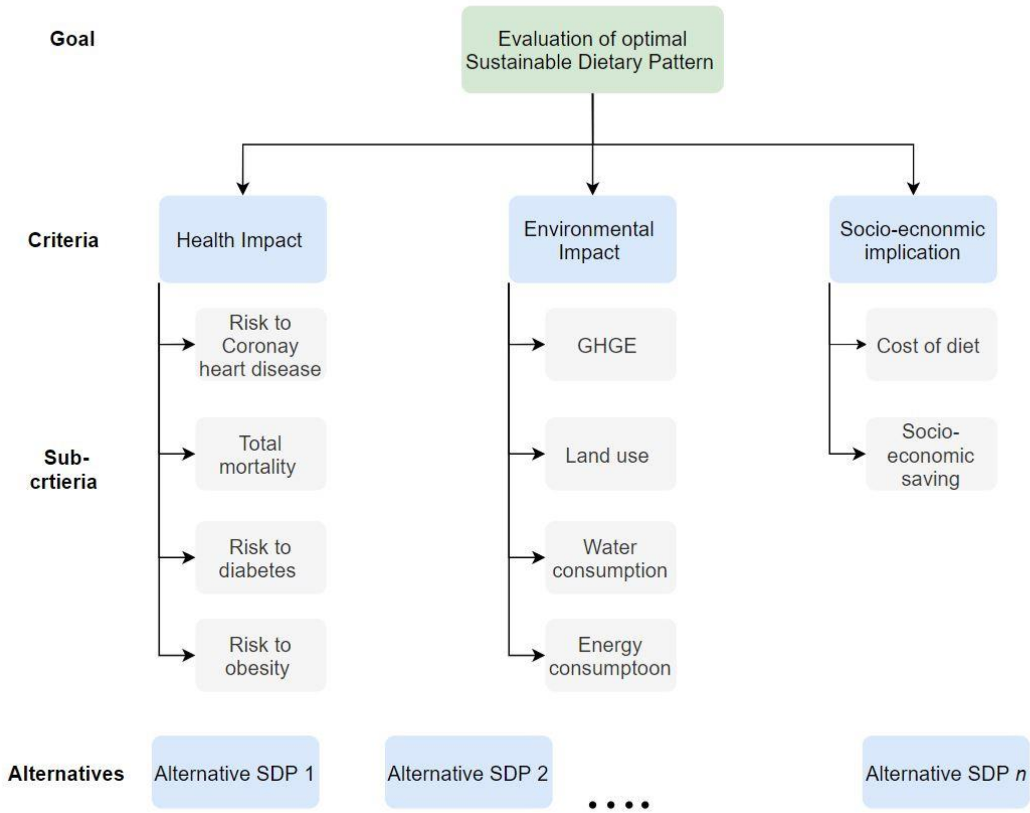

Figure 2: Hierarchical breakdown for assessing the performance of diet concepts.

Assuming we have ***n*** number of alternative sustainable diet concepts, the TOPSIS ranking for the alternatives can be achieved through the following:

Step 5: Construct the normalized decision matrix

In this step, the different attributes' dimensions are transformed into a non-dimensional attribute to allow comparison across the attributes. Using the method represented in Eq. (3), the matrix $(x_{ij})_{m\times n}$ is normalized to $R = (r_{ij})_{m\times n}$ which takes the form shown below

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \qquad i = 1,2, \dots, m; j = 1,2, \dots, n \qquad (5)$$

$$R = \begin{pmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{pmatrix}$$

Step 6: Construct the weighted normalized decision matrix

With the normalized decision matrix (R) computed from the previous step, the weighted matrix W from the A.H.P. method is integrated into the R. This results in a matrix calculated by multiplying each column of R with its associated weighted matrix W *represented in Eq. (4).*

$$V_{ij} = w_j \times r_{ij} \quad where\ i = 1, 2, \dots, n \qquad (6)$$

This computation results in a new matrix V, which is represented below

$$V = \begin{bmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & \cdots & w_n r_{1n} \\ \vdots & \ddots & \vdots \\ w_1 r_{m1} & \cdots & w_n r_{mn} \end{bmatrix}$$

Step 7: Determine the ideal and negative ideal solutions

In this process, two artificial alternatives A^+ (the ideal positive alternative) and A^- (the ideal negative alternative) are defined as:

$$A^+ = \{v_1^+, v_2^+, \dots, v_n^+\} = \left\{\left(max_j v_{ij} \middle| i \in I'\right), \left(min_j v_{ij} \middle| i \in I''\right)\right\}$$

$$i = 1,2, \dots, m; j = 1,2, \dots, n.$$

$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\} = \left\{\left(min_j v_{ij} \middle| i \in I'\right), \left(max_j v_{ij} \middle| i \in I''\right)\right\}$$

$$i = 1,2, \dots, m; j = 1,2, \dots, n.$$

Where I' is related to benefit attributes, and I'' is related to cost attributes

Step 8: Achieve the remoteness of all choices from A^+ and A^-

In the process, the separation measurement is done by calculating the distance between each alternative in *V* and the ideal vector A^+ using the Euclidean distance, which is given as Eq. (5) and Eq. (6)

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \qquad i = 1,2, \dots, m \qquad (7)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \qquad i = 1,2, \dots, m \qquad (8)$$

Where D_i^+ and D_i^- are the Euclidean distance from the ideal best and ideal worst, respectively. At the end of this, two quantities, namely D_i^- and D_i^+ for each alternative has been counted, representing the distance between each alternative and both (the ideal and the negative ideal).

Step 9: Determine the relative closeness to the ideal solution using Eq. (9).

$$CC_i^* = \frac{D_i^-}{D_i^- + D_i^+} \qquad (9)$$

$i = 1,2, \ldots., m$

Where CC_i^* Is the performance score.

Step 10: Rank the alternatives according to relative closeness to the ideal solution. All alternatives (sustainable diet patterns) are based on the performance score in this step. Figure 3 presents the continuous workflow of the integrated AHP-TOPSIS framework that is adopted to evaluate sustainable diet concepts. Step 1 to 9 presented above provide an elaboration of the components of the workflow.

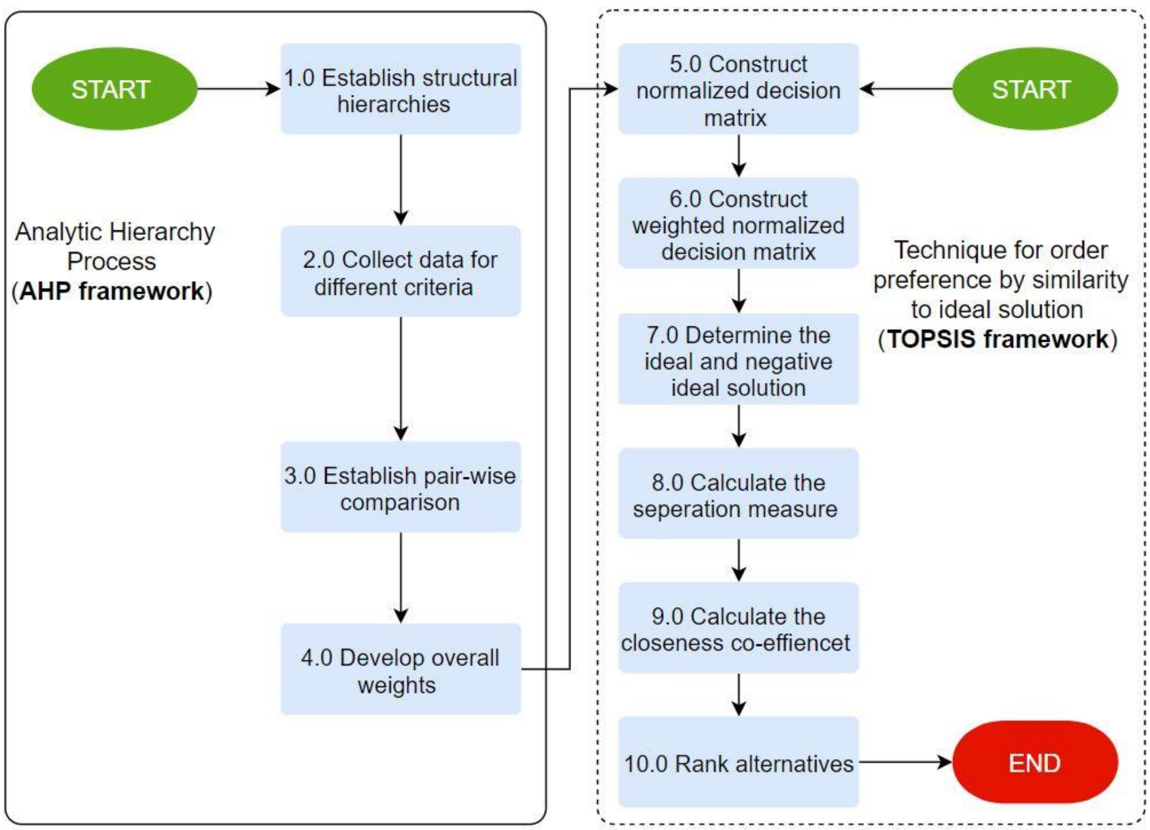

Figure 3: An integrated AHP-TOPSIS from selecting optimal diet concepts in the United States

3 Results

3.1 Historical interactions between the diet, health, and environmental trilemma

This section explores how United States diet shifts and lifestyles have rapidly worsened the health-environmental burden in the country. Figure 4 presents historical trends of the relationship between food demands in different geographic regions against United States. From Figures 4a and 4b, we observe that over the last 60 years, there has been a relative proportional increase in per capita calorie supply and a consistent increase in demand for animal-based protein across the globe. For the case of calorie demand per capita, the increase has been most significant in United States, Asia, South America, and Africa. We observe that the per-capita rate of increase has been 19.56% and 17.94% for United States and Asia, respectively. For instance, the calorie demand has increased by 53.96%, 31.66%, 30%, and 27.84 % in Asia, Africa, South America, and United States. However, the relative rate of increase on an annual basis within that same time frame is 17.94%, 12.35%, 1.66%, and 19.56%, respectively. This indicates that despite the significant increase in demand in Asia, Africa, and South America, the annual increase in consumption in America is more significant. Interestingly, in the 21st century, while other regions continue to experience an increase in demand for calories, United States has experienced a sudden plateau.

Similarly, we observe that the demand for protein (animal-based foods) has followed a similar pattern. Demand in Asia, South America, Africa, and United States is approximately 63.5%, 36.9%,31.27%, and 28% respectively. However, we observed 58.06%, 42.79%, and 40.57% annual increases in protein demand in Asia, South America, and United States, respectively. It is interesting to note that the demands in Europe have consistently decreased between 1990 and 2013. Likewise, United States has consistently experienced an increase in demand since 1960, but in the last decade has suddenly plateaued.

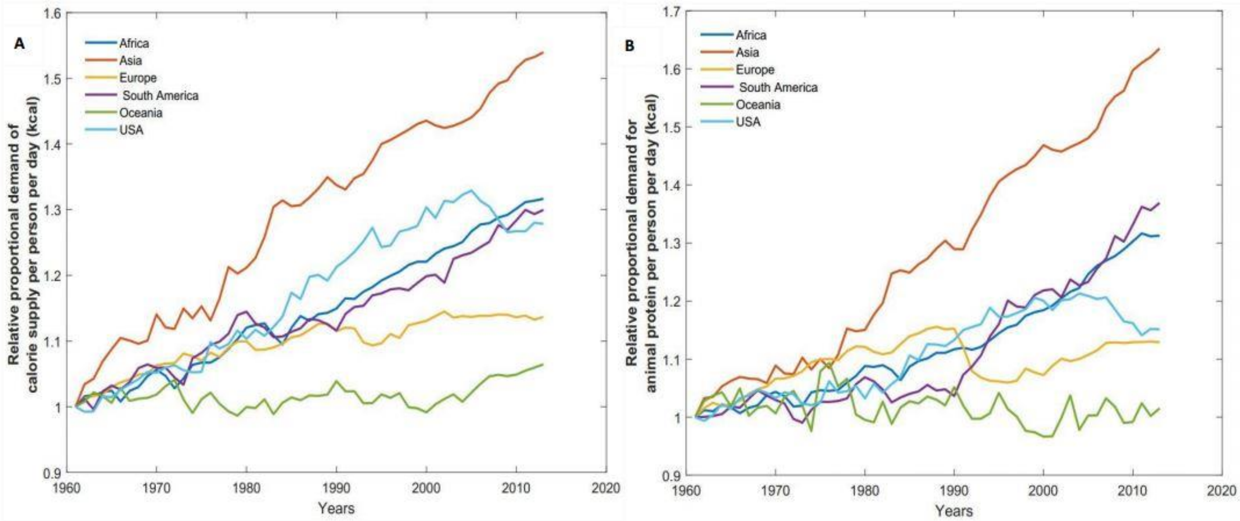

Figure 4: Relative proportional demand in animal-based protein and calorie be capital per day. (A) Estimated daily calorie supply per capita across all regions from 1961 to 2013. (B) Daily animal protein demand in each region from 1961 to 2013

Previous studies by many researchers such as [24], [25], and [26] have established a relationship between diet-related diseases such as diabetes and heart diseases and obesity and the consistent shift in diet towards an increased reliance on high calorie, animal-based, highly processed foods and sugar-sweetened beverages. As a result, the prevalence of overweight in adults has increased worldwide. Figure 5 illustrates regional increase in overweight among adults and children and the percentage of total death associated with non-communicable diseases. In the United States, overweight predominance has risen from 41.00% to 67.90% between 1975 and 2015, representing the single most significant increase globally. On the contrary, Asia has experienced a relatively lower increase from 17.00% to 32.26%. Also, in developing regions such as Africa, we observe a moderate rise from 10.51% to 28.89%. In Europe, we observe 39.20% to 58.64%. The increase in the prevalence of overweight consequently influences the global burden of disease and death associated with diet, which has significantly increased from 60.80% in 2000 to 73.63% in 2019. Within this same timeframe, the United States has been responsible for nearly 17.80% to 14.51% of such incidence.

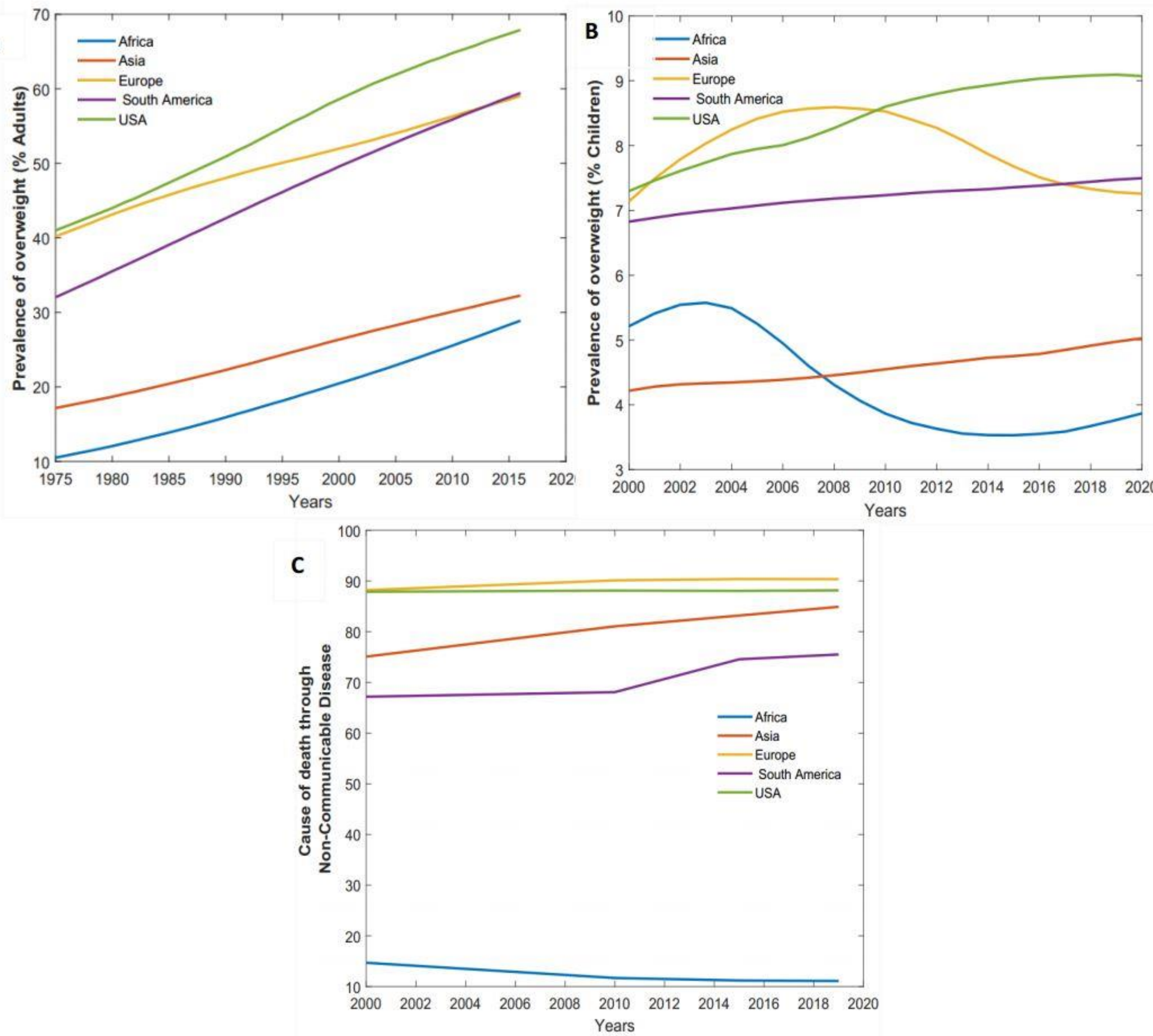

Figure 5: The prevalence of health-related implications of a consistent intake of unhealthy food over time.(A) Percentage prevalence of overweight in adults from 1975 to 2016. (B) Percentage prevalence of overweight in children under 5 years from 2000 to 2020. (C) Percentage total cost of death due to non-communicable diseases from 2000 to 2019

Aside from the health impact, the consequences of diet choices extend to impact our environment (Figure 6). This is evidenced in Figures 6a and 6b where we observe a relative proportion of agricultural land use and its corresponding GHGE. Globally, our arable land use for crop production has increased by more than 11.36%. Interestingly, we observe a continuous decrease in land use in Europe, and Oceania, probably due to technology 4.0 into agricultural production, which results in a steady reduction in GHGE from these regions. Notwithstanding, we see a consistent rise in the United State. In general, greenhouse gas emissions from agricultural production have increased since 1961. It has been the largest in developing countries such as Asia (378% increase since 1961) and Africa (263% increase since 1961). The United States has experienced nearly about 120% increase within that same timeframe.

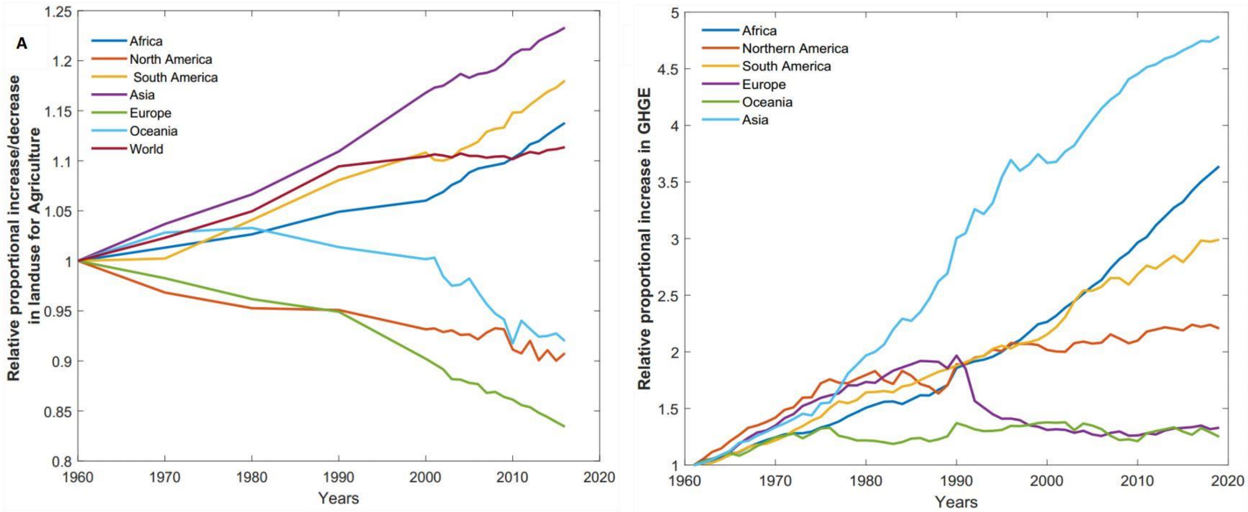

Figure 6: Relative proportional increase/decrease of agricultural land use and GHGE. (A) Relative proportional increase/decrease of land use from 1960 to 2016. (B) Relative proportional increase in GHGE from 1961 to 2019

3.2 Relevant environmental and health risk of highly consumed food group

Customarily, we decide every day on what to eat, considering the taste, nutritional benefits, safety, and, perhaps more recently, the environmental friendliness of the food. Recent evidence suggests that nearly 40% of the world's annual mortality is attributed to diet-related diseases such as stroke, coronary heart disease, type 2 diabetes, total cancer, and many others [27, 28]. Lozano, Naghavi [29] identified that nine out of the top fifteen risk factors for the consistent annual increase in global mortality were associated with diet choices. This implies that the choice of food and its corresponding quantity we take in is a significant determinant of our health and the sustainability of our environment. Our diets today pose a high risk to ill-health and threaten the achievability of sustainable development goals.

This section explores the relative environmental and health risks associated with 15 highly consumed food groups. The health outcomes considered include type 2 diabetes, stroke, coronary heart disease, total cancer, and mortality. In contrast, the environmental concerns include GHGE, land use, eutrophication potential, acidification potential, and water consumption. Figure 7 presents the relative risk to diseases and the environmental impact of 15 food groups. The data used was obtained from [29].

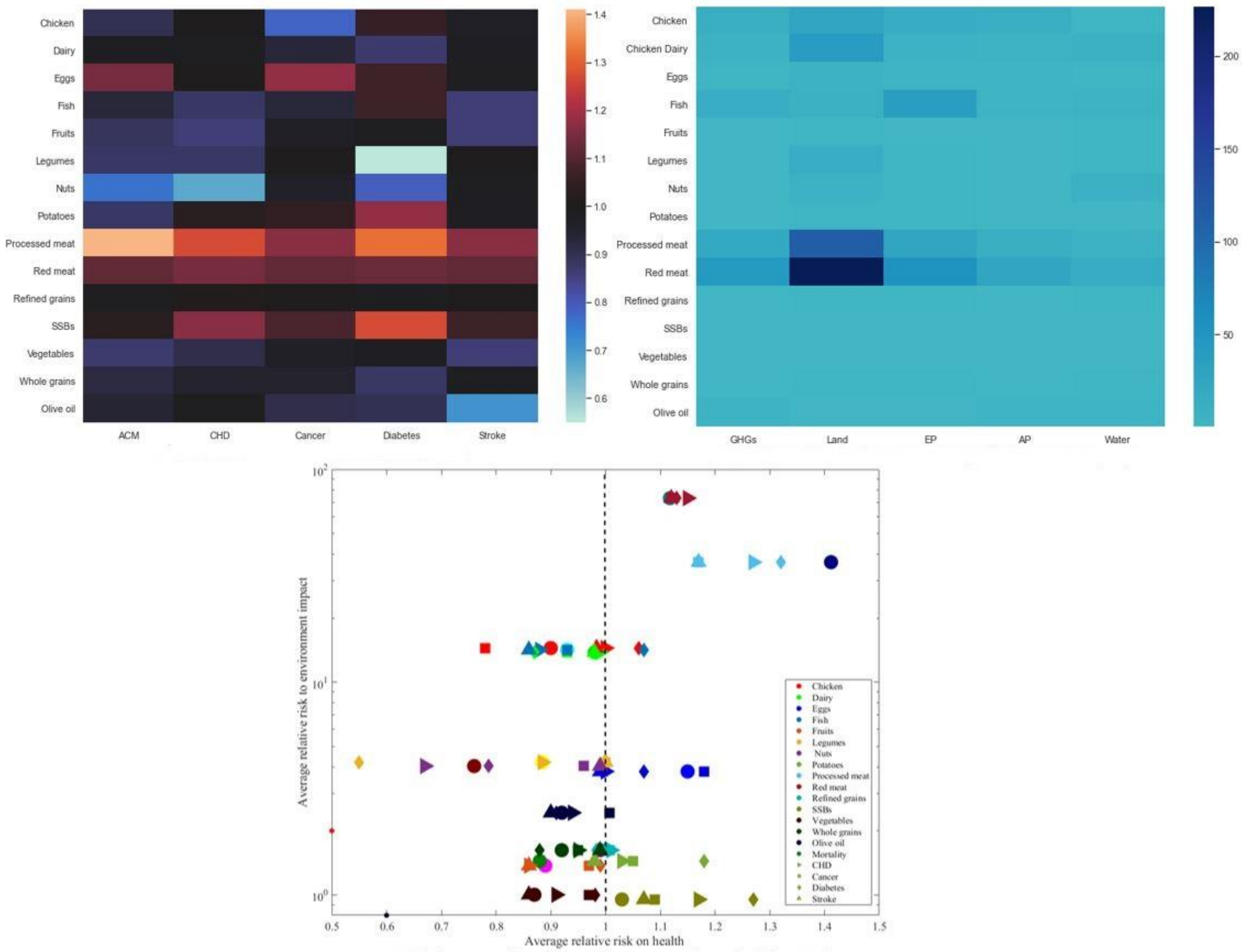

Figure 7: Relative Risk to diseases and environmental impact of 15 highly consumed food groups. (A) Relative risk to disease for different food groups. (B) Relative risk to environmental damage for different food groups. (C) Relative average risk to disease and environmental impact for different food foods.

It is essential to mention that if the relative risk is greater than 1, then the consumption of an additional serving of such food group poses an increased risk to disease. Likewise, relative risk less than 1 is correlated to a lower or decreased disease risk. From Figure 7, we observe that the additional consumption of vegetables, wholes, fruits, legumes, and fish are associated with reducing diseases risk to coronary heart disease, diabetes, total cancer, stroke, and total mortality. In addition, there are correlated to a lower environmental impact. Conversely, red meat and unprocessed meat consumption are associated with increased risk and environmental impact. This implies shifting diet behaviors towards food groups with lower environmental and health risks has the potency to reduce the diet-health and environmental implications. The following section describes the methodology developed to select and evaluate sustainable diet concepts.

3.3 Selected Sustainable diet concepts

Table 4 presents the results after applying the inclusion-exclusion criteria described in section 3. Diet patterns with (−) signs imply limited implementation cases and available data to support the claims of lower environmental footprint and health-related issues in the United States. Although there is literature to confirm these diet recommendations as sustainable diet concepts, there was little evidence from clinical or epidemiological studies and life cycle assessment or environmental impact modeling or input-output analysis on the impact of adopting these sustainable diets. In addition, the majority of results the authors found were focused on European countries, which is outside the scope of this study. Also, the authors discovered that many of the sustainable diet concept analyses were conducted in high-income countries with well-established diet guidelines.

Table 4: Selected sustainable diet concepts after the four-step inclusion/exclusion criteria

S/N	Sustainable Diet concept	Step1	Step 2	Step 3	Step 4	Status
1	The Mediterranean diet pattern	√	√	√	√	*
2	Healthy planetary diet (EAT-Lancet pattern)	×				-
3	Healthy vegetarian Diet pattern	√	√	√	√	*
4	Atlantic diet pattern	√	√	√	×	-
5	Diet Approach to Stop Hypertension (DASH diet)	√	√	√	√	*
6	Pesco-vegetarian	√	√	√	√	*
7	The healthy Nordic diet pattern	√	√	√	×	-
8	Paleolithic diet	√	√	√	×	-
9	Tradition Persian Medicine diet	√	×			-
10	Vegan diet	√	√	√	√	*
11	The healthy U.S Style Diet pattern	√	√	√	√	*
12	Chinese diet pattern	√	√	√	×	-
13	Western diet concept	√	√	√	×	-
14	Spanish diet pattern	√	√	√	×	-

15	Provegetarian food pattern	√	√	√	√	*
16	Pescatarian diet	√	√	√	√	*
17	Flexiterian diet	√	√	√	√	*

(Where S/N refers to Serial Number, * refers to a selected diet concept , - refers to rejected diet concept after comparing against the inclusion and exclusion criteria)

It is important to mention that other diet patterns have proportional magnitude variations in the quantity of animal and plant-based foods. Typical examples of diet patterns identified from the literature include meat partially replaced by plant-based food, meat partially replaced by mixed foods, meat + dairy partially replaced by plant-based foods [30, 31]. However, because of the high degree of variations and the absence of extensive literature on such diet concepts, they were excluded from the variety of sustainable diet patterns used in this study.

3.4 Overview of diet concepts

From Section 3.3, we observe that nine different sustainable diet patterns have been selected. Therefore, this section provides a high-level overview of the respective diet patterns and their corresponding food groups.

3.4.1 The Mediterranean diet pattern

Global interest in this diet pattern began in the early 1960s when it was observed that seven countries near the Mediterranean Sea had a lower incidence of chronic disease. The diet is often associated with countries bordering the Mediterranean Sea, including Spain, France, Italy, Greece, Turkey, Northern Africa, Middle Eastern, and Balkan countries. This diet pattern has been described as (i) daily consumption of unrefined cereals and cereal products, vegetables, fruit, olive oil, dairy products, and red or white wine; (ii) weekly consumption of potatoes, fish, olives, pulses, and nuts and eggs and sweets and monthly consumption of red meat [32].

3.4.2 Healthy vegetarian diet pattern

This diet pattern is devoid of any food product that contains meat or fish. In addition, diets containing poultry, seafood, and f lesh of any animal are strictly prohibited.

3.4.3 Diet Approach to Stop Hypertension (DASH diet)

This diet concept was introduced to control the risk of hypertension. The essential ingredients peculiar to this diet includes fruit, vegetables, and low-fat dairy products, including whole grains, poultry, fish, nuts, legumes, and limiting the intake of low-fat dairy products, red meat, sweets, and sugar-containing beverages. The DASH diet provides higher potassium, calcium, magnesium, and protein while lowering total fat, saturated fat, and diet cholesterol [33]. An excellent quantitative description of the design of this diet concept is presented by [34].

3.4.4 Pescatarian diet

This diet includes fish, dairy, and eggs but avoids all meats

3.4.5 Vegan diet

This sustainable diet concept does not contain any animal product. Instead, they are substituted by calcium-rich soy and extra portions of pulses. Protein sources for this diet design are similar to vegetarian. In addition, however, vegetable consumption is increased. A detailed description of this diet and the corresponding quantitative servings in proportion and key-related nutrients is presented by [35].

3.4.6 The healthy U.S style diet pattern

The healthy U.S diet style is recommended under the Diet Guidelines for Americans. This sustainable diet concept emphasizes consuming fruits, vegetables, whole grains, low- and fat-free dairy, healthy fat, lean meats, and poultry to reduce the risk to chronic diseases and meet daily nutrient needs. A detailed description of the diet recommendation and permissible quantity for different age groups in America is presented in 2020-2025 U.S.D.A Diet guidance [36].

3.4.7 Flexitarian diet concept

This sustainable diet concept can be regarded as a semi-vegetarian diet or perhaps a more plant-forward diet. Thus, the diet concept is less strict than a 100% vegetarian diet. The diet emphasizes incorporating plant-based foods and beverages, including eggs, meat, and dairy, into one's diet. However, it encourages a lower consumption quantity for meat and other dairy products [37].

3.4.8 Pro vegetarian food pattern

Pro vegetarian diet pattern has a preference for plant-derived foods but not the exclusion of animal foods. Its diet composition is similar to the vegetarian, howbeit the proportional intake of meat, vegetables and other food groups vary.

3.5 Results of assessment

3.5.1 Weight of criteria

Figure 8 represents the weights reflecting the relative importance of the evaluation criteria obtained from implementing the A.H.P. framework. One advantage of the technique is that it allows both qualitative and quantitative evaluation of criteria based on a preference scale.

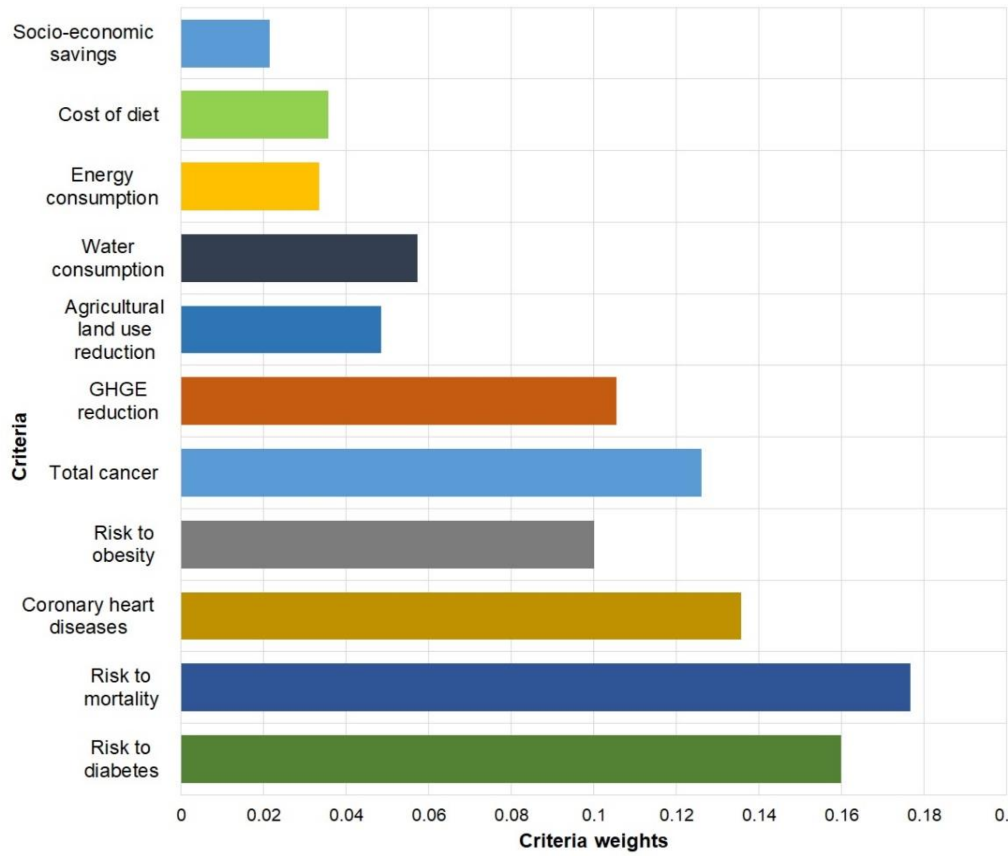

Figure 8: Weights of importance of criteria adopted to evaluate sustainable diet concepts.

Figure 8 shows that the risk of mortality (priority weight of = 0.18), coronary heart diseases (priority weight of 0.15), and diabetes was of a high priority compared to other environmental and socio-economic indicators. A possible explanation for these results may be attributed to the fact that health impacts have individual implications with selective socio-economic repercussions. Thus, participants in the survey could relate intimately/were familiar with these indicators compared to others. Another possible explanation is that the participants may have direct or personal experiences with the implication of these indicators, hence giving them a high priority. Nonetheless, we observe that the environmental indicators have a relatively lower weight; thus 0.11 and 0.0561 for GHGE and water consumption. The results may be explained by the fact that the implications of environmental indicators are collective while those of health are at an individual level. To ascertain the validity of the results of the A.H.P framework, we conducted a consistency test. As a result, the final consistency index (CI) and consistency ratio were 0.14 and 0.091, respectively. Since the C.R. < 0.1, it indicates that the reliability of the responses from the participants could be maintained. The indicator matrix obtained from the survey and the eigenvalue of each criterion is reported in the supplementary documents.

3.5.2 Health and Environmental impact evaluation results

Over the last half-century, multiple cohort studies have compared the health outcomes and environmental impact of different diet patterns such as Mediterranean, vegetarian, and vegan diets among individuals who consume them. A large portion of these studies has consistently observed a reduced risk of diabetes, heart diseases, hypertension, and total mortality compared to individuals on western or omnivorous diet patterns. In general, strict adherence to sustainable diet concepts offers significant health benefits. In addition, most studies have demonstrated that adopting healthier diets have some varying increased environmental sustainability. Figure 9 illustrates the relative reduction in health, socio-economic and environmental indicators by shifting current diet patterns to sustainable patterns.

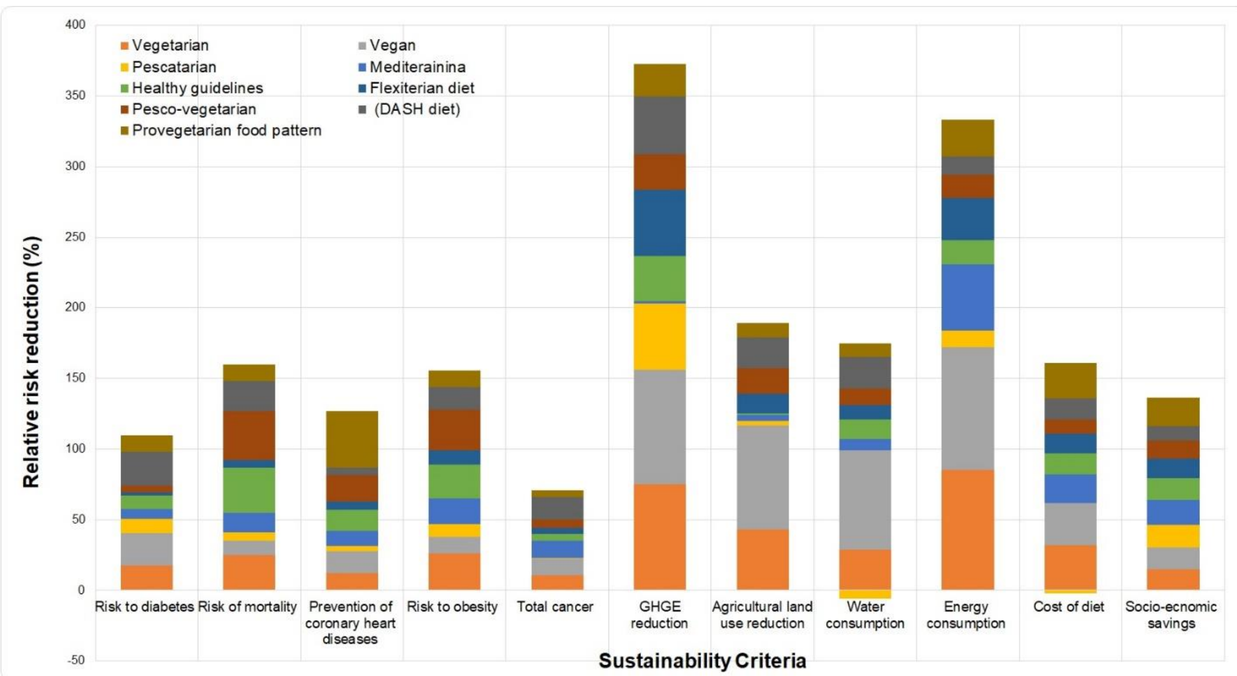

Figure 9: Relative reduction/increase in health and environmental impact of different dietary concepts.

It is observed from Figure 9 that a shift to sustainable diet concepts such as Vegetarian and Vegan diet would reduce the total GHGE, land use, water consumption, and energy use by (75.00% , 81.40%), (74.98% , 74.00%), (10.00% , 70.00%) and (86.00% , 87.00%) respectively. Furthermore, we observe a relative closeness in results due to the similar due to similar product composition that exists between the two diet concepts. Likewise, for health risk reduction, we observe that adherence to the Vegetarian and Vegan diet reduces the risk to diabetes, total mortality, heart diseases, obesity, and total cancer by (17.80% ,19.30%), (25.00% , 10.00%), (12.30% , 15.10%), (26.00% , 12.00%), and (10.40% , 11.70%) respectively. Shifting to other diet concepts such as the Mediterranean diet and the healthy US-style diet, we observe a relatively lower reduction compared to other diet concepts.

One of the surprising findings of the study was, adopting the U.S. diet style results in an average overall lower GHGE impact of 2% (reduction), water consumption of 14% (reduction), and an increase in energy consumption of 17% compared to other diet concepts. These results corroborate strongly with the studies of [38], who found a relative increase in GHGE from U.S. diet style.

It is important to mention that the results presented here are average values Life Cycle Assessment (L.C.A) studies on the selected diet concepts in the United States. The data collected for each diet pattern are isocaloric (equivalent in total calories).

3.5.3 Ranking from TOPSIS

Using the results obtained in sections 3.5.1 and 3.5.2, we ranked the diet concepts using the integrated AHP-TOPSIS decision model. From Figure 10, the Vegetarian, Vegan, and Provegetarian diets ranked first, second, and third, with a performance score of 0.553, 0.519, and 0.507, respectively. This is somewhat surprising as the vegan diet appears to have a better environmental impact reduction as compared to the vegetarian diet concept (see section 3.5.2). On the contrary, the vegetarian diet has higher health impact reductions for some indicators as compared to the vegan diet concept. From a socioeconomic perspective, the vegetarian diet concept has a slightly higher reduction than the vegan diet. However, the model adopted for the evaluation takes into consideration the criteria weights presented in section 3.5.1. To wit, we observe from Figure 8 that higher weights were allocated to health indicators as compared to environmental and socio-economic indicators. Consequently, influencing the overall performance score and ranking of vegetarian and vegan diet concepts.

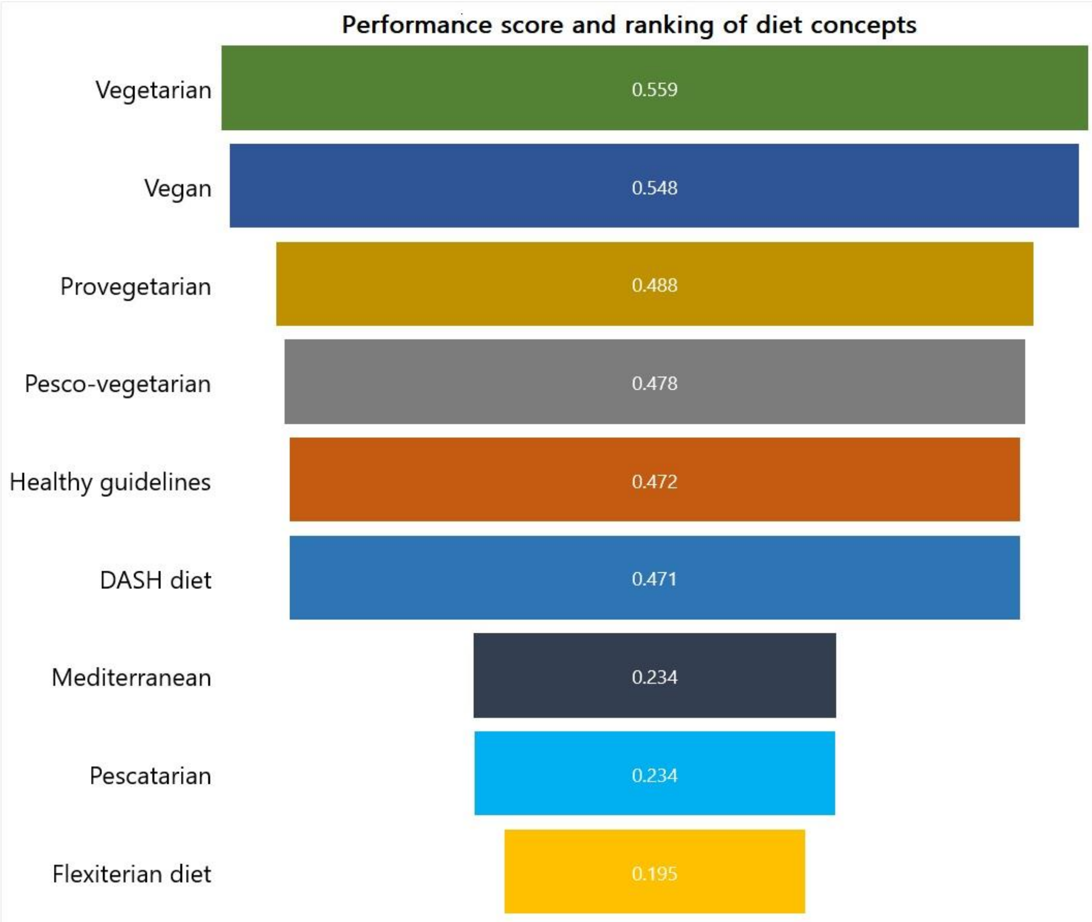

Figure 10: Ranking of dietary concepts using the TOPSIS framework.

The results imply that adopting and national-wide implementation of different vegetarian diet concepts can substantially reduce diets' environmental and health impacts. Our results corroborate strongly with previous research of [8], [9], and [15], who illustrated that the adoption of diets higher in plant-based than animal-based foods against the national Healthy US-style diet pattern would benefit the environment and the population's health. Furthermore, the results further reinforce previous research on the impact of diet on the environment and suggest that Vegetarian, Vegan, and Provegeterian diet pattern has the most sustainable impact on U.S. diet style. Despite these benefits, several bottlenecks and challenges exist that hinder the successful adoption of these concepts in America. The following section explores different challenges, provides recommendations, and proposes a dynamic methodological framework to ensure a sustainable food system.

3.6 Barriers in adoption and recommendations

So far, we have assessed which health, environmental and socio-economic factors are relevant to consumers, evaluated nine distinct sustainable diet concepts using sustainability metrics, and ranked these concepts to identify the optimal diet concept. Nonetheless, several challenges hinder the adoption and implementation of these sustainable diet concept. This section identifies the bottlenecks in implementing different sustainable diet concepts and presents recommendations to rebuild a resilient and sustainable food system. Table 5 summarizes the challenges associated with adopting candidate sustainable diet concepts.

Table 5: Bottleneck to implementing Sustainable diet concepts

S/N	Diet pattern	Bottleneck/Critical challenges in adoption	Recommendation
1	Vegetarian	▪ Risk of sub-optimal nutrients, including iron. ▪ The iron source for most vegetarians is non-haem which has a lower bioavailability. ▪ Consumer perception of vegetarian diet being expensive, not enjoyable, and inconvenient. ▪ Reluctance in most consumers to try novel foods which they are unfamiliar with ▪ Perceived nutritional need of meat (mostly as a source of protein), which is not provided. ▪ Perceived difficulty in preparing plant-based food.	Early familiarization during childhood Informative, easy to read, and straightforward labeling on food products to alleviate food neophobia (Clean labeling).
2	Vegan	▪ The Diet concept is regarded as inconvenient since its products are challenging to prepare. Also, ingredients for preparing meals are most often unavailable in stores.	Less processing of plant-based meat alternative with the intention of mimicking animal meat. (Reduced

		▪ The perception that plant-based food does not taste better than animal-based food. ▪ Meat consumption is highly ingrained in the culture of many hence the willingness to stop is difficult. ▪ Consumer perception that plant-based milk substitutes have a similar environmental footprint as that of animals. ▪ A general lack of awareness of the environmental burden of animal meat production and consumption.	preservatives and sodium) Proper communication of diet benefits
3	Pescatarian	Fear of the presence of heavy metals in food.	
4	Mediterranean diet	▪ Increase price of food items in the Mediterranean diet. ▪ It promotes diet diversity, while diet recommendations suggest the consumption of healthier foods. ▪ Socio-economic inequalities in domains such as diet variety, access to organic foods, and food purchasing behavior. ▪ The vague idea of the overall diet framework. ▪ Improper definition of the Mediterranean diet as different organizations and individual authors have presented a variety of diets labeled the Mediterranean.	Careful examination of the effectiveness of relying on a diet pyramid versus promoting the health full aspects of individual foods that are included in the pyramid is needed Development of interventions to promote the diet

5	Healthy U.S. style guidelines	▪ Limited access to supermarkets and grocery stores. ▪ Low-income ▪ Poor availability, quality and cost of healthy and fresh food components within the diet. ▪ Family influences and tension among family members' willingness to adopt a healthy diet.	Interventions to promote the DASH diet yet reflect the customer, economic and food available concern
6	DASH diet	▪ Lack of familiarity with the DASH diet menu options. ▪ The potential cost of preparing the recipes presented in the DASH diet was high. ▪ Unfamiliarity with some of the menus found in the DASH diet appeared distracting.	Optimized DASH diet with familiar recipes that conform the DASH diet pattern. Effective communication of DASH diet health information.

From Table 5, it is clear that widening the adoption of the sustainable diet concept presents a challenge, thus the need to understand the synergies in socio-economic, demographic, health, and environmental priorities. Sustainable diet concepts interact with consumer preference and wide array of social, economic and environmental systems, thus presenting a complex interaction driven by multiple factors. More importantly, a lack of information flow between the different actors and their respective systems exacerbate these shortcomings. Additional, knowledge on the trade-offs at varying Spatio-temporal scales is required; thus, we propose a conceptual system thinking approach for effective implementation of need. Figure 11 presents the conceptual framework that illustrates a holistic representation of sustainable diet concepts and their interconnections between actors, bottlenecks, components and different sub-systems. The elements in conceptual framework interact dynamically to give rise to predictable health, environmental and socio-economic impacts. The framework argues for a better and holistic integration of bottlenecks such as lack of knowledge and feedback across the interactions between the different components of the system and actors. Also, the framework argues for transparent sharing of information among actors to develop an optimized sustainable diet.

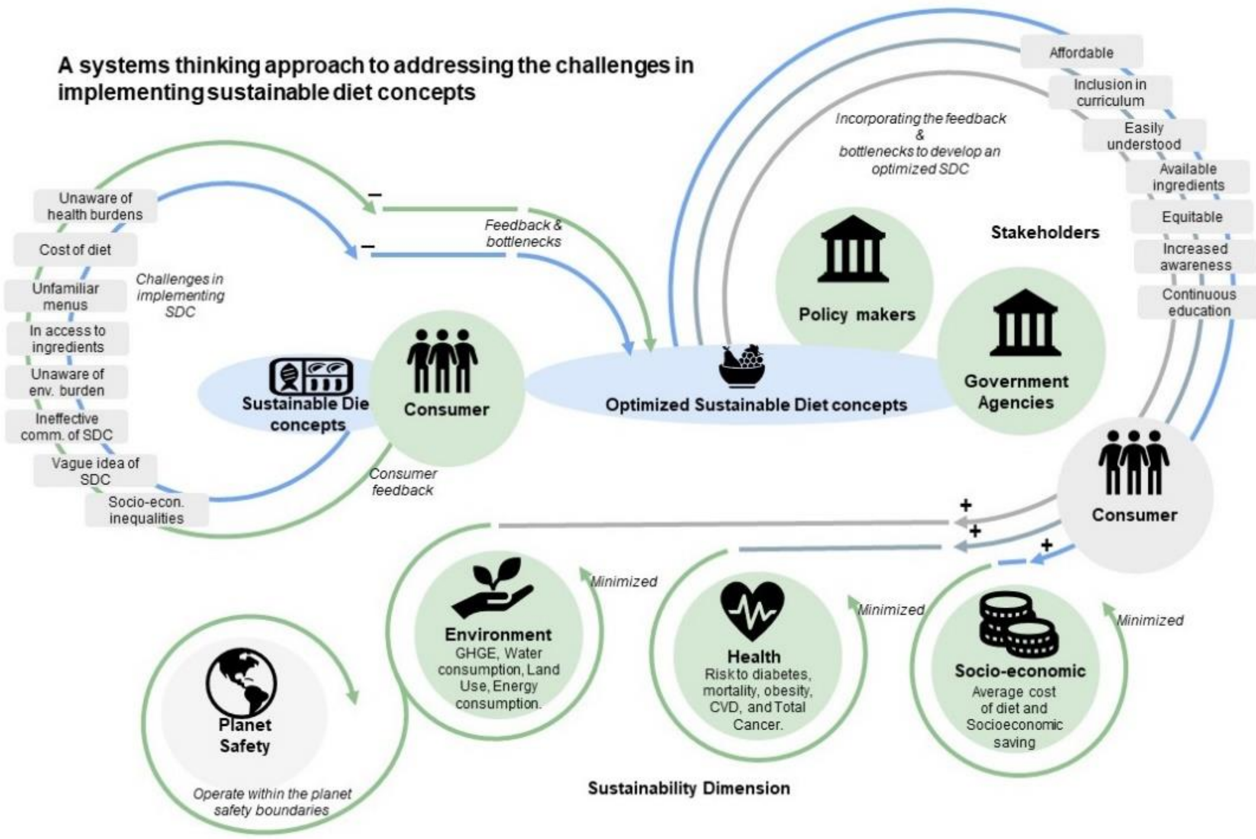

Figure 11: A system thinking approach to address the challenges of scaling up sustainable diet concepts to an optimized diet concept

Application of system thinking and related tools can be found in different fields such energy, financial sectors and policy making. Increasingly, these different fields recognize the necessity of system thinking approaches to addressing today's interconnected challenges. Thus the authors argue that the adoption of system thinking and related tools can help all actors of sustainable diet concepts to better plan for future interventions and wide adoption among consumers. Furthermore, policies can be enacted to introduce sustainable diet concepts to the population at an early childhood stage. It could be integrated into curriculums during early childhood education. Multi-sectoral efforts and campaigns from public organizations, local authorities, government, and non-governmental institutions to raise public awareness on the enormous benefits of sustainable diets will be paramount. Therefore, the proposed system thinking approach seeks to navigate stakeholders in implementation sustainable diet concepts toward a more comprehensive and broader picture by considering all interconnected factors to achieve a systemic change.

3.7 Limitations of the study

The novel framework also suggests that optimized sustainable diet concepts that take into consideration multiple conflicting objectives as well their trade-offs have the potential to address the diet- health-environment trilemma. One major limitation of this study is that the authors observed a moderate variability in life cycle assessment results despite considering similar diet concepts. These may be attributed to the choice of parameters, the definition of system boundaries, the decision of function units, and the uncertainty evaluation adopted during the assessment. More disturbingly, most of these life cycle assessment studies do not account for the type of agroecology which may improve the environmental outcomes.

4 Conclusion

The present study set out to evaluate the effectiveness of the implementation of sustainable healthy diet concepts in the United States. The study also examined the relationship between sustainable diet concepts and key factors that lead to improvement in human health, reductions in environmental damage and socio-economic benefits. Additionally, the AHP framework applied by the authors, provided an opportunity to curate expert opinions on which environmental-health-socio-economic indicators were of outermost relevance when considering resource allocation to optimize the adoption of sustainable diet concepts. The findings indicate that health indicators such as risk to mortality and cardiovascular disease are highly prioritized compared to other socio-economic, and environmental indicators. Through the application of mathematical modeling (AHP-TOPSIS) and a set of environmental, health and socio-economic indicators, vegetarian, vegan and provegetarian diet concepts ranked first, second and third respectively. The findings provide additional evidence that sustainable diet concepts which constitute more plant-based than animal-based foods are more beneficial to the environmental and population's health as compared to the national Healthy US-style diet concept which has an average overall lower GHGE impact of 2% (reduction), water consumption of 14% (reduction), and an increase in energy consumption of 17% compared to other diet concepts. However, the implementation and wider adoption of sustainable diet concepts is hindered by intrinsic socio-economic, cultural and behavioral barriers. These include a lack of understanding, limited access to food ingredients, and unfamiliarity with sustainable diet menus. Hence, the study proposed a novel conceptual system thinking framework to sustainable diet concepts, which takes into consideration these bottlenecks prior to implementation sustainable diets on larger scale. The proposed can potentially optimize sustainable diet acceptance by consumers and offset different health, environmental and socio-economic impacts. The novel framework shows the complex interactions and dynamics between diet concepts, social cultural challenges, food environment, key stakeholders and multiple subsystems. Taken together, it provides a holistic representation of optimizing sustainable diet initiatives and adoption among consumers. It would be interesting to assess the effectiveness of the conceptual system thinking approach through a practical application of system dynamic models, then translate the results through an intervention case study.

5 Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

6 Author Contributions

Prince Agyemang: Conceptualization, Investigation and Expert Survey, Methodology, Data curation, Writing (Initial draft) and Data Visualization. **Ebenezer M. Kwofie**: Conceptualization, Investigation and Survey, Resources, Writing (Review and Editing), Supervision. **Jamie Baum**: Conceptualization, Methodology, and Writing (Review and Editing).

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8 Ethics Statement

The selected human participants involved in this study were from a broader project for which the corresponding author was involved and as a follow up, were engaged in this exercise to provide their expert opinion on environment-health and socio-economic indicators in food system sustainability.

9 Acknowledgments

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.

CHAPTER THREE

3 Multi-objective modeling of risk to health and environmental impact under stringent mitigations policies: The case of Unites States

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Abstract

Various critical and invariant drivers can exacerbate the food system's multiple health, nutrition, and environmental burdens. Food choices are among the drivers shifting negatively to affect human health and environmental sustainability. In the United States, consumer food choices due to their dietary patterns are often unhealthy and sustainable, with average consumption patterns exceeding the daily recommendations of food such as red and processed and below recommendations for foods such as fruits and pulses. In this study, we conduct a multi-model assessment of the combined effects of health and environmental mitigation efforts on different critical and invariant drivers within the food system and their repercussions on the health-environment-diet trilemma. This is achieved by developing an end-end modeling framework that facilitates the test and application of machine learning for predictions at the policy level. The environmental drivers include Greenhouse gas emissions (GHGE), land use, energy consumption, and surface temperature change. Likewise, the health drivers include the prevalence of obesity and overweight, life expectancy and percentage of death due to diet-related diseases. The results suggest that substituting meat and beef production with a more resource-efficient agricultural product such as peas could reduce anticipated GHGE emission impact by 5-7% while reducing health impacts by 19-41% for the short-term goal of 2030. The machine learning pipeline was deployed to develop a novel decision support system: Food System-Rapid Overview Assessment using Scenarios (FS-ROAS). This decision support allows exploration of plausible stylized scenarios of the future food system in the United States under mid-medium- and long-term strategies. It is readily available online and can be accessed on any digital device.

Keywords: decision support system, critical drivers, sustainability, food choices

1 Introduction

According to the International Labor Organization, the agricultural sector employs more people than any other economy. Moreover, the agricultural sector, characterized by crop and livestock production, interacts with complex biological and climatic systems at varying spatio-temporal levels, overlayed by social and economic systems. These factors interact with consumer preference and a wide array of social norms [1]. Thuswise, human health and planetary safety are influenced by complex interacting ecosystems, land, labor, markets, food consumption, and diverse value chains referred to as the food system [2]. Within the food system, humans are the main drivers of change, much of which is attributed to commercial and mechanized farming and consumption patterns which have resulted in a decline in terrestrial vertebrates, invertebrates, marine species, and wildlife [3]. Additionally, soil and terrestrial nutrients are depleting, and excess nutrient runoff has become the leading cause of freshwater and marine eutrophication [4]. Ultimately, food production and consumption are significant contributors to climate change, responsible for nearly 30% of the global anthropogenic GHGE [5].

Additionally, the current global and regional consumption patterns are responsible for the prevalence of non-communicable diseases. A review of recent policy documents indicate that 38% of the global population are obese, 11.8% are overweight, and nearly 40% of global death are associated with unhealthy consumption patterns [6]. More disturbingly, obesity alone has a global economic impact of around $2 trillion annually, approximately 2.8% of global GDP [7, 8]. In the United States, it was estimated to be as high as $344 billion as of 2018, equivalent to 20% of total annual spending. Health impacts are the single most significant hidden cost within the US food system, with Americans paying an estimated $3.8 trillion per year in health-related costs [9]. Other diseases such as hypertension, cancer, and diabetes account for an estimated $604 billion in expenditure annually in the United States [10]. According to the United States Department of Agriculture, the agriculture sector accounted for 11.2% of total GHGE, with gases such as carbon dioxide from on-farm energy use, methane and nitrous oxide from livestock grazing and manure accounting for the continuous rise in surface temperatures [11]. In another report, the agricultural value chain consumed about 1.872 trillion of Btu of energy in 2016, representing about 1.9% of the total US primary energy consumption [12].

Studies over the past two decades have analyzed the components of the food system with the assumption that an improvement in the efficiency of each component can lead to whole system improvement. Thus, neglecting a comprehensive and holistic understanding of what happens in the whole system. Besides this, recent trends in Machine learning (ML) and big data have led to a proliferation of studies that leverage the vast available data to provide new insights into the dynamics of environmental and nutrition indicators for food system sustainability. Conventional modeling of the dynamics between environment and nutrition is resource-intensive and requires considerable human effort. ML models have the potential to comprehend the complex interactions among the driving factors that influence health, environment, and diet-related issues. Hamrani, Akbarzadeh [13] explored GHGE from agricultural production by exploiting three categories of ML algorithms. The LSTM model performed best with the highest R coefficient of 0.87 and the lowest mean squared error of 30.3 $mg.m^{-2}hr^{-1}$. Zhang, Di [14] attempted to use ML algorithms to predict field-level annual crop planting using historical cropland data. The models adopted were highly correlated (R2>0.9) to the crop acreage estimates from the USDA. National Agricultural Statistics Service. Research on this subject has augmented mechanistic models such as the Cellular Automato Markov Chain Model with Artificial Neural Network to incorporate several driving forces that highly impact land use and fertility in agricultural production [15].

If we now turn to the impact of the food system on human health, Menichetti, Ravandi [16] modeled US food supply of ultra-processed foods and demonstrated that an individual's increased reliance on such foods correlated to a higher risk of metabolic syndrome, diabetes, and elevated blood pressure. More recently, literature has investigated the influence of consumer choices and behaviors. Côté, Osseni [17] applied nine classification ML algorithms to predict vegetable and fruit consumption using a large array of features that captured the individual and environmental information related to diet habits. Dunstan, Aguirre [18] implemented three ML algorithms to predict the prevalence of obesity at the national level using purchase data. Nonetheless, most studies in this field have only focused on predicting one element or driver of the health-environment-diet trilemma, neglecting other elements/components of the food system

In this study, we conduct a multi-model assessment on the combined effects of health and environmental mitigation efforts on different critical and invariant drivers within the food system and their repercussions on the health-environment-diet trilemma. This is achieved by developing an end-end modeling framework that facilitates the test and application of ML for predictions at the policy level. The environmental drivers include GHGE, land use, energy consumption, and surface temperature change. Likewise, the health drivers include the prevalence of obesity and overweight, life expectancy, and percentage of death due to diet-related diseases. The results are translated into a decision support system that allows policymakers to explore diverse intervention scenarios and programs to build resilience in future food systems. As a case study, the authors deployed the ML framework to predict environmental and health drivers using US food production and consumption data. The results suggest that substituting meat and beef production with a more resource-efficient agricultural product such as peas could reduce anticipated GHGE emission impact by 5-7% while reducing health impacts by 19-41% for the short-term goal of 2030. However, these high-impact reductions can be achieved depending on the kind of substitution. The overall structure of the study takes the form of four sections. Section 2 is concerned with the methodology employed for this study.

Section three analyses and presents the findings of this research focusing on two key themes. The final section draws together the key findings and a brief critique of the findings

2 Method

2.1 Methodological framework

To explore the interconnectedness between the health-environment-diet dimension of the US food system, the authors propose a crucial framework in modeling the progress of sustainable initiatives that could reduce anticipated impacts (Figure 1). The method framework presented in Figure 1 consists of three main steps: the first focuses on gathering the necessary raw data for the modeling study. This includes obtaining data on environmental impact indicators such as land use, GHGE, energy consumption, and surface temperature change associated with agricultural production in the United States. Similarly, health-related impact data were collected, including the prevalence of obesity, overweight, and life expectancy. The data was collected on 13 food groups described in section 2.2. Next, food production and consumption data were gathered and correlated to health and environmental impact. It is important to mention that missing data is a common problem that appears in a real-world context and may compromise the performance of most models. Therefore, data imputing techniques were adopted to generate missing environmental, health, food production, and consumption data. The methodological approach's second step leverages nine ML configurations to predict health and environmental indicators. The ML model configuration defined a set of input features, feature engineering and selection process, hyperparameter optimization, ML algorithm testing, and deploying the ML model to create a web-based decision support system for policymakers and other stakeholders. A nested multi-output cross-validation step was included in determining the hyperparameters of ML algorithms. Similarly, multi-output regression models were adopted for fitting and prediction purposes. This step facilitated the elimination of information leakage during the forecasting step. After that, statistical coefficients were adopted to compare the best ML model configuration for each short-term and long-term forecasting. Finally, the practical significance of the performance difference between the ML models was tested. Further investigation was conducted to explore the potential of deploying the ML pipeline developed here into an online application that can support policy decision-making. This was achieved through a flask web framework built with the Scikit-learn library.

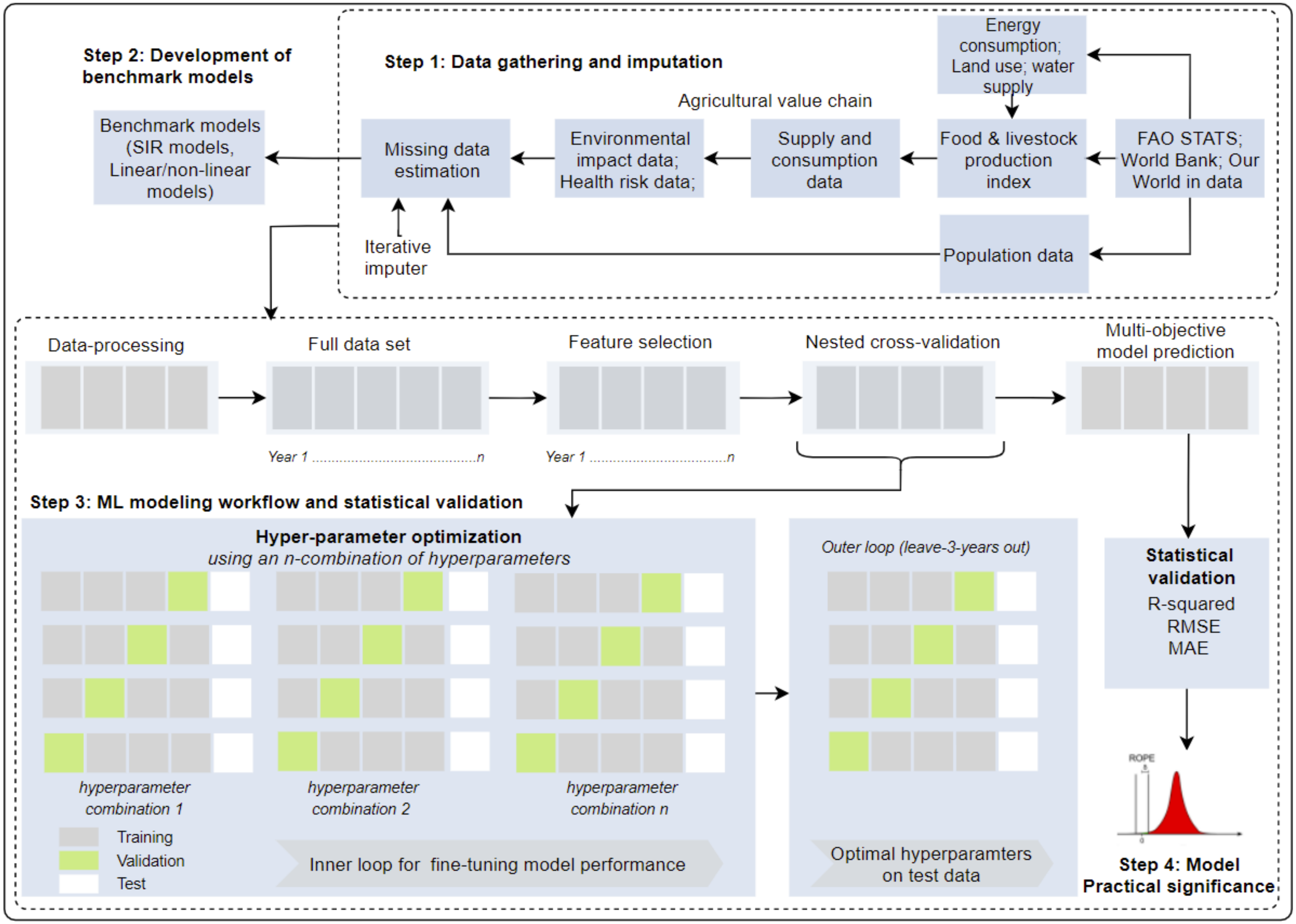

Figure 12: Method framework adopted to implement the project.

2.2 Data

2.2.1 Data grid

The dataset used in this study was sourced from the FAO Stats, World Bank Databank, and Our World in Data. The dataset ranged from 1961 to 2020. The dataset employed was segregated into three levels of the US food value chain—the first consists of crop and livestock production data, represented by the agricultural production index that consists of the food and livestock production index. The agricultural production index shows the relative level of aggregated volume of agricultural production for each year in comparison with a base period of 2014 to 2016 [19]. The second level captures food supply data representing the number of primary commodities and the number of processed commodities potentially available for human consumption in terms of caloric value (kcal/capita/day). In addition, the food supply data was adjusted to account for the total quantity of foods produced in the country and the number of imports and adjusted for changes in stock since the reference year [20]. Additional adjustments were made to consider part-time presence or absence, such as temporary migrants, tourists, and refugees. The data comprised vegetal products, sugar and sweeteners, vegetable oils, spices, eggs, milk, cereals, starchy roots, pulses, fruits, milk, and fish. Also, losses within the value chain which consisted of cereals, starchy food, and fruit, were reported in 1000 tons. Similarly, the amount fed to livestock, including cereals, starchy food, pulses, meat, and fish, was reported at 1000 tons. The final set of the data captured the environmental impact indicators of GHGE (kg CO_{2eq}), energy consumption for agricultural production (kg of oil equivalent per capita), land area (sq. km), and surface temperature change. Similarly, the health data consist of the shared cause of death due to non-communicable diseases, including the prevalence of overweight and obesity and life expectancy. A total of 32 attributes were used in the modeling study.

2.2.2 Experiment environment

All experiments on ML algorithms and end-to-end pipeline framework described in this study were implemented using python programing language and Scikit-learn library.

2.3 Risk indicators

This section describes the health and environmental indicators of interest to this study. Table 1 briefly describes the different indicators adopted for the study.

Table 6: Description of the health and environmental impact risk indicators.

	Risk indicators	Description/definition	Ref
	Environment		
1	Greenhouse gas emission	Refers to the emissions from direct on-farm agricultural energy use, which consist of carbon dioxide, nitrous oxide, and methane gas associated with fuel burning and electricity used in agriculture (kt of CO_2 equivalent)	[21-23]
2	Land use	Agricultural land refers to the share of arable land area, under permanent crops and permanent pastures (measured in 1000 sq.km).	
3	Energy consumption	This refers to the energy used for agricultural production (measure in kg of oil equivalent per capita)	
4	Surface Temperature change.	Refers to a country's mean surface temperature change due to agricultural production (measured in ℃)	
	Health		
5	Prevalence of overweight	Prevalence of overweight among adults, BMI and GreaterEqual; 25 (age-standardized estimate) (%) - Sex:Both sexes	
6	Prevalence of obesity	Prevalence of obesity among adults, BMI and GreaterEqual; 30 (crude estimate) (%) - Sex: Both sexes	
7	Percentage cause of death	Deaths - Non-communicable diseases - Sex: Both - Age: All Ages (Number)	
8	Life expectancy	It captures the mortality along the entire life course. It describes a population's average age of death (measured in years).	

2.4 Policy effort indicators

A range of economic, environmental, biophysical, and health policies have been explored in the literature to reach sustainable development goals by 2030 and reach regional food sufficiency across the globe by 2050. Aside from this, several food system transformation initiatives have been implemented across a multi-sectorial level to meet the Paris Agreement on climate change [24]. Among these efforts, evidence suggests that promoting a sustainable diet has been a key entry point to achieving a co-benefit of improving the population's health and reducing environmental emissions from the food system. Sustainable diets encourage the consumption of plant-based foods while advocating for a reduction in animal-based foods with specific attention to red meat and processed meat. According to (ref), a shift toward sustainable diets has demonstrated a lower risk of all-cause mortality by 8%. Likewise, (ref) reported a reduction of up to 24% and 9% in GHGE and land use due to adopting sustainable diet concepts such as vegan, vegetarian, and pescatarian diets in the United States. In this regard, policy efforts and recommendations have suggested reducing government subsidies for animal-sourced products since they are associated with higher GHGE [25]. Other authors [26, 27] have also recommended the removal of subsidies associated with animal-sourced products and a translation of investments to plant-sourced foods. [28, 29] suggested marketbased and regulatory policies as an effective approach to endorse vegetarian diets while condemning animal-sourced products.

However, food systems differ in size and structure from one country to another and between rural and urban areas especially in countries with substantial populations. For example, over 70% of the world's extremely poor rear animals are an important source of income and diet [30]. Additionally, the context of political setting and policy network vary from country to country with growing influence from different stakeholders. Aside from this, policymakers leverage several existing policy instruments, which are either regulatory, resource-focused, or viewed as a continuum of authoritative force. Thus, considering different factors, making a context-specific recommendation allows policymakers to explore diverse mitigation strategies while promoting healthy and sustainable food consumption within their regions.

2.5 ML workflow

This section presents an end-to-end ML workflow for the prediction of environmental

2.5.1 Preprocessing and missing data

The dataset consisted of a total 1398 datapoint with 8.38% missing data points, of which 70.08% were attributed to the predictors. Missing data for the continuous features variables were estimated using the information and relationship between non-missing variables. To eliminate any degree of bias or misinformed analysis, missing feature values were imputed using five mechanisms; then, we tested the performance metrics using a linear regression algorithm. The data imputers adopted include K-Nearest Neighbor (KNN) imputer, mean/median imputer, iterative imputation, expectation-maximization (EM Algorithm), and soft imputer approach. The KNN imputer algorithm imputes missing values in the dataset using values of observations for the neighboring data points. It identifies the neighboring data points by measuring the distance and the missing values. For a given environmental or health predictor y, the distance between samples i and j can be defined as

$$d(y_i, y_j) = \frac{|y_i - y_j|}{R_y} \qquad (1.1)$$

Where R_y is the range of the predictor. Several distance measures such as the Minkwoski, Manhattan, Cosine and Jaccard can be adopted. However, the Euclidean distance has been reported to give a higher efficiency and productivity compared to other techniques [31]. This is represented in Eq. 2

$$Dist_{xy} = \sqrt{\sum_{k=1}^{m} \left(x_{ik} - x_{jk}\right)^2} \qquad (1.2)$$

Where $Dist_{xy}$ is the Euclidean distance, k is the number of attributes of the dataset from $j = 1,2,3, \dots k$, k dimensions, x_{ik} values for j-attributed containing missing data and x_{jk} is the value of j-attributes containing complete data. The value of the k points that have a minimum distance is chosen then the weighted mean estimate given by

$$X_k = \frac{\sum_{j=1}^{j} w_j v_j}{\sum_{j=1}^{j} w_j} \qquad (1.3)$$

Where w_j is the nearest observed neighbors, of which the weighted value is given by Eq. 3 and v_j are complete values containing missing data.

$$w_j = \frac{1}{Dist_{xy}} \qquad (1.4)$$

The EM algorithm is an iterative method for dealing with missing data by a two-step process: the estimate (E-step) and maximize step (M-step) until convergence is approached. The E-step computes the expected value of $\mathrm{I}(\theta; \mathrm{x}, \mathrm{y})$ given the observed data x and the current parameter estimate θ_{old}. Mathematically, this step can be defined as

$$Q(\theta; \theta_{old}) = [l(\theta; x, y)|x, \theta_{old}] \qquad (2.1)$$

$$= \int l(\theta; x, y) p(y|x, \theta_{old})\, dy \qquad (2.2)$$

Where $p(y|x, \theta_{old})$ is the conditional density of y given the observed data, x, assuming $\theta = \theta_{old}$. The M-step maximized over θ the expectation computed in Eq. 2, thus

$$\theta_{new= \, max_\theta} Q(\theta;\ \theta_{old}) \qquad (2.3)$$

Where θ_{old} is set to θ_{new}.

Similar to the KNN imputer algorithm, the iterative imputer generates multiple copies of the data set and integrates to obtain the optimal values. Each feature is imputed sequentially, allowing prior imputed values to be used as inputs for the subsequent model in predicting features. This approach is implemented through the Multivariate Imputation by Chain Equations technique in the fancyimpute Scikit-learn library [32], where initial values can be either mean, median or constant. The prediction of missing data points starts from the variable with the fewest missing values using RidgeCV or Bayesian-Ridge regression model [33].

2.5.2 Feature selection using information gain

Generally, feature selection algorithms attempt to identify and remove irrelevant and redundant features from the training dataset by generating an optimal subset of features. Consequently, reducing the computational time for the learning models and enabling the models to operate faster and more effectively. The performance of a feature selection technique is often evaluated using ML models. In this study, three feature selection techniques were tested and compared: filter, wrapper, and embedded methods.

The filter method selects relevant features with high correlation to the target variables by employing correlation matrixes such as Pearson's R, Spearman's rho, and Kendell's tau. Equations 4 to 8 present a general and representative evaluation of the correlation matrixes adopted when employing the filter method. For a given set of two features a and b:

Correlation coefficient:

$$r(a,b) = \frac{cov(a,b)}{\sqrt{Var(a)}\sqrt{Var(b)}} \quad (3)$$

Where $cov(a,b)$ is the covariance of a and b and $Var(.)$ is the variance.

Pearson correlation coefficient:

$$r(a,b) = \frac{\sum a_i b_i - \sum a_i \sum b_i}{\sqrt{N\sum a_i^2 - \left(\sum a_i^2\right)^2}\sqrt{N\sum b_i^2 - \left(\sum b_i^2\right)^2}} \quad (4)$$

Symmetric uncertainty (SU):

$$SU(a;b) = \frac{2I(a;b)}{H(a) + H(b)} \quad (5)$$

Where $H(.)$ is the entropy of a feature

Mutual information:

$$I(a;b) = \sum\sum p(ab) log \frac{2I(a;b)}{p(a) + p(b)} \quad (6)$$

Where $p(.)$ is the probability density function.

Information distance

$$d(a;b) = \frac{H(a|b) + H(b|a)}{2} \quad (7)$$

Where $H(a|b)$ is conditional entropy of a given b.

Euclidean distance:

$$d(a, b) = \sqrt{(a_i - b_i)^2} \qquad (8)$$

Although there are other methods, such as the Laplacian and Fisher scores, this study adopted the above. The wrapper method employs an iterative approach to evaluate the performance of different subsets of the input. It ultimately selects the high-ranked variables that result in the best ML model performance. Otchere, Ganat [34]reported that it outperforms the filter method; however, it is computationally expensive and easily prone to overfit. Similar to the filter method, there are several wrapper methods. The forward selection, backward elimination, and exhaustive and recursive feature elimination methods were employed according to the recommendations of [35]. The backward elimination evaluates the performance of all input features and eliminates the worse using their respective p-value. The best-performing input features are then used in the model training process until a predetermined number of features are exhausted. The recursive elimination conducts a rigorous iterative search by creating models with the inputs and evaluating their respective performance. In the process the worst performing features are removed and the remaining features are continuous used to create models. Finally, the features are ranked in order of their elimination.

Similarly, the embedded method employs an iterative feature selection and model training approach. This results in a model emphasizing features contributing to the model training process. A typical example of the embedded technique is LASSO regularization, one of the most widely adopted methods that penalize features based on a predefined threshold. In the LASSO regularization method, if a feature is irrelevant, its penalized to 0 and removed, thus leaving important features for model training. Other regularization techniques include RIDGE.

2.5.3 Cross-validation strategy

The dataset used in this study can be described as data-poor; thus, cross-validation is pertinent to determine the effectiveness of the ML algorithm implemented. It is important to mention that since there were several environmental and health risk targets, a multi-output cross-validation approach was adopted for the study. Additionally, the multi-output cross-validation allows optimizing the model's performance and estimating the model's optimal hyperparameters and coefficients. It enables ML models to overcome the challenge of overfitting during the training step. Thus, the dataset was divided into three independent set: a training set, a validation set, and a test set used to estimate the performance of the optimized ML models. For the validation dataset, a nested cross-validation approach required the data to be split twice in a nested leave three years out; cross-validation was applied (Figure 1). Thus, in the outer loop, data for three years was held out, while an $n-3$ year of validation data was subjected to the inner cross-validation loop. ML model hyperparameters and coefficients were estimated within the inner cross-validation ($n-4\ years\ of\ data$) and then employed to predict the environmental and health impact indicators held in the outer loop. The outer loop presented an opportunity to evaluate the generalized performance of the full modeling procedure prior to implementation on the test dataset. The whole procedure above was repeated for all model configurations. The study also compared the performance of nested cross-validation to naively using a single layer of non-nested cross-validation. Table 1 presents the pseudo algorithm for nested and non-nested cross-validation methods as applied to this study

Nested vs non-nested cross-validation Algorithm 1
procedure GetCrossValidationAccuracy
$cv_{inner} \leftarrow Kfold\ (shuffle\ , n_{split}\ = 5)$
$cv_{outer} \leftarrow Kfold\ (shuffle\ , n_{split}\ = 3)$
$y_{train} \leftarrow lables$
$y_{train} \leftarrow lables$
$X_{fearures} \leftarrow calculate\ features\ of\ X_{train}$
$clf \leftarrow GridSearchCV(estimator = XGB, parameter, cv =\ cv_{inner})$
$clf.fit(x_{train}, y_{train})$
$non-nested\ score \leftarrow clf.best\_score\_$
Nested score $\leftarrow cross\_val(clf, x_{train}, y_{train}, cv =\ cv_{outer})$

2.5.4 ML algorithms

Since the data employed in this study is a continuous dataset, the study employed six standard machine learning regression algorithms, namely: Random Forest (RF), Multi-layer Perceptron (MLP), Support Vector Regression (SVR), KNN, Logistic regression (LR), Bi-clustering and Ada boost techniques, extreme gradient boosting (XGB) and decision Tree. In addition, the SVR with linear and radial base function kernels (SVR lin and SVR. rbf) were implemented in this study. Finally, each model's pipeline and hyperparameters were designed, implemented, and estimated using the sci-kit learn. Table 2 presents a brief overview of the different models employed and their respective hyperparameters estimated from the study.

Table 7: Summary of ML models and their respective hyperparameters adopted in this study

S/N	Algorithm	Description	Hyperparameters
1	LASSO	Linear regressor that performs variable selection and regularization	Alpha = 0 , fit_intercept = True, max_iteriation = 1000; tol=0.1

2	RF.	Ensembled regressor that averages the output of multiple regression trees	ccp_alpha= 0.01, max_depth = 2
3	SVR	It leverages kernels, sparse solutions, and vector control of margins around several support vectors to estimate continuous multivariate functions	C=2, cache_size=, 100, coef0= 0 , degree= 3, epsilon= 0.3, gamma = 'auto', kernel='rbf'
4	Ridge	It is a least square error function with an L2 regularization term (alpha) which addresses issues of multicollinearity in during modeling	alpha=10, tol= 0.01, solver="saga", alpha=10,tol=0.01, solver="saga", max_iter= 1500,
5	Adaboost	Ensemble of shallow trees in a sequence where each new tree minimizes the residuals of the previous tree	Learning rate = 0.01, loss = 2 , n_estimators = 70
6	MLP	Artificial neural network that uses a nonlinear weighted combination of the features to predict the target variable	
7	XGB	It is an ensemble learning algorithm that builds models consisting of multiple decision trees	alpha = 0.8, ccp_alpha =0.001, learning_rate =0.1, max_depth= 2, min_samples_leaf= 3, Loss= 'squared_error', min impurity_decrease = 0
8	KNN	Its is a non-parametric algorithm that intuitively approximates the association between variables by averaging the observations around their neighborhood	leaf size=10, n_neighbors=4 P=1
9	Multi-output nested cross-validation	It is a technique for overcoming biases during hyper-parameterization under diverse model selection	k-inner loop=5, k-outer loop= 3 for n = 8

2.6 Statistical validation

2.6.1 Model evaluation and selections

Five statistical indices were employed to evaluate the model prediction accuracy compared to the observed data. The statistics extracted a comparison between the observed dataset and the predictions of the different models adopted to estimate the environmental and health risk indicators. These statistics include the coefficient of determination (R^2, Eq. 9), Root mean squared error (RMSE, Eq. 10), normalized Root, mean absolute error (MAE, Eq. (11)), and Root mean square error (RMAE, Eq. (12))[36].

$$R^2 = \frac{[\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})]^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2} \quad (9)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(Y_i - X_i)^2} \quad (10)$$

$$MAE = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{i=1}^{n}|Y_i - X_i| \quad (11)$$

$$RMAE = \sqrt{\frac{\mathbf{1}}{\boldsymbol{n}}\sum_{i=1}^{n}|Y_i - X_i|} \qquad (12)$$

Where X_i and Y_i are the observations and estimation values at the ith time step, respectively. $\bar{X}$ and $\bar{Y}$ are the average value of simulations and estimations, respectively, and n is the number of samples. However, to ensure linearity in discussing the performance of the different models and case studies, we introduce a new parameter called the α–parameter. This is represented in equation 13.

Table 8: Statistical coefficients used to access the quality of the estimations

S/N	Statistical coefficient	Symbol	Objective
1	Root mean squared error	RMSE.	Minimized
2	Root mean absolute error	RMAE.	Minimized
3	R-Squared	R^2	Maximized
4	Mean absolute error	MAE.	Minimized

Equation (13) has been formulated considering the individual objectives of the different statistical coefficients, as illustrated in Table 1. Since R-Squared is to be maximized and all should have a value less than 1, we subtract the obtained value from one such that the objective will be to minimize alpha, and models with smaller α are considered of better quality

$$\propto -parameter = RMSE + NRMSE + (1 - R^2) + MAE \ (13)$$

3 Results

3.1 Performance of data imputation techniques

Missing data problems are common challenges every domain deals with data. In such instances, data can be handled by different techniques depending on how much data is missing and, more importantly, analyzed to ensure it provides a suitable solution. Figure 2 compares the performance for missing data imputation using mean/median imputer, KNN imputer, and iterative imputer. The predicted dataset from the above imputation techniques was fit the linear regression model, and an RMSE and R2 value were computed for each approach. The results illustrate that the iterative imputer performed better than other algorithms with an RMSE value of 5.33, while the KNN imputer performed worst with an RMSE value of 6.2. Hence the iterative imputer algorithm was adopted in the ML pipeline for the modeling exercise.

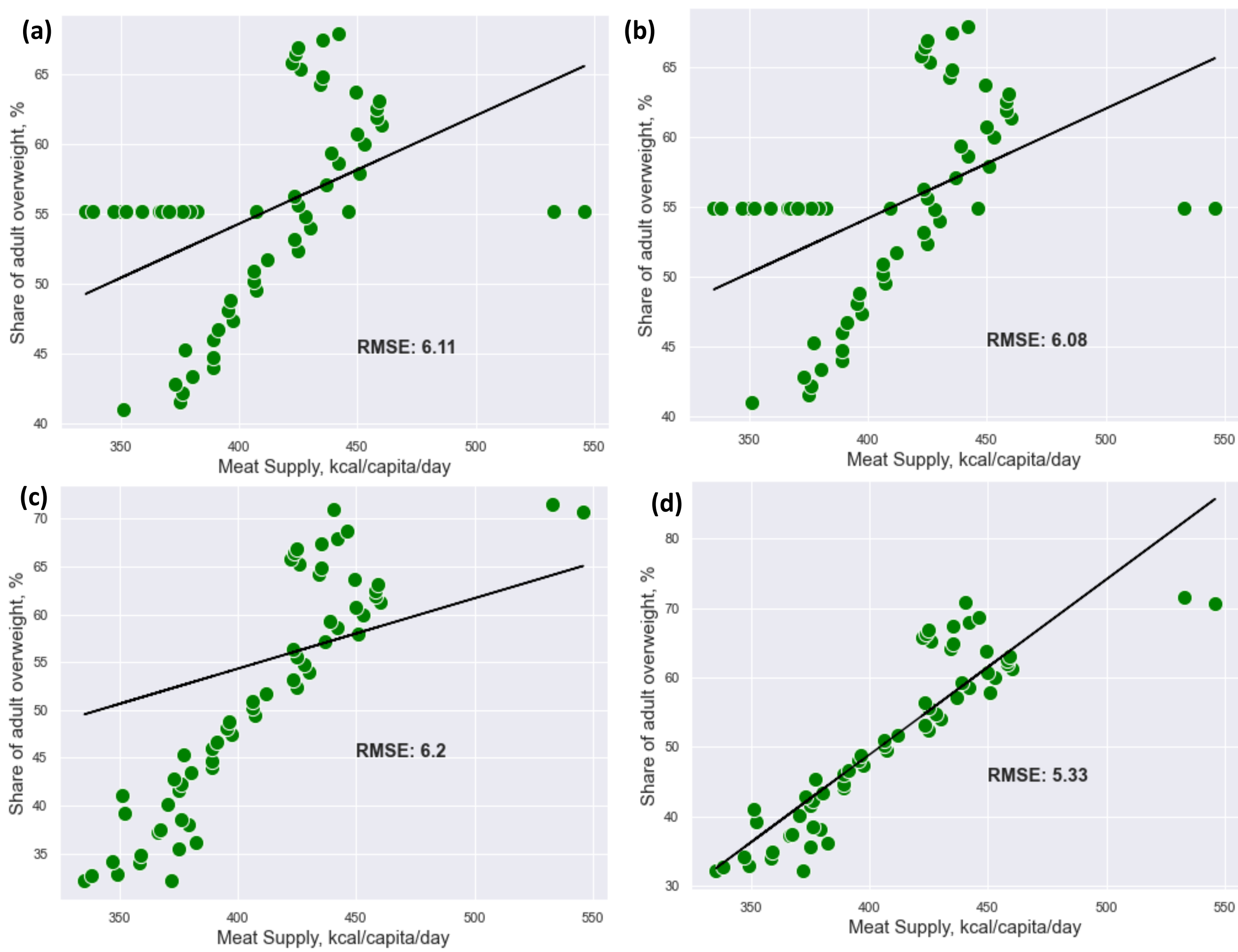

Figure 13: Performance comparison of different data imputation techniques ((a) median imputer, (b) mean imputer, (c) KNN imputer, and (d) iterative imputer)

3.2 Feature extraction

Feature selection is often associated with obtaining a subset of original data, improving a model's prediction performance. Table 4 presents the results of comparing three categories of feature selection techniques against using all features available and testing the performance of the SVR model. It is important to highlight that the performance testing of the subsets generated from the different feature extraction techniques was estimated with default hyperparameter values. The objective of adopting this approach was to explore the influence of different feature subsets generated by different feature engineering techniques, ultimately influencing the proposed end-to-end ML framework.

From Table 4, it can be observed that the model performance reduces with different data subsets of features. Apparently, the wrapper techniques for feature selection have a greater model performance than all other methods, with R2 values ranging between 0.759 to 0.917. However, they are computationally expensive. The results corroborate strongly with the work of Rao, Shi [35], who reported on the high performance of the filter method compared to other feature engineering techniques.. In comparing the different feature extraction methods, forward elimination with a subset of 12 features obtained the highest R^2 value of 0.917, while the ridge selection technique obtained the worst R2 of 0.341. Likewise, the Pearson correlation method with a subset of 16 features obtained the best RMSE value of 0.167, while the ridge model resulted in the worst RSME of 0.723. For the case of the Pearson correlation, a threshold of -0.5 was set to extract features with a more significant correlation. Similarly, a threshold value of -0.2 was set for the spearman correlation method. Thus, all features with a correlation lower than this threshold were removed in the training process. Value closers to +1 demonstrated a strong positive relationship for the two correlation methods employed, while the corollary can be described for values closer to -1. Figure 3 presents a sample of the feature extraction from the respective methods and their corresponding measure values. In Figure 3(f) features with correlation values within the epsilon (±0.03) neighborhood of 0 showed little or no relationship. A typical of such relationship was observed for (Cereals-LSF and Fruits-LS), (Meat-LSF and Startcy Rts-LSF), and (Meat-LSF and Eggs-FS) when implementing the Spearman correlation method.

Nonetheless, features with values closer to +1 demonstrated a strong positive correlation. The ANOVA F-value presented in Figure 3a measured the relationship between the features and the target values. It is important to highlight that creation of subsets is inexhaustive; however, the set in Table 4 was developed for brevity. Overall, the generated feature subsets did not significantly outperform the conventional approach of using the entire feature set in building the ML pipeline. However, the conventional approach's R2 (0.921) and RMSE (0.177) values when deployed through the SVR algorithm outperformed all feature extraction techniques.

Table 9: Comparison of different feature selection methods

Subset #	Feature selection algorithm	Selected Subset	**Model training performance using SVR Algorithm**	
			R2	RMSE.
1	Convention approach	Using all features	**0.921**	**0.177**
	Filters			
2	Spearman Correlation coefficient	20 features	0.597	0.527
3	Pearson correlation	16 features	0.627	0.162
4	Mutual information	16 features	0.895	0.282
5	Chi-squared Anova approach	20 features	0.661	0.582
	Wrappers			
6	Forward elimination	15 features	0.913	0.281
		12 features	0.917	0.216
7	Backward elimination	16 features	0.759	0.321
		13 features	0.898	0.271
8	Recursive elimination	15 features	0.904	0.236
		10 features	0.879	0.235
	Embedded method			
9	LASSO	19 features	0.422	0.654
10	Ridge	19 features	0.341	0.723
11	Tree	18 features	0.641	1.215

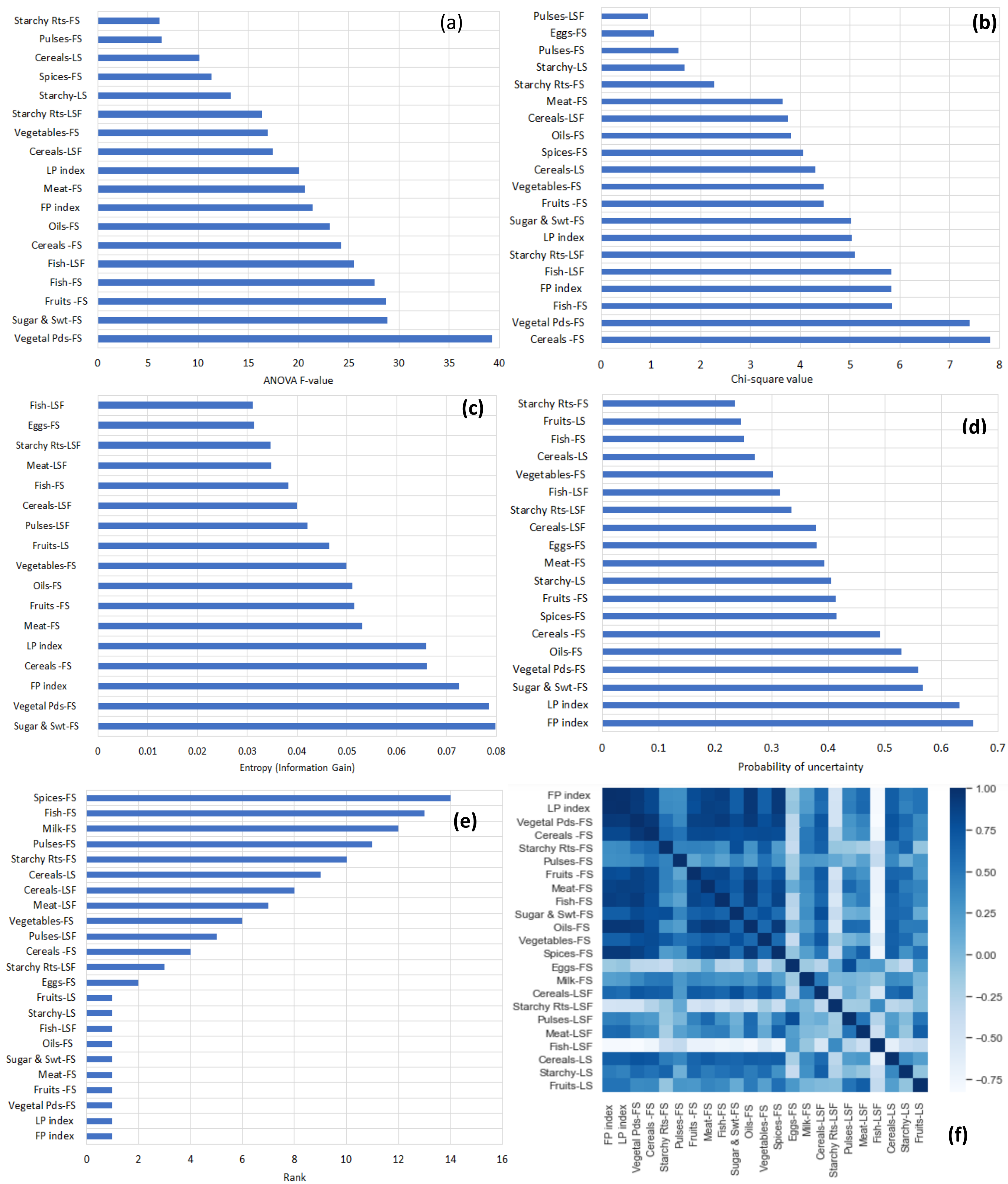

Figure 14: Comparison of feature selection methods ((a)Feature importance using the ANOVA F-value, (b) Using the chi-squared method, (c) Feature importance using Tree method, (d) Using the Mutual information method (e) Using the recursive feature selection method, (f) Using the Pearson correlation method)

3.3 Nested and non-nested cross-validation

Figure 4 presents the generalized performance estimated with and without using the multi-output nested cross-validation procedure for all ML algorithms employed in this study. From Figure 3, we can observe that the generalization performance estimated using the nested cross-validation is lower than non-nested. The average accuracy observed for non-nested and nested cross-validation across all models was 0.884 and 0.879, respectively. Similarly, the largest difference of 0.322 was observed between the non-nested and nested using MLP algorithm, while the lowest difference was observed for the KNN algorithm. The non-nested frequently results in an optimistic result, resulting in a biased model selection. A possible reason for this observation is that the tunning process automatically selects the model with the highest inner cross-validation score, hence an error being propagated into the general performance of the model. Additionally, a relatively larger number of hyperparameters and a probable larger standard deviation from inner cross-validation can result in an overestimation of the performance, which consequently influences the full ML pipeline.

Table 10: Accuracy of different algorithms

S/N	Algorithm	Non-nested	Nested	Difference
1	LASSO	0.882	0.879	0.003
2	RF	0.894	0.890	0.004
3	SVR	0.915	0.907	0.08
4	Ridge	0.902	0.886	0.016
5	MLP.	0.446	0.124	0.322
6	XGB	0.924	0.912	0.012
7	KNN	0.726	0.746	-0.020
8	AdaBoost	0.931	0.920	0.011
Average		0.884	0.879	0.014

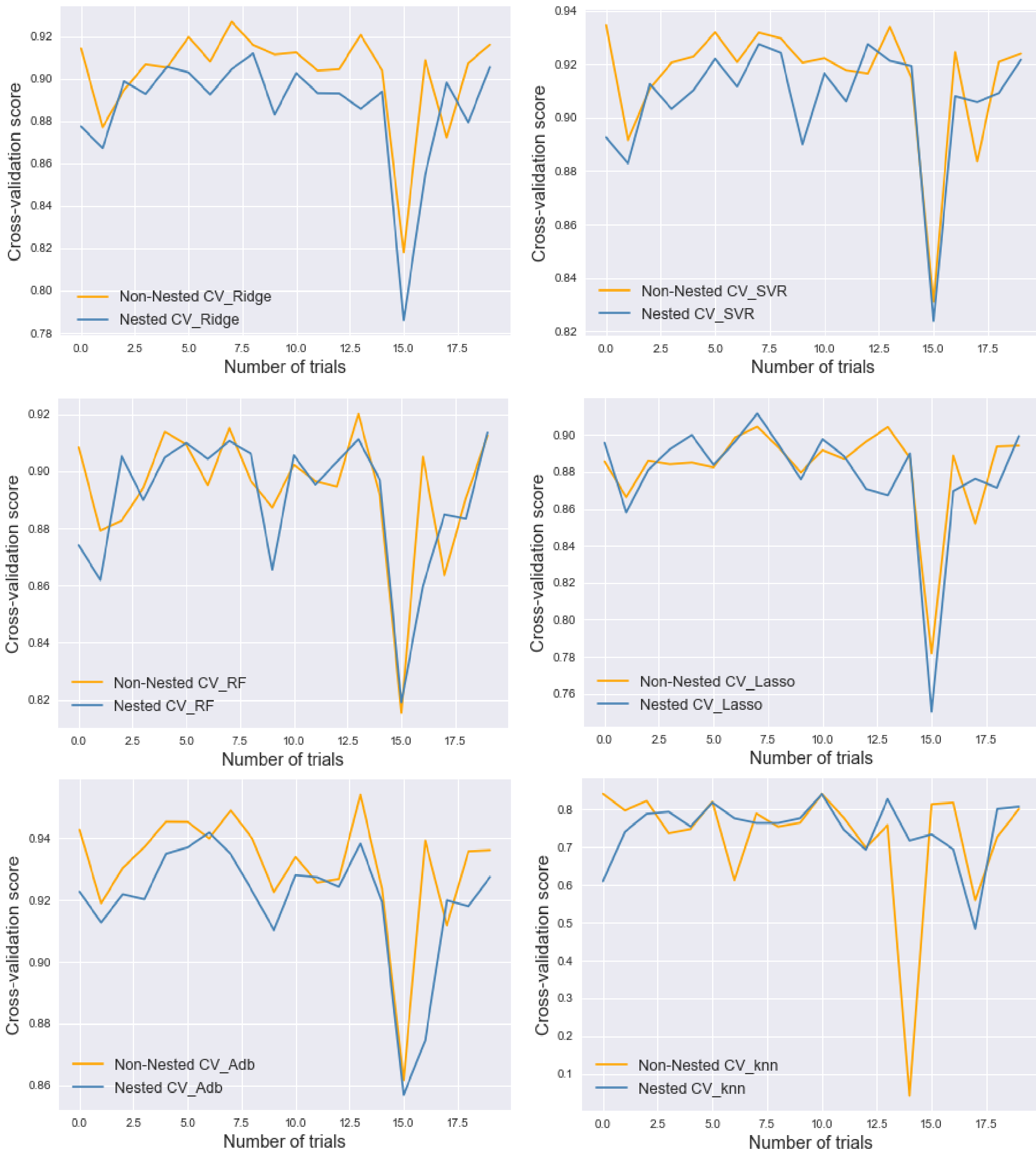

Figure 4: Nested and non-nested cross-validation of ML confifure using diet-health dataset

3.4 Performance of forecasting

3.4.1 Prediction performance

Table 6 presents a statistical performance of the different ML models applied in different end-to-end frameworks. To ensure collinearity in comparing the performance of the respective models, the $\propto -parameter$ value was computed for each sustainability dimension, and then an average value was determined. From Table 6, we can observe that the SVR, KNN, and the Ridge models ranked first and second with an $\propto_H$ of 4.304, 5.732, and 6.163, respectively, when predicting health risk. Similarly, from an environmental impact point of view, RF, XGB, and AdaBoost models ranked first, second, and third, respectively, with $\propto_E$ of 2.863, 2.93 and 3.218, respectively. Approximately 70% of all models performed well as when predicting environmental risk compared to health risk indicators. Figures 5 and 6 illustrate the fitting of the observed test dataset against the model prediction. For brevity, six model representations are provided.

Table 11: Model performance during predictions

S/N	Health risk (Average metric)					Environmental impacts (Average metric)				
	R^2	RMSE	MAE	RMAE	$\propto_H$	R^2	RMSE	MAE	RMAE	$\propto_E$
LASSO	0.801	3.256	3.015	1.736	8.206	0.825	5.763	3.712	1.927	11.577
RF	0.781	4.211	3.679	1.918	10.027	0.9	1.147	0.75	0.866	2.863
SVR	0.858	1.272	1.618	1.272	4.304	0.827	6.059	3.819	1.954	12.005
Ridge	0.843	2.546	2.034	1.426	6.163	0.865	1.846	1.11	1.054	4.145
XGB	0.786	4.062	3.346	1.829	9.451	0.89	1.221	0.739	0.86	2.93
Adaboost	0.823	3.129	2.438	1.562	7.306	0.842	1.668	0.611	0.781	3.218
KNN	0.85	2.56	1.713	1.309	5.732	0.86	1.944	1.096	1.046	4.226
MLP	0.801	3.256	3.015	1.736	8.206	0.825	5.763	3.712	1.927	11.577

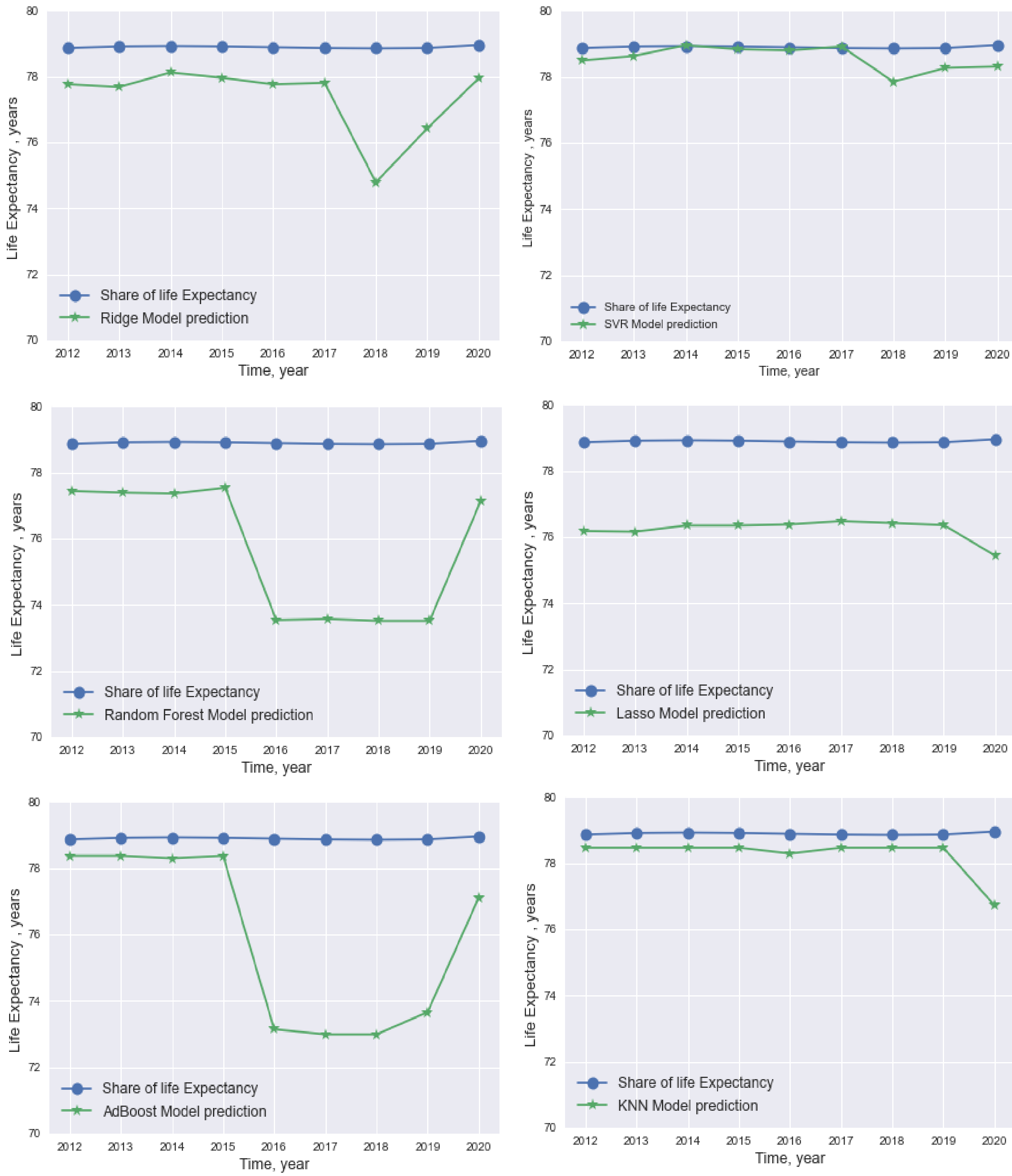

Figure 16: Model forecast performance and forecasting for health risk (Life expectancy)

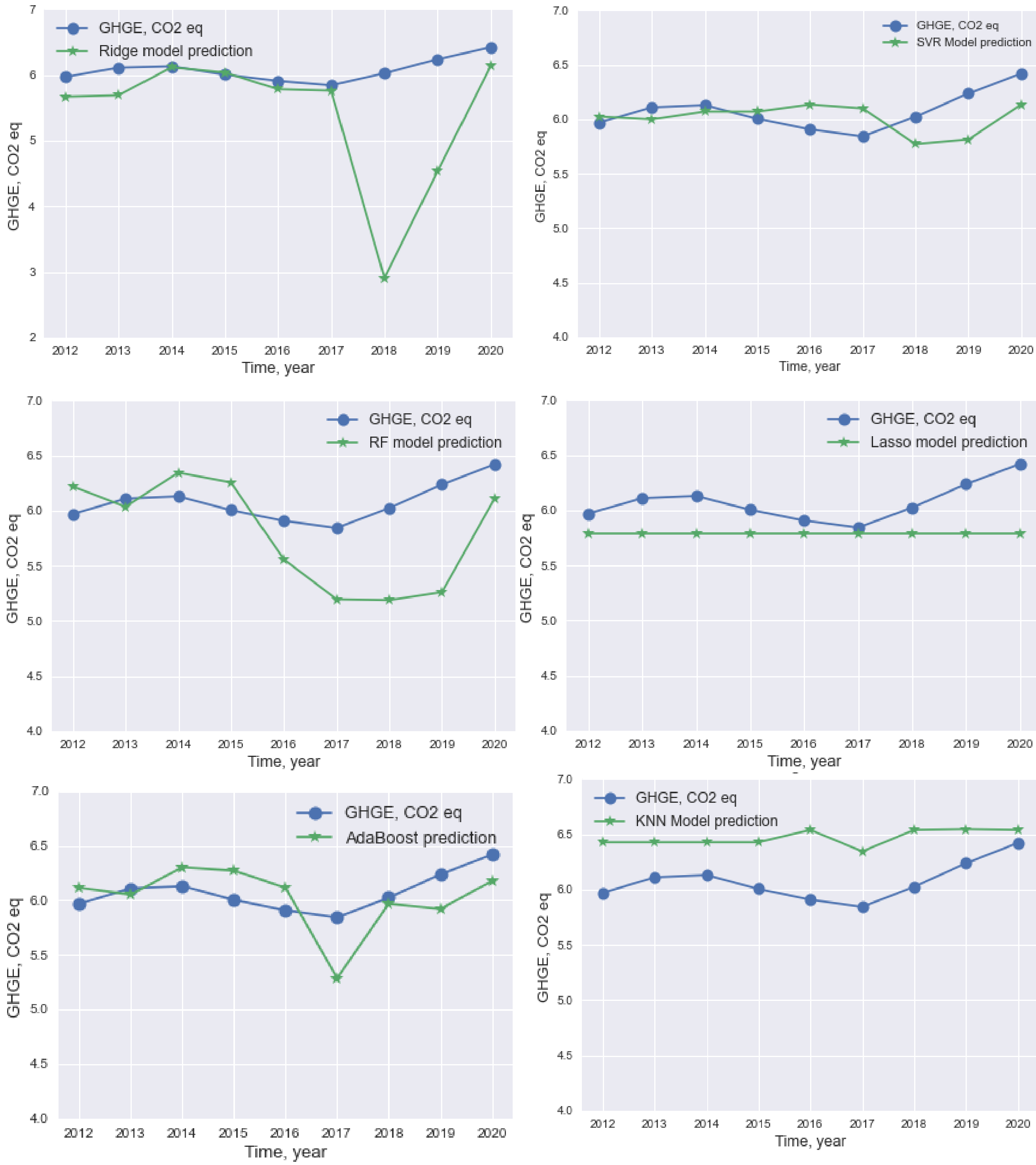

Figure 6: Model forecast performance and forecasting for health risk and GHGE.

3.5 Implications on short-term policy on the diet-health-environmental trilemma (2030)

So far, this study has developed an end-to-end ML pipeline that consists of data imputation, feature selection, cross-validation, training, and prediction of environmental and health implications of diet patterns in the United States. This section leverages the best model discussed in section 3.4 to explore the future health and environmental impact of food choices in the United States through two different lenses, thus short- and long-term scenarios. Scenarios are powerful tools that provide snapshots of unforeseen paths in the future. It is worth noting that the term scenarios used in this context emphasize projections, forecasts, and predictions into the future using logical plots and narratives governed by the present data and ML models. The scenarios constructed are around critical issues that provoke actions to shape the future of the US food system. Three dominant critical drivers, namely food and livestock production, consumer demand/supply, and food loss/waste along the value chain, will be key in addressing food choices' health and environmental burdens. The paragraphs below present the respective scenarios and their potential implications. It highlights key policy implications.

3.5.1 Scenario 1: Wide adoption of sustainable diets such as vegan and vegetarian diet concepts

In this scenario, the US food system sustainably provides more healthy diets. Consumers are gradually shifting towards greater consumption of pulses, approximately 25% more than the current by 2030 and reaching 62% by 2050. Similarly, food losses along the value chain are reduced by 32% at the end of 2030 and 71% by 2050, with the wide adoption of circular economy concepts. Government agencies and other non-governmental agencies embark on several campaigns to promote the consumption of vegetables and raise taxes while reducing cattle production subsidies. Overall, a 20% annual subsidy for cattle production is achieved at the end of 2030, which subsequently rises to 45% by 2050.

3.5.2 Scenario 2

The US population becomes very familiar with sustainable diet concepts in this scenario. Campaigns by government agencies and other healthy diet organizations have gained momentum within the country. Subsequently, meat consumption is reduced by a staggering 27% by 2030 and 42% by 2050. Due to the massive campaigns and public education on sustainable healthy diets, pulses and vegetable consumption will increase by 29% and 32%, respectively, at the end of 2030. By 2050, the next generation of consumers will adopt a strict vegetarian, and vegan diet as pulse consumption increases to 52%, while vegetable consumption rises to 82%. The government continues to remove subsidies on livestock production and reinvents them in producing sustainable health plant-sourced food products—sugars and sweeteners consumption has also reduced drastically. The circular economy becomes the US population's culture, resulting in over 36% of food waste and loss of value by 2030 and approximately 58% reuse by 2050.

Figures 7 and 8 present snapshots and logical plots of the narratives governing the scenarios considering human health and environmental drivers.

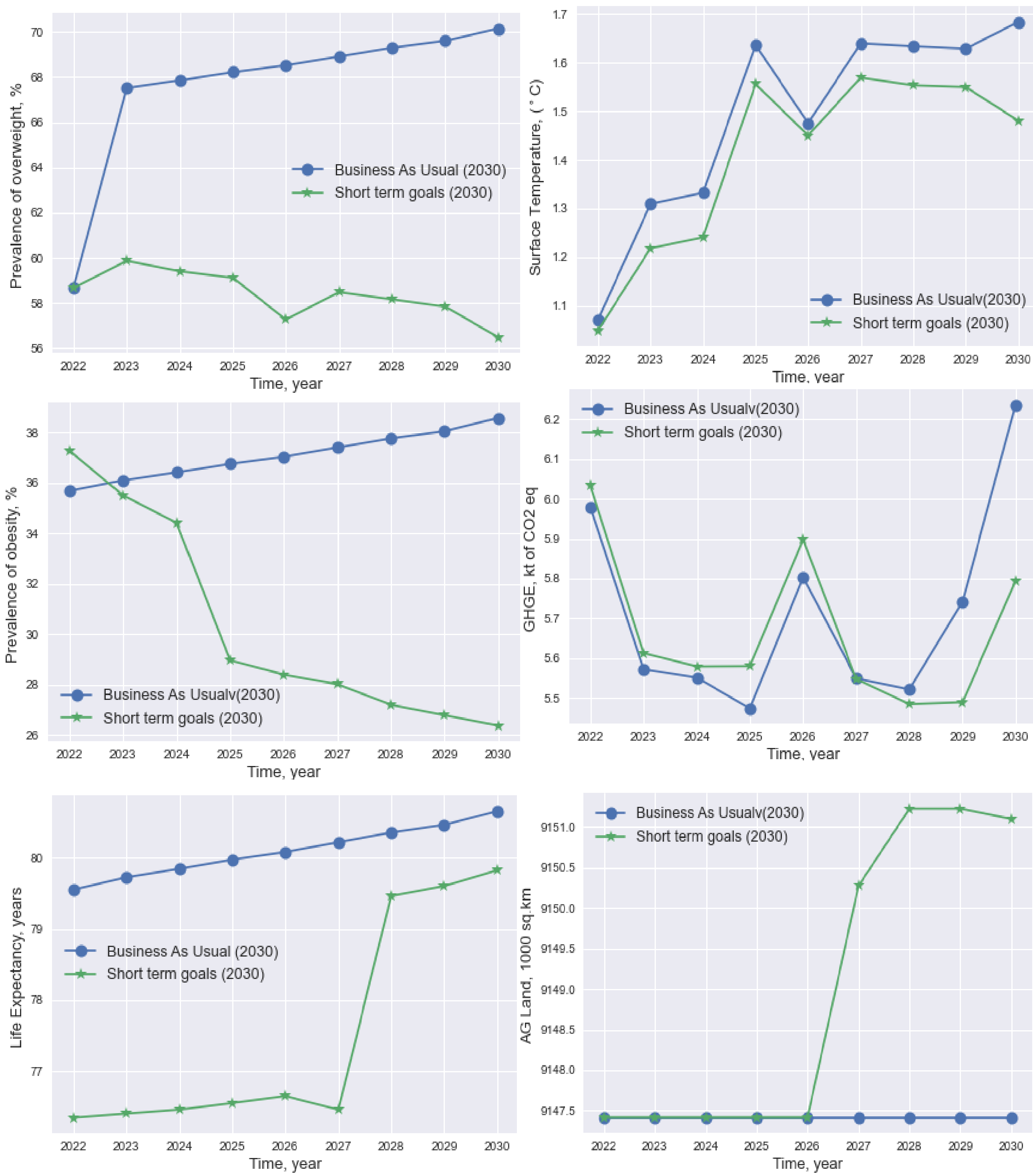

Figure 7: Snapshot of the health and environmental implications in the context of scenario one compared to the business-as-usual approach.

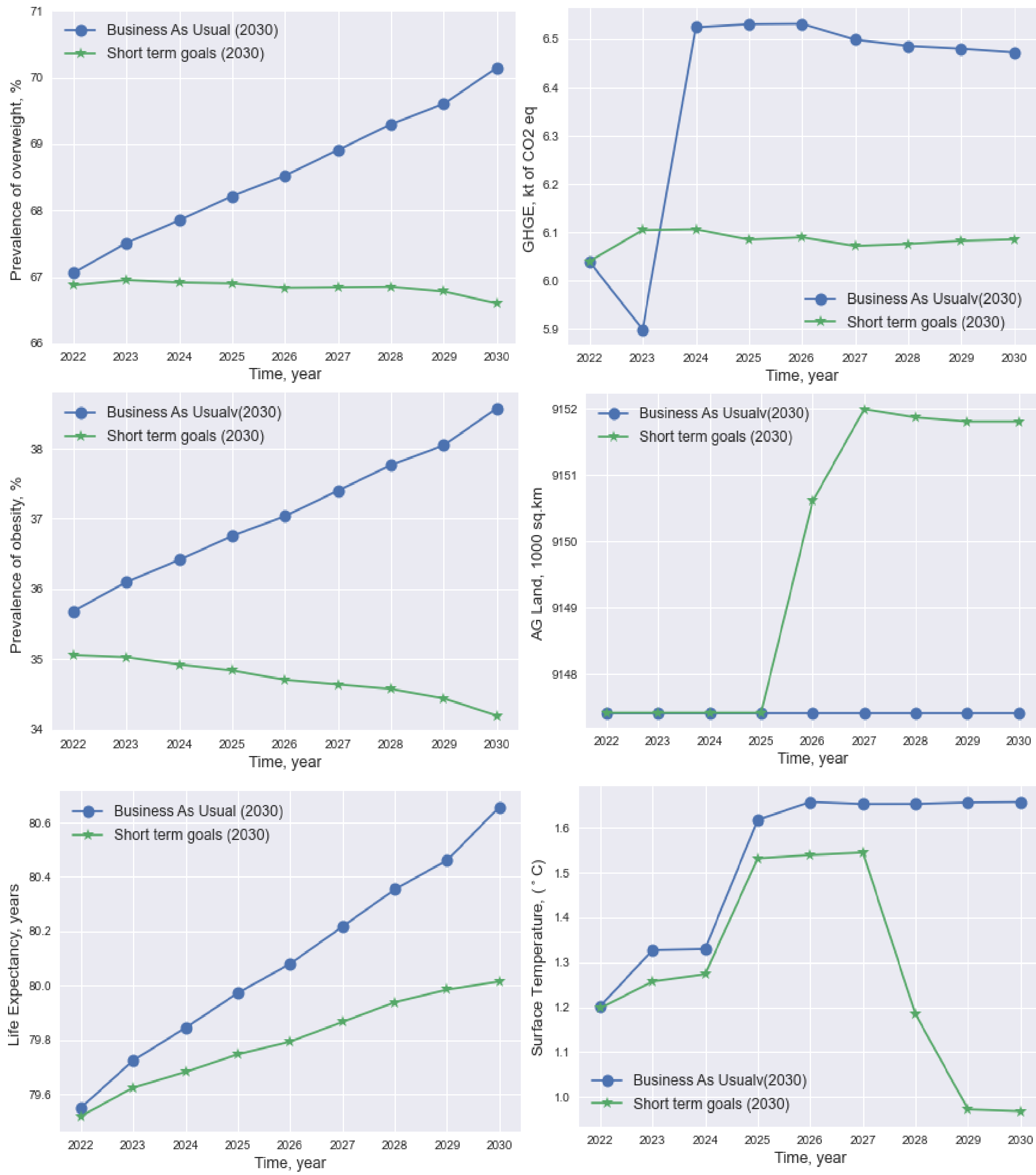

Figure 8: Snapshot of scenario two's health and environmental implications compared to the business-as-usual approach.

From the snapshots of the two-stylized scenarios, encouraging the adoption of vegetarian diet concepts in scenario one results in an almost 19% reduction in the prevalence of overweight by 2030. Similarly, obesity prevalence can be minimized by almost 32% by addressing the environmental dilemma through the business-as-usual approach. This reduction is almost 41% from the model's prediction at the end of 2022; despite the health benefits and potential increase in life expectancy postulated by this scenario, the environmental impact, such as agricultural land, increases but is not very significant (0.04% increase). This observation can be attributed to potential technological farming practices such as vertical farms and aquaponic, which maximize land for greater production. Interestingly, the surface temperature reduces by 12%. In the second stylized scenario, for a short-term object, overweight reductions (5%), obesity prevalence reductions of 11%, and a 1% increase in life expectancy can be achieved. Howbeit, from an environmental perspective, 6% reductions in GHGE and 42% reductions in surface temperature can be achieved. Despite these potential reductions, the percentage of deaths due to non-communicable diseases increase, while there is no significant change in agricultural land use. Aside from these scenarios presented, many intermediate scenarios can be developed with a broad range of possibilities but bounded by the variables adopted in this study and the critical driving forces. To provide policymakers and food system analysts the opportunity to explore countless scenarios which can guide different decisions regarding food production, supply, and losses within the US food value chain and their respective influence on the health-diet-environment trilemma, the next section presents a novel decision support system.

3.6 Development of decision support system

Scenarios can be powerful tools to explore the implications of different decisions in potential futures. Pairing scenarios with critical drivers such as GHGE, life expectancy, and prevalence of obesity and overweight provide an opportunity for several images of the future of US diet patterns. As such, this section captures the deployment and development of a decision support system using the ML algorithms presented in this study to enable stakeholders/policymakers to explore diverse scenarios. The novel decision support system- Food System-Rapid Overview Assessment using Scenarios (FS-ROAS) provides an opportunity to pursue food system transformation with diverse environmental and health implications. It allows short-, medium- and long-term exploration of diverse scenarios with high connectivity to food and livestock production, consumer supply, and food loss or waste within the US food system. For a short-term exploration of different scenarios and potential health and environment, FS-ROAS allows exploration to 2030, while the mid-term and long-term allow exploration to 2040 and 2050, respectively. The above timelines were selected because as time horizons expand from months to years to decades, forecasts of human decisions become untrustworthy. This is due to the intrinsic indeterminism of complex dynamic systems interconnecting with our food system and a poor understanding of human interaction with diverse ecological systems.

4 Conclusion

Our choices today have the potential to shape tomorrow's world, thus allowing an endless list of possible future outcomes. However, this study has shown that health and environmental targets can be achieved under stringent policy mitigation strategies. For example, substituting 15% of meat consumption with pulses and vegetables results in 19% to 25% reductions in GHGE in the context of the two-stylized scenarios presented in this study. Additionally, surface temperature reductions as high as 12% can be achieved under similar conditions. ML algorithms were deployed using a flask framework to develop FS-ROAS. FS-ROAS presents an opportunity to explore intermediate scenarios that could materialize within the US food system. It is transparent, easily assessable, and can be used on any digital device. The results suggest that substituting meat and beef production with a more resource-efficient agricultural product such as peas could reduce anticipated GHGE emission impact by 5-7% while reducing health impacts by 19-41% for the short-term goal of 2030. This novel decision support system assists our understanding of choices' potential health and environmental implications.

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CHAPTER FOUR

4 A food system sustainability compass: A case of a Dashboard for Improving Sustainable Healthy Food Choices for stimulating consumers toward sustainable and healthy diet choices.

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Abstract

Consumers choose what to eat considering the taste, nutrition, safety, and, perhaps more recently, the environmental friendliness of the food. Recent evidence suggests that nearly 20% of the total annual mortality in the United States is attributed to unhealthy food choices. Also, unhealthy food choices are a significant threat to environmental sustainability. Previous studies have typically implemented either nutritional and health nudges or environmental labels to influence consumer decision-making. However, very few studies have simultaneously assessed consumer food choices considering both dimensions. Here, we present a Dashboard for Improving Sustainable Healthy (DISH) food choices, an intuitive and transparent toolbox that simultaneously maps out environmental footprints, nutritional, and health implications of food products. The results on the DISH simulator are based on an integration of environmental life cycle assessment and nutrient and health profiling. Furthermore, this study examined the influence of a novel score, the Environmental-Nutritional Score (EnN score), and its associated nudges on consumer choices when applied to two fast foods. A sensitivity analysis revealed the robustness of the EnN Score with variations between 0.75% and 1.31% when comparing the two products. The EnN score for the food products was 2 and 3 with associated nudge interventions of "Don't eat too often" to "This food is encouraged." The results of data collected from 112 correspondents suggest that, with the EnN score, less cognitive processing was required to make healthy and sustainable decisions. Statistical inspection of the results suggested that factors such as DISH modules, nudges, awareness, and diet patterns considerably influenced healthful food choices (sig<0.001). 41.9% of participants purchased foods with 'higher EnN score ratings' for the food categories. Also, 64.3% of participants rated the DISH simulator 4-star and 5-star, strongly suggesting the effectiveness of the concept during the purchasing decision. The data support the idea that EnN scores and corresponding nudge interventions could be extended to the American

community's fast foods. It also suggests the need to re-align how environmental-nutrition messages are reinforced among consumers to stimulate purchasing decisions.

Keywords: EnN score, sustainability, nudging, simulator, environmental footprint,

5 Introduction

In the United States (U.S.), over 78 million people are estimated to be obese, associated with chronic diet-related diseases such as coronary heart disease, stroke, type 2 diabetes, and colorectal cancer [1, 2]. These diseases are responsible for seven out of ten deaths in the U.S., killing more than 1.7 million Americans annually [3, 4]. The high prevalence of obesity-related chronic diseases has been linked with consumers' food choices and unhealthy dietary patterns [5-8]. Aside from this, nearly 117 million people, thus about 50% of American adults, have one or more chronic diseases [4, 9]. Many of these diseases are preventable as they are related to unhealthy dietary patterns [10-13]. Currently, obesity-related illness estimated health care cost is a staggering $190.2 billion annually in the U.S [14]. Looking forward, researchers stipulate that if consumer dietary patterns continue to go unchecked and the current trends persist, the medical cost and its associated economic loss in productivity of obesity-related illness could rise by $48 to $66 billion and as high as $580 billion in the U.S. by 2030 [15]. Hence, it is essential to take pre-emptive actions to develop levers to reduce and control these conditions.

At the environmental level, our food choices contribute to 48-79% of water and land resource consumption at the household level [16]. Furthermore, consumer food expenditure has been identified as a pivotal contributor to environmental concerns such as climate change [5]. Recent studies have also mapped out the environmental impacts of consumer food choices, demonstrating that a simple shift to low-carbon food choices could reduce greenhouse gas emissions (GHGEs) from the food system. Weber and Matthews [17] leveraged the Consumer Expenditure Data (CEX) reported by the U.S. Bureau of Labor Statistics to estimate the GHGEs from U.S. households. Although this was at the national level, subsequent studies by Jones and Kammen [18] observed individual consumer behavior through the CEX and estimated GHGEs from individual foods. Boehm, Wilde [19] linked the U.S. household food expenditure data from the National Household Food Acquisition and Purchase Survey (FoodAPS) to the Economic Input-Output Life Cycle model to establish a correlation between GHGE's different household socio-demographics. However, these studies failed to link consumer choices to their health, as health and environmental concerns pose a significant challenge to consumer quality evaluation of food.

Other researchers have developed digital solutions such as online household carbon footprint calculators to reduce emissions regarding consumer lifestyle choices [20]. However, one fundamental limitation is that this platform does not provide an educational component for consumers to understand the impact of their food choice on climate change and other environmental burdens such as eutrophication. There are several technology-based tools to help consumers record or monitor their dietary intake at set intervals. These tools include scanner-and-sensor-based technologies [21, 22], web/computer-based technologies such as the Automated Self-Administered 24-hour dietary recall (ASA24) [23], or mobile technologies such as MyPlate [24]; or Lose It! [25]. While these tools allow consumers to track their diet, they require users to record the time and type of food, usually after purchase. These tools do not satisfy the increasing consumer desire to understand how their food choices impact environmental sustainability. Above all, a recent consumer report by International Food Information Council 2021 Food & Health Survey (IFIC 2021) revealed that almost 60% of consumers recognize the need for food products they purchase or consume to be produced in an environmentally sustainable way, thus an increase from 54% in 2019. However, there is not a tool available to provide consumers the capability to assess the impact of their food expenditure on GHGEs and evaluate the nutritional implications and economic cost of their food choices. Therefore, this presents an opportunity to provide consumers with an easy-to-use tool grounded on the best science to provide decision support for real-time exploration of different food choices to improve health and environmental impact at the time of purchase because when these tools or the information are deployed at the point of decision-making, there is a higher chance of influencing consumer behavior [26].

In recent years, many interventions, including behavioral, lifestyle, economic measures, and legal regulations, have been tested and promoted to increase consumer consumption of healthier foods. Among the existing interventions and strategies, methods targeting consumer perception, instead of those limiting consumers' choices, seem to have a more significant impact on improving the effectiveness of healthy diet campaigns [27]. These methods are often associated with the term "nudge," which refers to changing people's behavior without the constraint of options [28]. Because the environment in which individuals make choices can be altered and influence the decision-making processes, nudging focuses on enabling and changing behaviors and decisions that are beneficial for society (*e.g.*, public health) rather than delivering information or changing society's values system. For example, a school cafeteria in New England (North America) asked their students—before they ordered their meals—whether they would have fruit or juice with their lunch, and the intervention resulted in 70% of students consuming one of those options in opposition to 40% in the control group [29]. An intervention at a buffet restaurant in Denmark changed the sequencing design of its service, combining and separating fruits and vegetables. The change increased self-served fruits and vegetables while reducing the total calorie intake [30]. Gonçalves, Coelho [26] demonstrated how a social norm nudge, a message conveying fruit and vegetable purchasing norms positioned strategically in a Portuguese supermarket, affected consumers' purchasing habits categorized as less healthy and healthy. The study measured 1,636 customers over three months. The results demonstrate that the nudge intervention positively affected the purchasing habit of consumers categorized as less healthy, while those with healthy habits were slightly negatively affected.

With the ongoing challenges related to sustainability and nutrition, the information used for implementing a food choice nudge is essential. Research shows a poor understanding by consumers of the dynamic relationship between dietary choice, the food ecosystem, and other interrelated systems [6, 31, 32]. This is because the information which may be effective in improving consumer food choices, such as nutrition information, is complex and difficult to convey in a clear and actionable manner. Although consumers in the U.S. [33] and Europe are knowledgeable about climate change [34, 35], they remain uninformed about the broader environmental impacts of their food choices [36, 37]. Therefore, simple, graphic, and easily understandable messaging will be critical to delivering a digital platform that promotes healthy and sustainable choices and supports chronic disease prevention.

Therefore, this study presents a digital platform that leverages the benefit of both worlds and is an excellent opportunity to enhance consumer health while meeting their sustainability goals. The current literature supports the effectiveness of informational and nudging techniques to reorient consumer behavior toward sustainable food consumption [38-40]. Therefore, implementing nudges using a novel digital technology is based on the assumption that we can cumulatively achieve considerable positive health and environmental impacts by guiding people toward small, subtle adjustments in their daily dietary routines. We **hypothesized** that providing information on nutritional and environmental implications of consumer food choices will lead to healthy and sustainable food intake that supports chronic disease prevention and minimizes diet choices' environmental impact. The proposed digital platform, Food Choices Overview Dashboard (DISH): (a) draws practical attention to the nutritional implications of diet choices and how it contributes to healthy living at the point of food choice/decision-making. This was achieved by translating the assessment of the potential risk components (total energy, total sugars, saturated fat, sodium) of the two food products in alignment with the U.S. dietary guidelines using the Health Star rating and Food Compass score algorithms. The Health Star Rating algorithm generates a score rating from 0.5 to 5.0 stars, signifying least and most healthy, respectively. (b) provides consumers with environmental impact information of chosen foods (ecosystem quality and human health impact). This was achieved by conducting a case study's environmental life cycle assessment and translating the results into monetary burdens using Ecotax and Ecovalue monetization techniques. (c) Provide an interactive avenue for environmental-nutrition trade-off analysis and comparison of different choices to enable consumers to make an informed decision. To test and validate the effectiveness of DISH, two fast-food menus are compared and tested among 112 individuals. DISH presents an opportunity to integrate the present consumer food data streams to drive food choices toward sustainability and health. The technology acts as an intelligence hub between nutrition and health modelling, environmental life cycle assessment, and decision-making, unlocking the true potential of consumer food choices at the point of purchase. The remaining part of the paper proceeds as follows: Section two presents the methodology employed in this study. The third section presents the findings of the research, focusing on three key themes: (a) an analysis of the results of the life cycle assessment and nutrition and health modelling, (b) the development of the decision support system, and (c) data gathered from consumer testing of the DISH.

6 Method

6.1 Method framework

In recent years, the dilemmas between health and environmental impacts have motivated consumer purchase of either meat or plant-based alternatives. Aside from this, nudges associated with different food products have also stimulated consumers toward certain decisions [41]. This section proposes a method framework that integrates health and nutrition profiling, environmental impact quantification, and nudges into a decision support system. The method framework adopted for this study consists of five stages (Figure 1). The first step focuses on calculating the Health Star Rating (HSR) and Food Compass Score (FCS) to provide a degree of healthiness and nutritional perspective to promote healthy diet choices among consumers. The HSR algorithm consists of five steps: determining the food product category, identifying its relevance toward policymaking, the form of product, calculating the baseline and modifying scores, then translating these scores to HSR that expands from 1 to 5 stars. Similarly, the FCS compares food through a weighted score around nine food domains ranging from 1(least healthful) to 100 (most healthful). In step two, an environmental Life Cycle Assessment (eLCA) is conducted considering a cradle-to-gate perspective using the ReCiPe (mid-point and endpoint) impact assessment method and OpenLCA software v1.10. The results of the eLCA are translated to monetary equivalence to determine the economic value of the environmental releases from the two food products. Then, the results of steps one and two are integrated into the Environmental-Nutrition Score (EnN score) using a modified multi-criteria decision modeling (MCDM) approach, which will be discussed in detail in section 2.4.3 (Step 3). Figure 1 shows a four-point scale with associated nudges is adopted to stimulate consumer choice and preference. The fourth step focuses on developing the decision support system or a simulator using an agile product development cycle. Multiple feedback, corrections, and modifications were made based on consumer feedback on the initial version of the simulator. Finally, the simulator was tested through a consumer survey to determine its influence on consumer purchases for two fast-food products: plant-based burgers and animal-based burgers. It is important to highlight that animal-based burgers are made from cattle beef. In contrast, plant-based burgers contain major ingredients such as black beans, soy, wheat, rice, and other ingredients highlighted in the Supplementary Document. The survey results were analyzed using the Statistical Package for Social Science (SPSS) software 28.0.

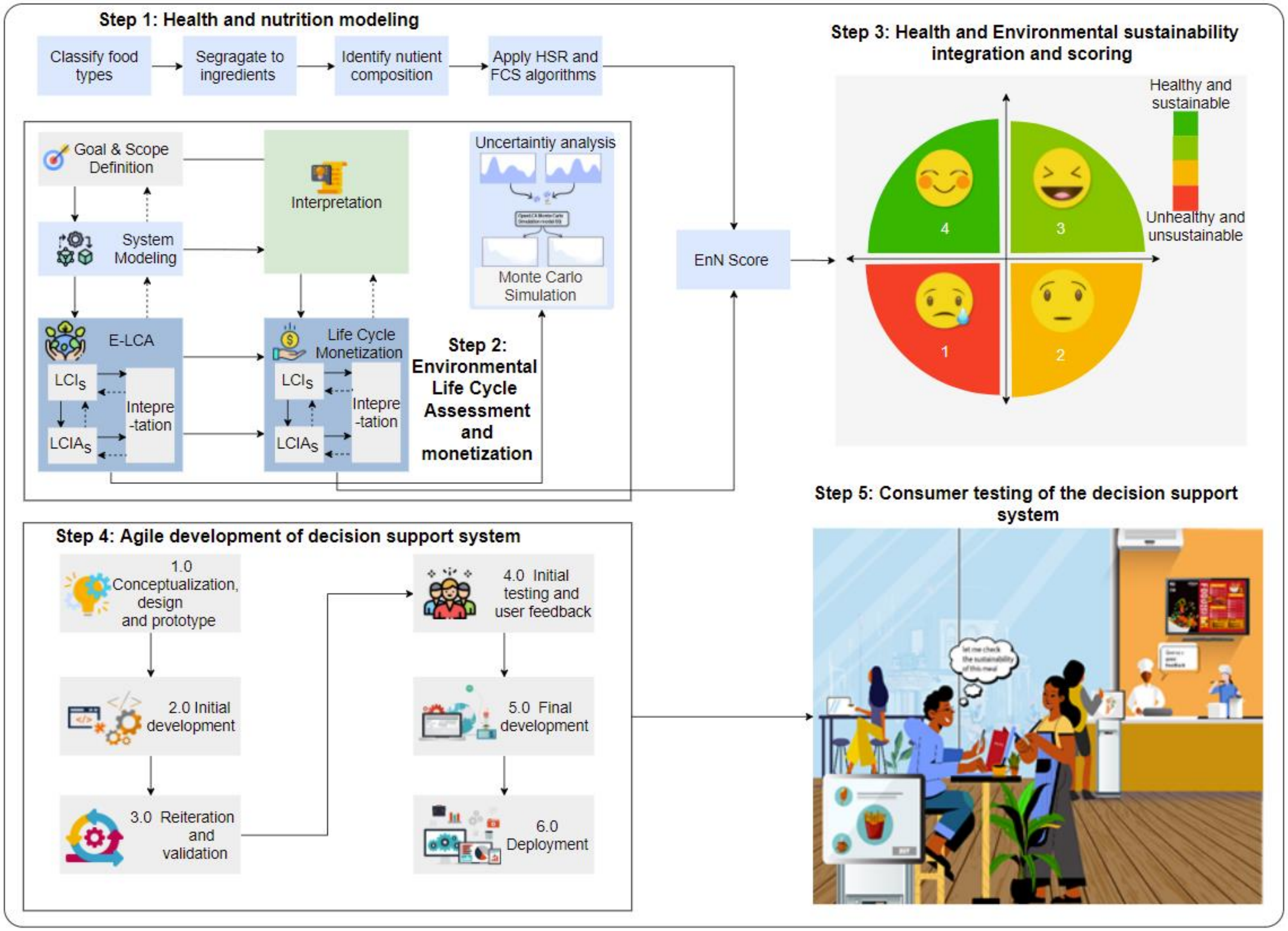


Figure 17: Method framework adopted for the study

6.2 Health and nutrition modeling

6.2.1 Calculating Health Star rating

In high-income countries, processed food constitutes about two-thirds of the total dietary intake, which implies its substantial influence on the population's health. As many such recommendations and nutrient profile guides have been implemented to improve nutrition literacy, guide consumers, and promote healthier diets. Among these is the HSR score; the HSR is a metric adapted to relay the healthiness of a food. This metric was adopted because it provided an easy approach to comparing two products with similar ingredients and had a graphical approach that consumers readily understood. The HSR of the two food products adopted was calculated according to the "Guide for Industry to HSR calculator"[42]. First, baseline values were calculated using the American Dietary Recommendation on the calories, saturated fat, total sugar, and sodium content per 100g. The four components are considered due to their negative association with increased risk of chronic disease. Next, modifications were calculated for Fruits, Vegetables, Nuts, Legumes (FVNL%), protein, and fiber. Then, the HSR score was computed by the difference between the baseline and modifying points. Finally, the score was converted to the rating system based on a predefined scoring matrix and food category (See Eqn 1.0). The HSR ranges from 0.5 to 5.0 stars: thus, the higher the star rating, the healthier the product.

$$Final\ HSR\ score\ = HSR\ baseline\ points\ - (\mathrm{V\ points}) - (P\ points\ ) - (F\ points) \qquad (1)$$

Where $HSR\ baseline\ points$ captures the energy, saturated fat, total sugars and sodium, $V\ points$ consist of HSR fruits, vegetables, nuts and legumes, $P\ points$ represents the protein content, and $F\ points$ represents the fiber content of the selected food.

6.2.2 Calculating Food compass score

The FCS algorithm utilized nine domains: Nutrient ratios, vitamins, minerals, food ingredients, additives, processing, specific lipids, fiber and protein, and phytochemicals. Each of the nine domains consisted of different attributes against which scores were calculated (See Supplementary Document). In total, 54 attributes constitute the nine domains of the FCS. Next, an average value was calculated to represent each domain, then summed to provide a food compass for each food product. It is important to mention that three specific domains: fiber and protein, lipids, and phytochemicals, were half-weighted. The final compass score ranged from 1 to 100 representing least healthful and most healthful, respectively. The final compass score was calculated using Eqn 2.0 presented below

$$FCS\ = 100 - \left(\frac{\max score\ - original\ score}{score\ range}\right) \times 99 \qquad (2)$$

Where the original score is obtained when each domain score is calculated as an average of their respective attribute score for the desired product, and then the domain scores are summed. The max score is the maximum score a product can obtain across all domains.

6.3 Environmental Life Cycle Assessment

The eLCA is an approach adopted to evaluate and quantify the impact of processes, products, and systems, considering different inputs and outputs at different life cycle stages. The eLCA adopted for this study was according to ISO 14044 standards [43]. The following paragraph provides the general steps adopted to complete the eLCA of the two food products.

6.3.1 Goal and scope

The goal of the eLCA is to compare the environmental impact per serving of two different burgers available in the United States. The first burger comprises beef, while the other consists of major ingredients such as black beans and soy plant substitutes. The functional unit adopted for the two products in this study were: plant-based burgers (414g) and animal-based burgers (431g) per serving, ready for consumption. In addition, 284.6 g of plant-based burger patties and 268 g of animal-based burger patties per serving were adopted during the modeling processing.

6.3.2 System boundary

Since the proposed simulator, DISH, is postulated to guide consumers' decisions at the point of purchase, a cradle-to-consumer approach (cradle-to-gate perspective) was adopted for a ready-to-eat burger. The end of life of the two burgers was excluded from the analysis because it was assumed that the end-user was immediately consuming the food product. Figure 2 presents the system boundary to produce plant and animal-based burgers.

6.3.3 Life cycle inventory

This study relied on secondary data from National Agriculture Statistic Service Quick Stats (NASS Quicks Stat), Roman L. Hruska U.S. Meat Animal Research Center (USMARC), USDA NASS Agricultural Chemical Usage Field Crops Summary Reports, USDA Agricultural Service Report, USDA FoodData Central and other published sources. Table SD10 to SD14 of the Supplementary Document provides a detailed inventory for the eLCA of cattle feed cultivation, production, slaughter, packaging, and distribution to retailers and burger-producing outlets. These processes were modeled after the works of [44], who conducted an eLCA on beef production systems in the United States. However, the process was modified to include ground beef production, burger pattie, and a full burger ready for consumption after the production step. The feed cultivation step constituted an inventory of corn silage, grain, Alfalfa, pasture (grass), and utilities.

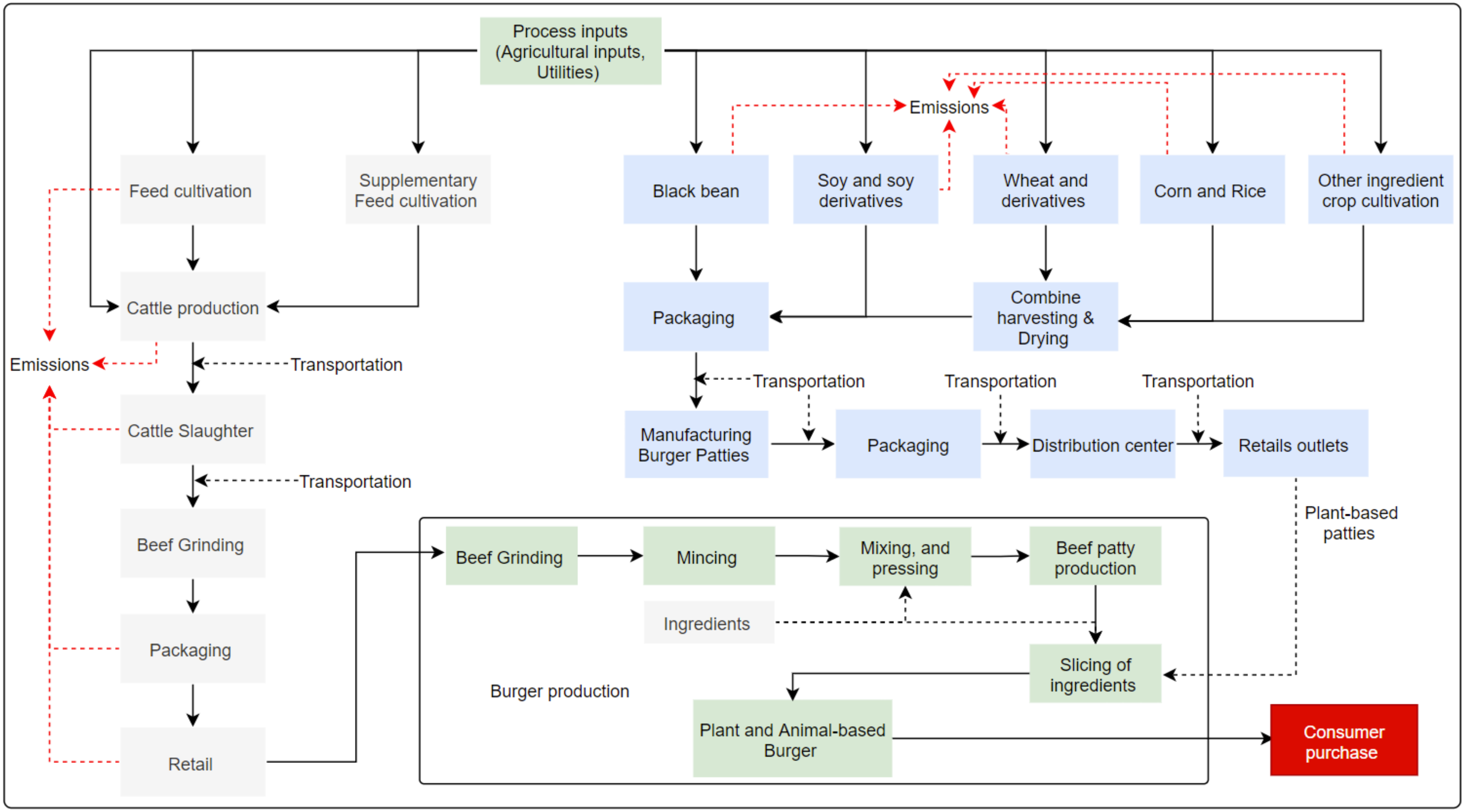


Figure 18: System boundary for beef-burger and plant-protein alternative burger production

Similarly, cattle production consisted of supplementary feed, utilities, and feedlots. Additionally, all chemicals used in cattle slaughter and conversion to beef were considered. The by-products of the cattle slaughtering step to produce beef included: food-grade bones, muscle, blood, edible offal, hide, and Fat C3, which received an economical allocation of 12.5% for the cattle slaughtering step. The packaging level included packaging materials (cardboard), consumables, utilities, and transportation in the inventory. The retail process captured packaging resources (such as paper labels), consumables, land use, waste, utilities, and transportation to burger-producing outlets. Runoff, leaching, and operational emissions were described for some value stages. The beef-based burger production step was modeled after USDA FoodData Central data and other online sources. This consisted of mincing ingredients (such as onions and garlic), mixing, forming, and roasting burger patties, roasting buns, and slicing additional ingredients or toppings such as tomatoes and onions.

Likewise, Table SD1 to SD9 consists of the inventory for the plant-based protein-rich alternative, made from eighteen different crops with black beans, wheat, soy, cooked brown rice, and corn as the predominant ingredients. Cultivation of the raw materials for the predominant ingredient was modeled using data from NASS Quicks Stat. After harvesting, corn, wheat, and rice were assumed to be dried to acceptable limits of 12%, 13%, and 12%, from an initial moisture content of 19.4%, 20%, and 21%, respectively. This assumption was made according to the recommendations of USDA agricultural commodity requirements. This assumption was applied to the corn silage and corn grain used for cattle production.

Notwithstanding, Alfalfa, a feed for cattle production, is often dried in open space, while beans are left to dry to an acceptable limit before harvesting; hence inventory was not included in the drying step of these agricultural commodities. The inventory for plant-rich-protein burger patties was modeled after Morningstar Spicy Black bean burger patties published life cycle reports. All emission factors associated with crop cultivation were estimated using the 2019 refinement of the 2006 IPCC Guidelines for Greenhouse Gas Intervention Tier 1 model (See Supplementary Document for the equations of this choice of method). The energy and electricity needed to achieve the drying limits for each crop were estimated using the Iowa State University Research Farm 2015 progress report. The plant-based burger inventory consists of crop cultivation, harvesting, processing ingredients (fiber, flavor, oil, legume-based additives, and proteins), transportation, plant-burger pattie production, and full burger production. The recipe adapted to produce plant-based and animal burgers were cross-referenced with USDA recommendations. Tables 1 and 2 summarize the inventory, data types, and sources for the respective life cycle phases adopted in this study.

Table 12: Summary of inventory data types and sources for a plant-based burger (See SD Tables S1 to S9 for complete inventory data)

S/N	Life Cycle phase	Process flow	Source
1	Cultivation	Field data, Fertilizer, Pesticides, Other chemicals, Utilities, Emissions	NASS Quick STAT Pradhan, Shrestha [45] IPCC model, 2019 update (Tier 2)
2	Raw material production	Spices, Onion powder, tomato juice and ketchup, red bell pepper, and auxiliary ingredients.	Ecoinvent 3.3 Agribalyse
3	Harvesting and field processing.	On-farm combine harvesting, drying of corn, wheat, and rice, rice processing (milling), and transportation to a storage facility.	Morning Star Farm, USDA Iowa State University Research Farm Progress report 2015.
4	Packaging and Transport	Folding boxboard carton Cardboard	Ecoinvent 3.3
5	Burger Pattie manufacturing	Utilities(Electricity, Natural gas, water), wastewater, solid waste	Morning Star Farm LCA report
6	Packaging of Pattie	Plastic film, Adhesives, WHDPE	Morning Star Farm LCA report
7	Transportation to retail	Transportation to distribution centers and retail, distance traveled	Morning Star Farm LCA report
8	Whole Burger production	Ingredients, plant-rich-protein pattie	Morning Star Farm LCA report, USDA FoodData Center

Table 13: Inventory data types and source for animal-based burgers (See SD Table S10 to S14 for complete inventory)

S/N	Life Cycle phase	Process flow	Source
1	Feed Cultivation and Supplementary feed	Field data (corn grains, corn sillage, pasture), Fertilizer, Pesticides, Other chemicals, Utilities (land area, water consumption, energy or fuel), Emissions to the soil, air, and water(Nitrous oxide)	Ecoinvent, BASF, 2010 NASS Quick Stats, Pradhan, Shrestha [45], IPCC model, 2019 update (Tier 2)
2	Cattle production	Supplementary feed, Primary feed, Utilities (water, energy consumption), Feedlot operations, calf Transport of feed, emission to air, water, and soil (enteric methane), excretions during grazing	IFSM BASF 2011
3	Cattle slaughter and chilling	Chemicals, Disposal of animal by-products, transport	Ecoinvent

4	Packaging and transportation	Packaging resources (Allumion alloy, HDPE, Latex), consumables, utilities, transportation, emissions, waste	Ecoinvent 3.3
5	Ground beef production	Deboning of beef, fresh trimming, and grinding	Ecoinvent
6	Retail	Packaging, consumables, land uses, utilities, transport, air emission, waste	BASF 2010
7	Burger Pattie manufacturing	Utilities (electricity, natural gas, water	BASF, 2011, Ecoinvent, U.S. Life Cycle Inventory (LCI)
8	Preparation of ground beef Pattie	Ground beef, ingredients, source of heat, electricity	USDA FoodData Center Online resource
9	Whole Burger production	Ingredients, ground beef-burger pattie	USDA FoodData Center

6.3.4 Life cycle impact assessment

The eLCA of the two food products was modeled in OpenLCA v1.11.01 working environment using Ecoinvent cutoff LCI and Agribalyse database. It is an open-source software developed by Green Delta. The environmental impact assessment of the two products relied on ReCiPe 2016 Mid-point (H) and Endpoint (H) impact assessment methods. The ReCiPe method presents eLCA results of a modeled product system in sixteen mid-point impact categories and twenty-two endpoint impact categories which cover: global warming potential, non-renewable energy use, land use, and respiratory inorganics. The endpoint results are further aggregated to reflect three areas of protection: human health, ecosystem quality, and resource use. In addition, the world 2010 (H) normalization method was applied during the assessment.

6.3.5 Life cycle monetization(LCM)

Life cycle monetization is a methodology to determine the economic value of the environmental releases on society during eLCA. It provides a single score or weight that conforms to the ISO standard 14040/44 [46]. Also, the monetization approach captures the trade-offs between the human health, ecosystem, and resource scarcity endpoint categories during eLCA. In this study, the eLCA results were monetized using the Environmental Prices monetary perspective. However, in the absence of appropriate equivalent monetary values for impact categories, proxies from the MMG method and Ecovalue were adopted. It is important to mention that the monetary units adopted were presented in 2015€. Hence a conversion was performed according to the ISO 14008 guidelines, which provide a monetary evaluation framework of environmental impacts. In other words, the monetary values were inflated by the consumer price index and then transformed to 2022-$\$_{eq}$ by purchasing power parities using the relations presented below:

$$X_t = X_b \times \frac{CPI_t}{CPI_b} \qquad (3)$$

Where X_t is the currency in the target year, X_b for the currency in the base year, CPI is the consumer price index in the years ***t*** and ***b*,** respectively. According to the U.S. Bureau of Labor Statistics, the inflation value was 21.98% between 2015 and 2022. Table 3 presents the monetary values per impact category adopted for this study. The environmental prices can be based on either environmental price as a weighting factor or an external cost; however, the latter is adopted to quantify the external environmental cost. The environmental price as an external cost combines the hierarchist and individualistic perspective of the ReCiPe mid-point assessment method.

Table 14: Environmental prices per impact category for LCM

Impact category	**Reference unit**	€2015 to 2015 $	**$2019 to $2022**	
Fine particulate matter formation	2015 €/kg PM10-eq	39.2000	$	57.8097
Fossil resource scarcity	2019 €/M.J.	0.0105	$	0.0155
Freshwater ecotoxicity	2015 €/CT Ue-e	0.0361	$	0.0532
Freshwater eutrophication	2015 €/PO4–e	1.8600	$	2.7430
Global warming	2015 €/kgCO2–e	0.0570	$	0.0841
Human carcinogenic toxicity	2015 /kg 1,4 DB-eq.	0.0991	$	0.1461
Human non-carcinogenic toxicity	2015 /kg 1,4 DB-eq.	0.0991	$	0.1461
Ionizing radiation	2015 €/ kg kBq U23 5-e	0.0461	$	0.0680
Land use	2015 €/m².a	0.0845	$	0.1246
Marine ecotoxicity	2015 €/kg 1,4 DB-eq.	0.0074	$	0.0109
Marine eutrophication	2015 €/ kg NO3-e	3.1100	$	4.5864
Mineral resource scarcity	2019 €/ kg Sb-e	6.6500	$	9.8070
Ozone formation, Human health	2019 €/ kg NOx eq	0.0100	$	0.0147
Ozone formation, Terrestrial ecosystems	2019 €/ kg NOx eq	0.0100	$	0.0147
Stratospheric ozone depletion	2015 €/Kg CFC–11–e	30.4000	$	44.8320
Terrestrial acidification	2015 €/Kg SO2-e	4.9700	$	7.3294
Terrestrial ecotoxicity	2019 €/kg 1,4 DB-eq	8.6900	$	12.8155
Water consumption	2015 €/m³	0.0010	$	0.0015

(Note: water consumption, fossil resource scarcity, and mineral resource scarcity were adapted from the EPS and MMG method, respectively, with a baseline year value of 2019)

6.3.6 Uncertainty analysis at the LCI and Life Cycle Impact Assessment (LCIA) level

To ascertain the validity of the conclusion of the eLCA, an uncertainty analysis was conducted using Monte Carlo Simulation with 1000 iterations using OpenLCA software. This allowed the authors to estimate the uncertainty ranges to conclude the respective environmental impacts. Uncertainties associated with the inventory data are introduced at the LCI level, and its cumulative effects are translated to product system models during impact assessment. The Monte Carlo Simulation relies on the predefined probability distribution of the LCI model. It runs it repeatedly for 1000 iterations to allow statistical analysis of the characterized LCIA profiles of the two product systems. In this study, LCI models were assumed to be of a lognormal distribution, further validated through statistical analysis of LCIA profiles. The statistical analysis was performed using MATLAB functions which measure the variabilities and uncertainties in the simulated inventory containing the impact parameters. Maximum likelihood estimation was applied to assess the characteristics of the LCIA profiles using nine hypothetical distributions thus normal, lognormal, triangular, uniform, Rayleigh, beta, gamma, Weibull, and kernel. Two test statistic parameters, p-value, and chi-squared, were adopted to compare the probability density function of each hypothesized distribution of the product system models for plant- and animal-based burgers. The simulated dataset for the product system during the LCI was assumed to be a lognormal distribution; thus, a test was conducted to check the consistency with the hypothesized distribution. The chi-squared statistic is mathematically given as:

$$\chi^2 = \sum_{i=1}^{n}(Ob_i - E_i)^2/E_i \quad (4)$$

Where *n* is the number of bins, Ob_i is the number of counts in bin ***i*** and E_i is the expected frequency of the hypothesized distribution in bin ***i***. It is important to mention that the test statistics implemented in MATLAB either reject the null hypothesis at a 95% confidence level or otherwise.

6.3.7 Limitation and assumption

The current comparative study relied on several assumptions. First and foremost, it relied on the assumption that consumers will directly eat the product at the point of purchase; thus, the packaging for a burger during purchasing for consumption was excluded. Additionally, animal-based burgers refer to burgers made from beef (cattle). The data adopted to model this burger was obtained from the USDA FNDDS database by adopting Cheeseburger (Burger King) ingredients and nutrient composition. Similarly, a plant-based burger is a rich-protein alternative made from soy, black beans, and wheat. According to the Morning Star Report, wheat used to produce burger pattie was imported from Canada; however, due to the unavailability of data, it was modeled after wheat production in the United States using NASS Quick Stats. As a rule of thumb, impact results for eLCA are monetized using the same cost perspective in life cycle monetization. However, proxies from other methods, such as MMG, were adopted due to the unavailability of scores or weights for fossil resources, mineral resources, and ozone formation.

6.4 Decision-making model: The concept of Entropy

Several subjective and objective weighting and ranking methods are commonly used in decision-making. For example, subjective methods such as the Delphi, pairwise comparison, and the Analytical Hierarchy process are often used during weight indexing. Other objective weighting indexes include the entropy method and vertical and horizontal methods. While subjective methods are prone to human disturbance and biases, leading to deviations in weights, objective methods eliminate such biases, making their results according to the information provided [47].

6.4.1 Entropy weight method

The Shannon entropy weight method is an objective weighting method that elicits the weights of criteria based on the available data and reflects its degree of dispersion. The method has been extensively studied and practically applied across the medical, social, ecological systems, engineering, and many other decision-making fields. The entropy weight method was first introduced from thermodynamics to information systems by [48]. The uncertainty of signals in communication processes is called ‘‘information entropy’’. The lower the information entropy, the higher the weight, and vice versa. It is relevant in decision-making because it clarifies the intrinsic information transferred to the decision-maker by measuring the contrasts between data sets.

6.4.2 Matrix of alternative and ist of criteria for Entropy weighting

The two products, thus plant-based burgers and animal-based burgers, served as the list of alternatives for the decision modeling. Nonetheless, to navigate the decision-making against the alternatives, a list of criteria or attributes was generated to capture the alternatives' environmental impact and nutrient and health profile. Table 4 presents a brief description of each criterion and its corresponding objective

Table 15: Performance characteristics of environmental-nutrition criteria for assessment

S/N	Criteria	Description	Objective
1	Human health cost	It describes the external environmental impact cost associated with the endpoint area of human health protection.	Minimized
2	Ecosystem cost	It describes the external environmental impact cost associated with the endpoint area of ecosystem health protection.	Minimized
3	Resource scarcity cost	It describes the external environmental impact cost associated with the endpoint area of natural resource protection.	Minimized
4	Health Star rating	It is an indicator used to measure the degree of the healthiness of food on a scale of 1 to 5.	Maximized
5	Food compass score	It is an indicator used to measure the degree of the healthiness of food on a scale of 1 to 100.	Maximized

6.4.3 Integrated health and environmental impact modeling using Entropy and linear combinations

Figure 3 presents a flowchart model of the coupled Entropy-linear combination framework utilized in this study to evaluate the environmental-nutritional implication of the two food products.

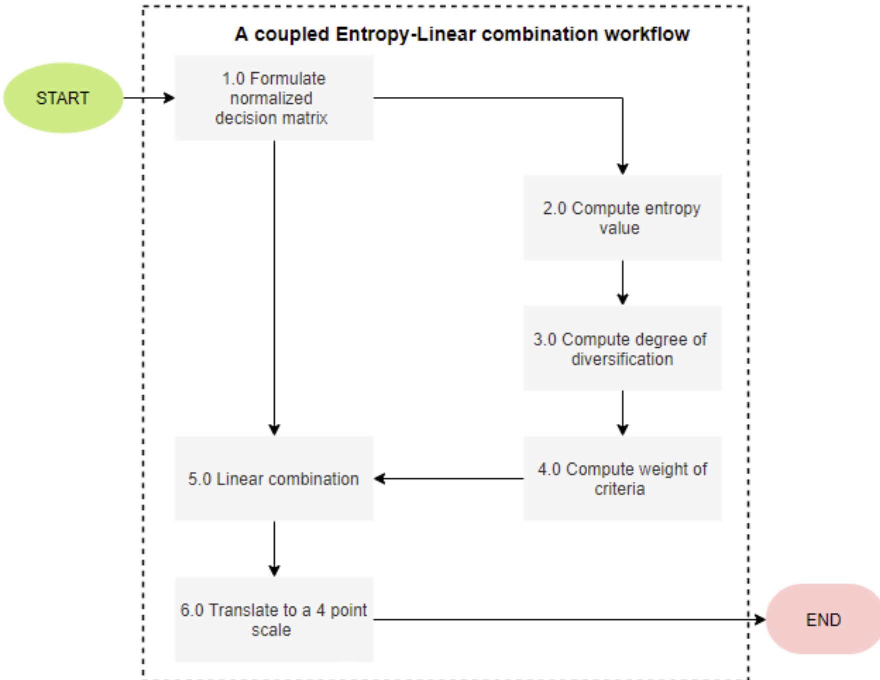


Figure 19: Flow chart of the Entropy-TOPSIS framework

The following paragraph presents a systematic description of the steps and formulas involved in implementing the framework.

Step 1: Compute the normalized decision matrix

Step 2: Compute the entropy value

The entropy value h_i is computed using Eq. (4)

$$h_i = -h_0 \sum_{j=1}^{m} p_{ij}.lnp_{ij}, \qquad i = 1, \dots n, \qquad \dots \dots \dots \dots (4)$$

where h_0 is the Entropy constant and is equal to $(\ln m)^{-1}$, and $p_{ij}.lnp_{ij}$ is defined as 0 if $p_{ij} = 0$

Step 3: Compute the degree of diversification using Eq. (5)

$$d_i = 1 - h_i, i = 1, \dots n \qquad \dots \dots \dots (5)$$

Step 4: Computing the objective weight (degree of importance) using Eq. (6)

$$w_i = \frac{d_i}{\sum_{s=1}^{n} d_s}, \qquad i = 1, ..n \quad \dots \dots (6)$$

Step 5: Compute the weighted normalized decision matrix and translate it to a four-point scale using a linear combination across

$$\sum_j^n w_j = 1$$

$$V = (v_{ij}) \;\dots \dots \dots \dots \dots (7)$$

$$where \quad v_{ij} = p_{ij}.w_j {}_{+\cdots\dots+}\; p_{nj}w_n$$

6.5 Development of a decision support system

Having conducted the eLCA, nutrient profile modeling, and implementing a modified MCDM, the next step was to translate the results into a sustainable healthy food choice simulator to navigate/stimulate consumers toward healthy and sustainable diet choices at the point of purchase. This was accomplished by following the agile product development cycle presented in the following steps. The first step focused on an initial development stage where we mapped out the user experience using flowcharts and designed a low-level and high-level fidelity user interface using draw.io and Adobe User Design tools, respectively. Next, a working prototype was developed and validated with consumers, food vendors on campus, and other key stakeholders involved in the project. The next step focused on iterating and validation**.** Here, an initial beta version of the simulator was released so that key partners could test its user-friendliness and usability. In addition, initial data was collected on the user experience and the effectiveness of the simulator in communicating the desired information to the consumer. This feedback led to the development of a second version of the simulator. The front-end development was executed using HTML and CSS programming languages during this step. Advanced libraries such as React, View, and Angular were also used in front-end development. Similarly, the back-end development database was set up using relational databases like MySQL. This stores the data in the form of tables. Also, Node.js was used as a server engine to run JavaScript or execute back-end codes. Finally, the different patches and modules of the simulator were deployed online. This step ensured that API keys, database connections, and online cloud storage keys were safely coded or secured. Next, all codes are transferred from a local computer to the server (GitHub/Gitlab). Gitlab serves as a repository to host the front-end and back-end development codes. From here, we used a hosting service such as Heroku, which connects to GitHub/Gitlab to power the application online

6.6 Consumer survey

The consumer survey and testing of the proposed simulator received ethical approval from the Institutional review board on an engaging human subject in research. Prior to the survey, all participants were given information about the purpose of the survey and were required to select a checkbox to indicate their consent as required by federal or state regulations and University of Arkansas policy. All participants who failed to give their consent were exempted from the study.

6.6.1 Questionnaire design

The questionnaire proceeded by collecting data on the demography of participants, which include: gender, age, level of education, and affiliation. Next, participants were asked about the frequency of consuming either an animal-based burger or a plant-based burger, to which six questions were asked at this level. Among these questions was a test on the predisposition of consumers' preferences prior to the experiment to fully ascertain the simulator's impact. Next, the questionnaire sought to determine the participant's smartphone behavior. Questions such as participants' frequency of using digital devices to purchase food and their level of comfortability using a five-point Likert-type were administered. Furthermore, participants were provided with the opportunity to explore the proposed simulator. After this, participants were asked about the ease and usability of the simulator, their understanding of specific indicators presented on the simulator, their recollections of results and nudges presented on the simulator, and their level of awareness of the environmental and health implications of the two food products using a Likert scale. Finally, the purchasing options and their underpinning factors, level of trust and recommendations for improving the simulator, and whether implementing it on a larger scale would aid in sustainable decisions were collected. Full details of the questionnaire administered are attached in the Supplementary Document, and the survey instrument can be viewed at [49].

6.7 Data analysis

The data collected from the survey were analyzed using descriptive statistics. The mean, standard deviation, frequency, and percentages were used to analyze the effect of sample size and were generated using SPSS version 25. The difference in frequency and continuous variables was analyzed using χ^2-square statistics, t-test, and analysis of variance. Also, a linear regression model was used to investigate the factors that influenced participants' choices of food products at the point of purchase.

7 Results

7.1 Environmental impact results

7.1.1 General LCA results

The environmental impact assessment for the plant-based and animal-based burgers across 22 endpoint impact categories is presented in Table 4. The results show that the plant-based burger has a significantly lower environmental burden than animal burgers across 21 endpoint impact categories. Thus, the environmental burden of plant-based burgers ranged from 99.63% to 19.18%, lower than that of animal-based burgers. It can be observed that impact categories such as human non-carcinogenic, land use, marine eutrophication, and stratospheric ozone depletion have lower environmental impacts for a plant-based burger when compared to the animal-based burger, corresponding differences ranging between 0.03% to 1.79%. Furthermore, to establish which impact categories were most relevant to comparing the two food products, the impacts were normalized using World Impact (2010)H method. The results illustrated that the top six impact categories are fossil resource scarcity, mineral resource scarcity, global warming, fine particulate matter, water consumption, and land use. The normalized scores for these impact categories exceeded 5E-5 person equivalence. Normalized scores are comparatively lower for a plant-based burger than an animal-based burger, thus illustrating a higher environmental burden. The mid-point impact assessment results of the two food products are presented in Supplementary Document Table SD16.

Table 16: Summary of the mid-point environmental burden for plant-based and animal-based burgers.

S/N	Impact category	Unit	Impact result	
			Animal-based burger (ABB)	Plant-based burger (PBB)
1	Fine particulate matter formation	DALY	9.32E-03	3.36E-03
2	Fossil resource scarcity	USD2013	1.06E+03	2.14E+03
3	Freshwater ecotoxicity	species.yr	2.04E-06	8.66E-08
4	Freshwater eutrophication	species.yr	3.45E-06	2.66E-07
5	Global warming, Freshwater ecosystems	species.yr	1.18E-09	9.54E-10
6	Global warming, Human health	DALY	1.43E-02	1.16E-02
7	Global warming, Terrestrial ecosystems	species.yr	4.32E-05	3.49E-05
8	Human carcinogenic toxicity	DALY	2.32E-03	9.77E-04
9	Human non-carcinogenic toxicity	DALY	1.59E-01	4.57E-04
10	Ionizing radiation	DALY	1.34E-06	7.38E-07
11	Land use	species.yr	4.64E-04	1.76E-06
12	Marine ecotoxicity	species.yr	1.18E-07	1.72E-08
13	Marine eutrophication	species.yr	2.54E-08	1.4E-10
14	Mineral resource scarcity	USD2013	7.1E+0	2.76E+0
15	Ozone formation, Human health	DALY	2.3E-05	7.54E-06
16	Ozone formation, Terrestrial ecosystems	species.yr	3.37E-06	1.17E-06
17	Stratospheric ozone depletion	DALY	4E-05	7.18E-07
18	Terrestrial acidification	species.yr	1.09E-05	3.38E-06
19	Terrestrial ecotoxicity	species.yr	1.14E-04	3.82E-08
20	Water consumption, Aquatic ecosystems	species.yr	1.48E-08	1.02E-09
21	Water consumption, Human health	DALY	5.778E-03	2.27E-03

22	Water consumption, Terrestrial ecosystem	species.yr	3.13E-05	1.37E-05

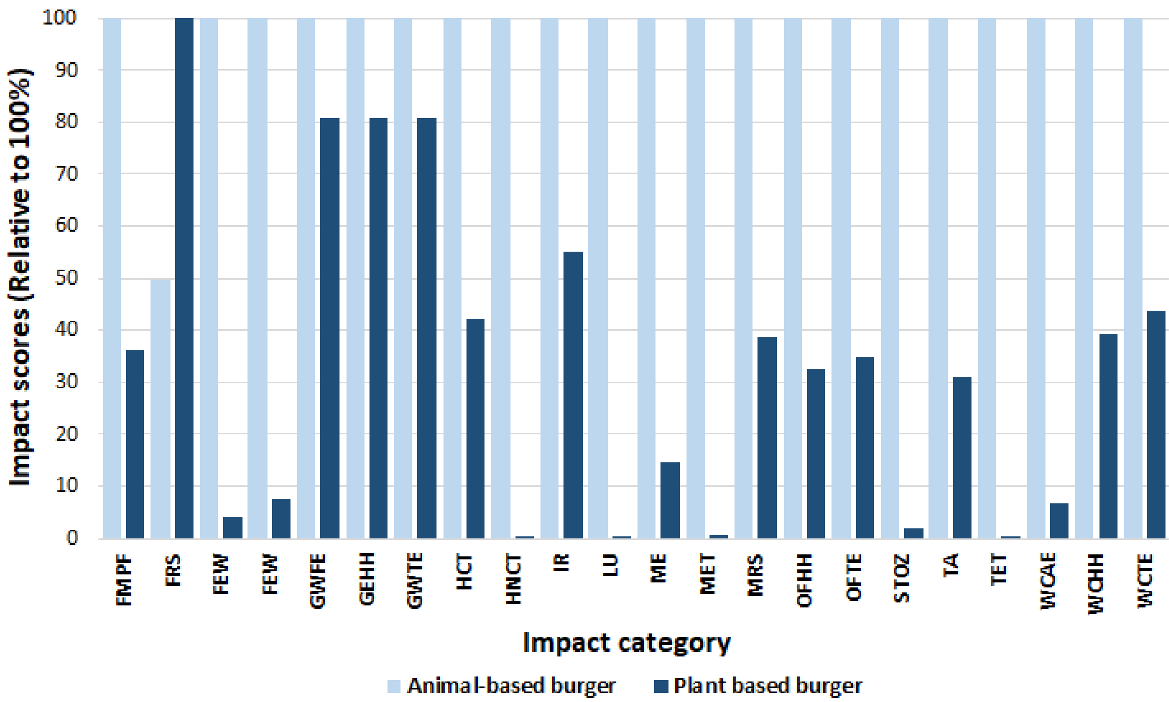


Figure 20: Environmental impact of plant-based and animal-based burgers across 22 impact categories (The meaning of the abbreviations used here are provided at the end of the paper).

7.1.2 Process contribution

Figure 5 presents the process or value chain environmental burden contribution across the 22 endpoint impact categories for plant-based and animal-based burgers. From Figure 4, feed cultivation is responsible for 32.6% to 71.8% and 52 to 83.85% of the environmental burden across all impact categories for plant and animal burgers, respectively. Hence accounting for the highest environmental impact contributor. On the contrary, the whole burger preparation process and its ingredients have the most negligible impact, corresponding to 0.67% to 10.84% and 0.01% to 3.2% for plant and animal burgers. The cattle production value chain contributed to the highest impact, thus 44.76%, 37.56, and 68.02%, for climate change, land use, and eutrophication. This is probably due to the enteric methane released during cattle grazing and production. Similarly, 55% of land use was associated with cattle production, while 24.55% was attributed to burger pattie ingredients. In the contest of plant-based burgers, the cultivation value chain contributed to 95% of the burden associated with global warming. This observation could probably be due to methane emissions from rice farms. While approximately 58% of land use for plant-based burgers was associated with cultivation. Interestingly, both food products' burger pattie manufacturing was associated with lower environmental burdens. Packaging and transport were responsible for a relatively low share of the different value chains' environmental burdens.

7.1.3 Uncertainty analysis of LCIA results

The uncertainty analysis conducted on the LCIA profiles of each product system was based on a lognormal probability distribution. A Monte Carlo Simulation was run with 1000 iterations at a 95% confidence level to estimate the uncertainties associated with two eLCA models. Table 5 presents the 95% confidence interval for the LCIA mid-point impact categories. The findings indicate that in 95% of the cases, the characterized results of the eLCA of the two product systems would fall within the upper (UL) and lower limit (LL). As shown in Table 5, the coefficient of variation ranges between 3.45% to 24.35% and 14.17 to 16.52% for the PBB and ABB, respectively. The CV is a normalized indicator that describes the disparity in the impact categories. A closer inspection of Figure 6b shows a more significant uncertainty introduced into global warming and water consumption impact scores. Impact scores for other indicators showed a lower degree of variance. Similarly, Figure 6a reveals a steady trend in the CV scores and the error bars for the impact categories. However, it does suggest a relatively high introduction of uncertainties associated with terrestrial ecotoxicity and water consumption. The uncertainty ranges illustrated in the error bars were derived from the probability distribution computed for each impact category (Figures 6c and d). Figures 6c and d show a lognormal profile for both product systems, which corroborates strongly with the hypothesized lognormal distribution at the LCI level. Additionally, the observed consistent trend in CV and error bars for the impact category can be attributed to the robustness and ability of the lognormal distribution to resist outliers at the LCI level.

Table 7 presents the best-fitting hypothesized distribution for the LCI for the two product systems. From the results in Table 7, we can affirm that the LCI model and data for the two product system exhibit a lognormal distribution and other types of distribution, such as kernel, gamma, and normal distributions. Howbeit, for animal-based burgers, only lognormal and gamma were accepted. One significant advantage of using the pre-calculated distribution in OpenLCA software is that it reduces the computational during uncertainty analysis. From Table 7, the lognormal distribution illustrated the best fit with a chi-square of 11.3090, 9.6781, and a p-value of 0.1256 and 0.1389 for plant-based and animal-based burgers. Thus accounting for less dispersion and data variability in the current LCI for the study. Also, as a rule of thumb, a lower CV suggests less uncertainty and higher confidence associated with an impact category. Thus the results imply that the environmental profiles developed for ABB and PBB food products are well represented by the impact categories and provide a more appropriate premise for impact assessment comparison. The probability density function for all impact categories is presented in the Supplementary

Document (See Figures SD4 and SD5 for a plant-based burger and Figures SD 6 and SD 7 for an animal-based burger). Figure 7 shows the animal-based burger model's distribution of six impact categories.

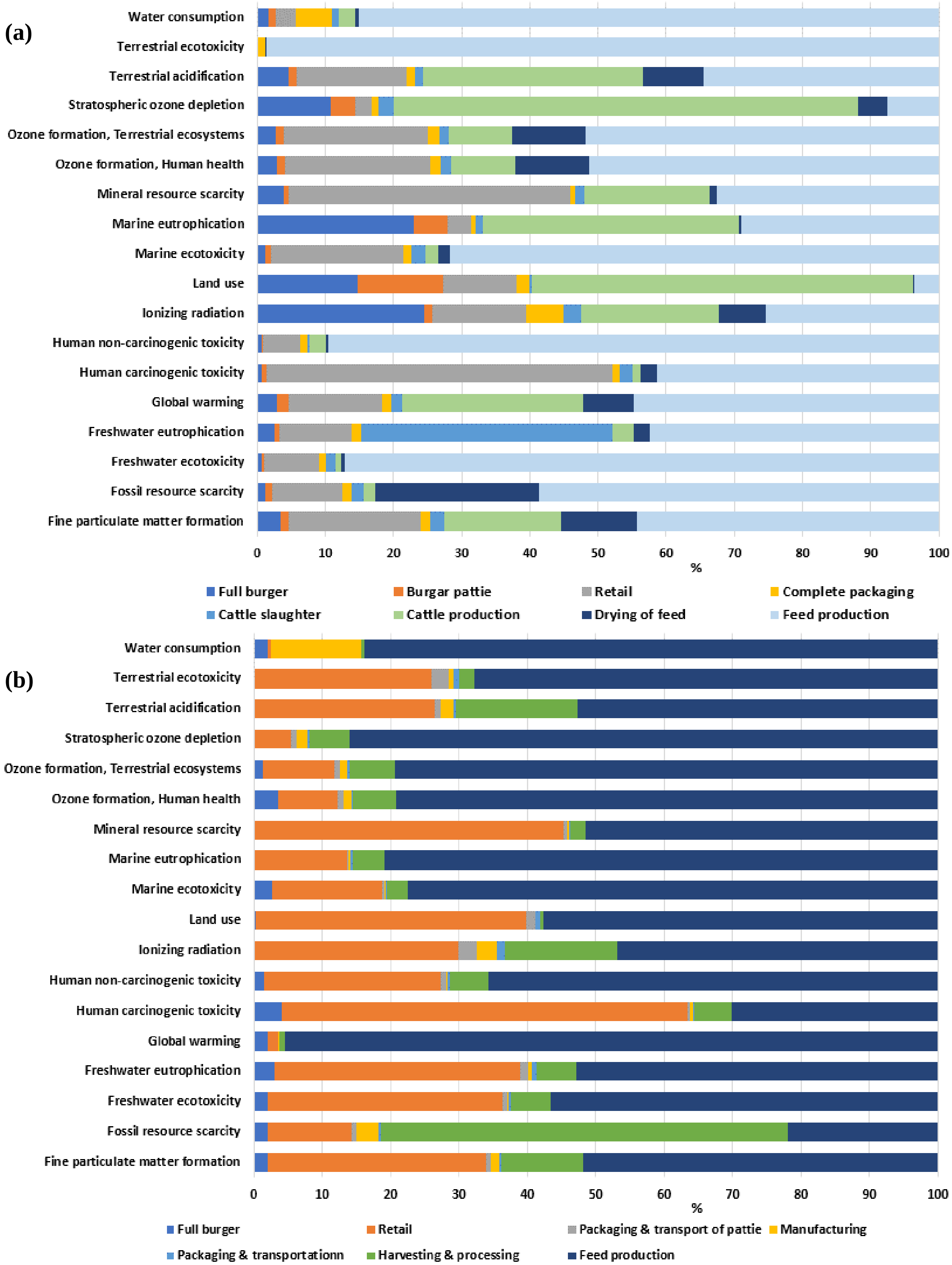


Figure 21: Environmental impact distribution of the different life cycle phases for (a) beef-burger and (b)plant-based burger

Table 17: Uncertainties for characterized LCAI profiles for plant and animal-burger

		Mean		**Standard deviation**		**CV**		**LL (5% percentile)**		**UL (95% percentile)**	
Impact category	**Reference unit**	**PBB**	**ABB**	**PBB**	**ABB**	**PBB**	**ABB**	**Plant**	**Animal**	**Plant**	**Animal**
Fine particulate matter formation	kg PM2.5 eq	1.5E+00	1.7E+02	5.3E-02	2.4E+01	3.45%	14.17%	1.4E+00	1.1E+02	1.7E+00	2.6E+02
Fossil resource scarcity	kg oil eq	2.1E+02	8.6E+03	1.0E+01	1.2E+03	4.80%	14.38%	1.8E+02	5.6E+03	2.5E+02	1.3E+04
Freshwater ecotoxicity	kg 1,4-DCB	4.7E+01	6.3E+03	1.5E+00	9.2E+02	3.21%	14.57%	4.2E+01	4.1E+03	5.1E+01	9.9E+03
Freshwater eutrophication	kg P eq	2.0E-01	1.9E+01	6.3E-03	2.7E+00	3.20%	14.28%	1.8E-01	1.2E+01	2.2E-01	2.9E+01
Global warming	kg CO2 eq	3.8E+03	3.5E+05	9.2E+02	5.0E+04	24.35%	14.19%	1.6E+03	2.2E+05	7.9E+03	5.4E+05
Human carcinogenic toxicity	kg 1,4-DCB	2.1E+02	3.9E+03	6.4E+00	5.6E+02	3.09%	14.23%	1.9E+02	2.5E+03	2.3E+02	6.1E+03
Human non-carcinogenic toxicity	kg 1,4-DCB	9.8E+02	2.7E+07	3.3E+01	3.9E+06	3.41%	14.19%	8.7E+02	1.7E+07	1.1E+03	4.2E+07
Ionizing radiation	kBq Co-60 eq	2.5E+01	7.1E+02	9.2E-01	1.0E+02	3.71%	14.20%	2.2E+01	4.5E+02	2.8E+01	1.1E+03
Land use	m2a crop eq	1.8E+02	4.7E+05	5.8E+00	6.7E+04	3.17%	14.18%	1.6E+02	2.9E+05	2.0E+02	7.3E+05
Marine ecotoxicity	kg 1,4-DCB	6.6E+01	4.5E+03	2.1E+00	6.4E+02	3.25%	14.28%	5.9E+01	2.8E+03	7.2E+01	6.9E+03
Marine eutrophication	kg N eq	3.4E-02	6.4E+02	1.1E-03	9.1E+01	3.28%	14.19%	3.1E-02	4.0E+02	3.8E-02	9.8E+02
Mineral resource scarcity	kg Cu eq	9.1E+00	2.2E+02	2.9E-01	3.1E+01	3.14%	14.20%	8.2E+00	1.4E+02	1.0E+01	3.3E+02
Ozone formation, Human health	kg NOx eq	2.9E+00	1.7E+02	1.4E-01	2.5E+01	4.72%	14.21%	2.6E+00	1.1E+02	3.4E+00	2.7E+02
Ozone formation, Terrestrial ecosystems	kg NOx eq	3.0E+00	1.8E+02	1.4E-01	2.5E+01	4.78%	14.21%	2.7E+00	1.1E+02	3.6E+00	2.7E+02
Stratospheric ozone depletion	kg CFC11 eq	2.9E-04	3.2E+00	1.7E-05	4.5E-01	5.86%	14.19%	2.5E-04	2.0E+00	3.6E-04	4.9E+00
Terrestrial acidification	kg SO2 eq	4.7E+00	1.0E+03	1.6E-01	1.5E+02	3.33%	14.16%	4.2E+00	6.3E+02	5.2E+00	1.6E+03
Terrestrial ecotoxicity	kg 1,4-DCB	2.2E+03	9.2E+06	2.1E+02	1.5E+06	9.20%	16.52%	1.9E+03	5.3E+06	3.8E+03	1.5E+07
Water consumption	m^3	1.6E+02	6.0E+03	1.7E+01	9.2E+02	10.89%	15.26%	1.1E+02	3.8E+03	2.2E+02	1.0E+04

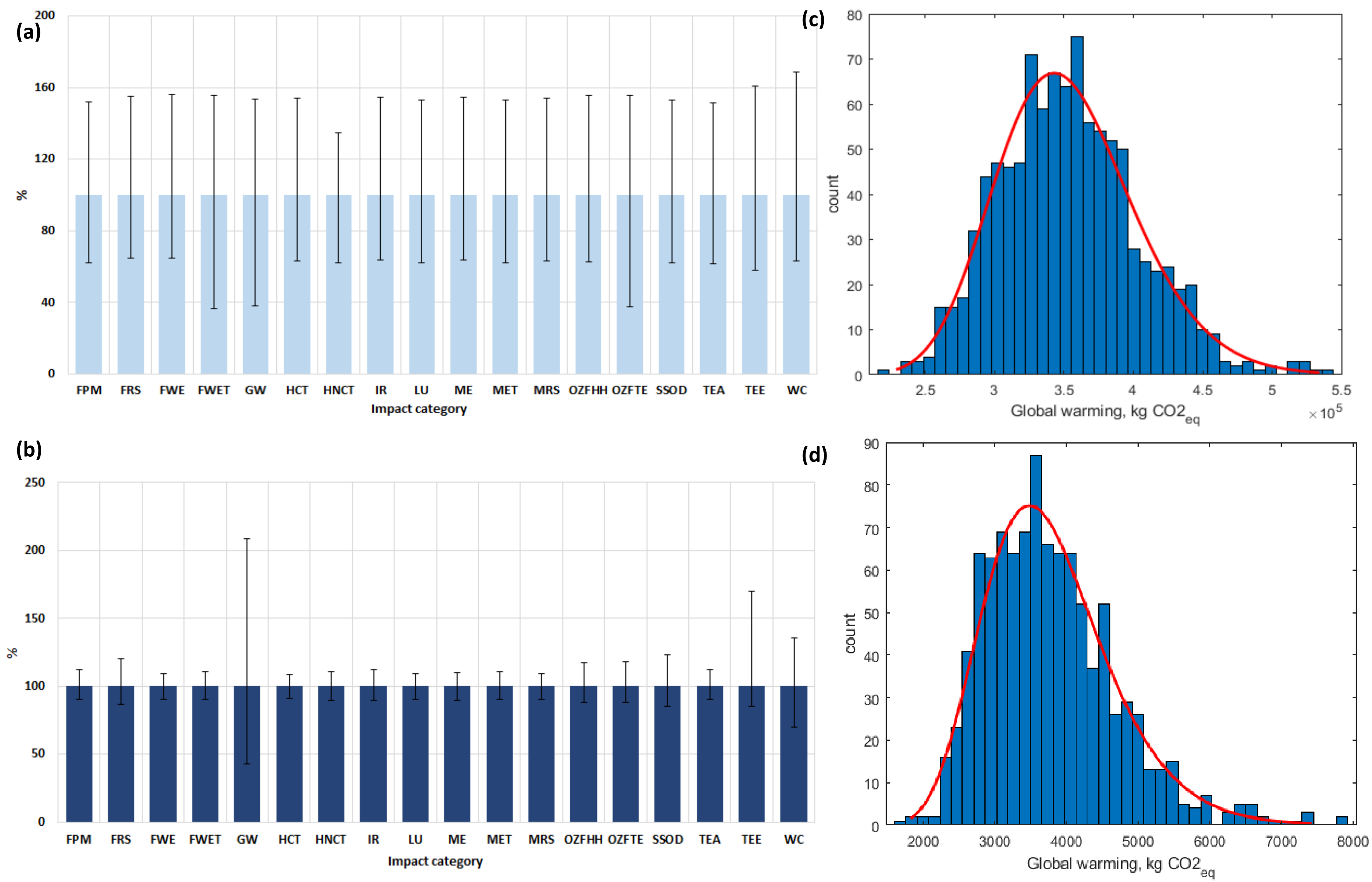


Figure 22: Uncertainty analysis for animal and plant-based burger: a and b: Uncertainties for characterized LCIA profiles; c and d: Probability distribution of characterized GWP 100 profile (40 bins each)

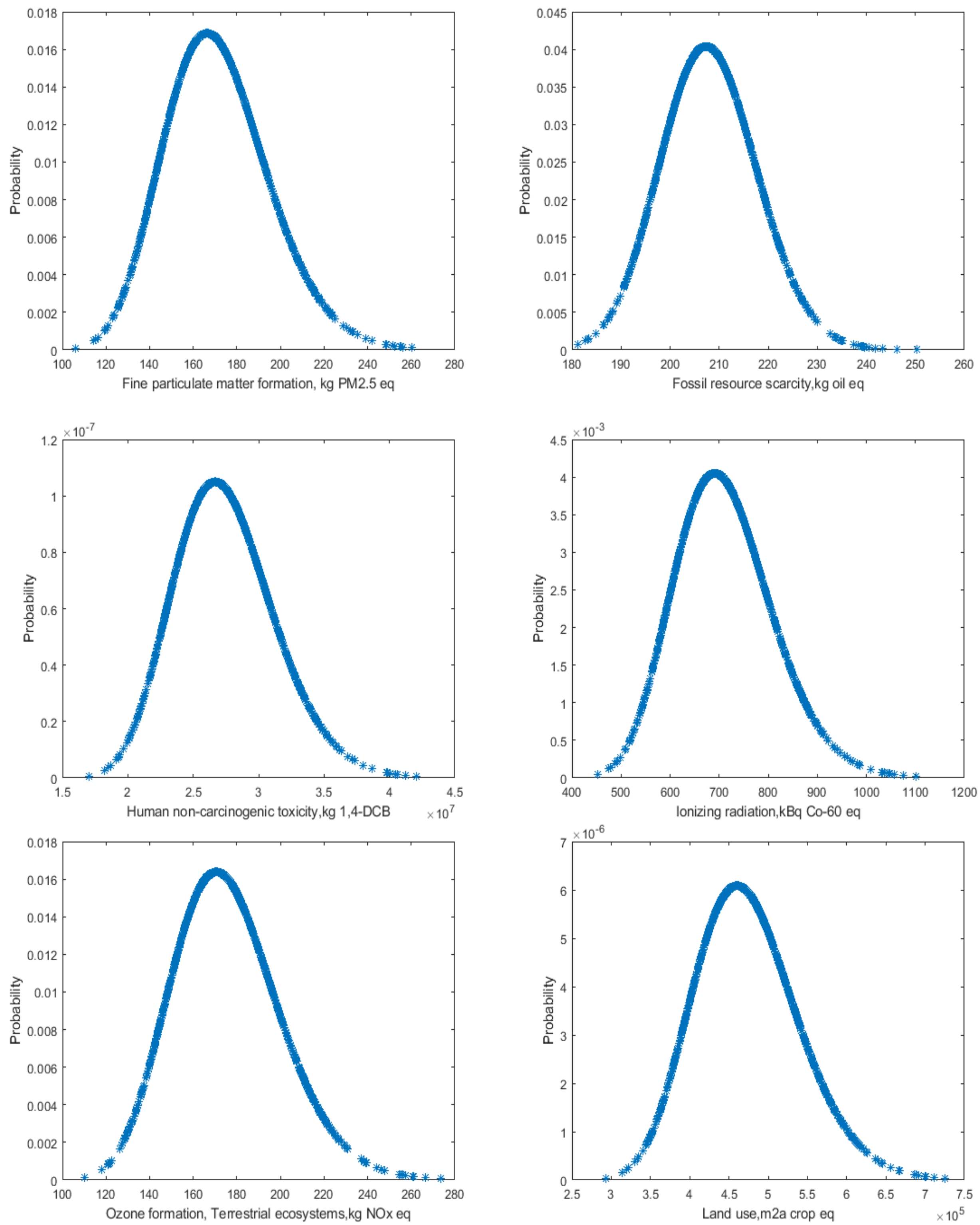


Figure 23: Probability profile for the LCAI of the animal-based burger model

Table 18: Goodness of fit results for LCIA model

S/N	Hypothesized distribution	Statistics (chi-squared)	P-value	H_o	Statistics (chi-squared)	P-value	H_o
		Plant-based burger			Animal-based burger		
1	Normal	11.9030	0.1038	Accepted	33.4751	8.4940E-6	Rejected
2	Lognormal	11.3107	0.1256	Accepted	9.6781	0.1389	Accepted
3	Uniform	Inf	0	Rejected	Inf	0	Rejected
4	Triangular	Inf	0	Rejected	Inf	0	Rejected
5	Exponential	23,166	0	Rejected	43,627	0	Rejected
6	Gamma	11.3183	0.1253	Accepted	12.5116	0.0515	Accepted
7	Kernel	8.3613	0.4982	Accepted	17,287	0	Rejected
8	Weibull	92.1244	1.09E-17	Rejected	93.6413	1.15E18	Rejected
9	Rayleigh	11,094	0	Rejected	1728.7	0	Rejected

7.2 External environmental monetization

By adopting the environmental price and MMG monetization methods, Figure 7 presents a translation of the endpoint environmental impacts into external cost capturing the different components of protection areas per serving of PBB and ABB. A threshold contribution of 1% was set for the external cost associated with the impact categories. Over 99% of the total external cost was associated with resource scarcity; thus, mineral resources and fossil resource scarcity. On the one hand, the human health costs of a plant and animal-based burger serving were \$0.2 and \$0.58, respectively. On the other hand, the associated ecosystem cost was \$0.08 and \$0.002, respectively. What is distinctive about external monetization is that it simultaneously offers a single monetary evaluation of different product systems.

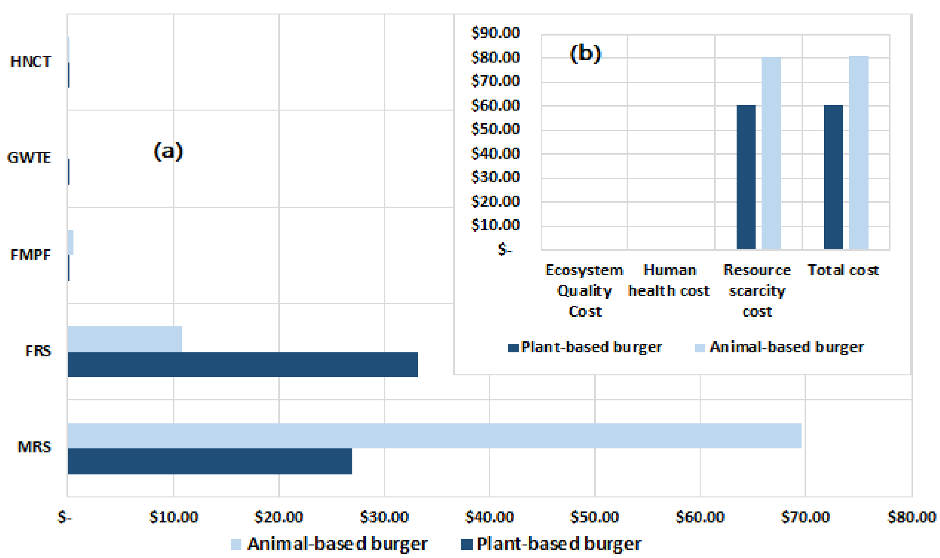


Figure 24: Life cycle costing for plant-based and animal-based burgers ((a) Mid-point cost (b) Endpoint cost)

7.3 Health and nutritional outlook

7.3.1 Health Star Rating and Food Compass Score

The HSR system provides convenient and easy guidance for consumers to make informed and healthier eating choices. It comprises the HSR algorithm, a graphic representation, and an associated nudge that serves as an educational campaign. This section presents the results of implementing the HSR algorithm and associated nudges. The graphical representation was put into effect when developing the decision support system (see section 3.5). The HSR algorithm considered the nutritional composition of the two food products (See Table 8). Therefore, the first step involves determining the category of food products. Both products are not dairy food, hence do not fall in either category one (non-dairy beverage) or three foods (oils and spread) but category two products. It is also important to establish that the calculation of the HSR of the product had no policy relevance or implications. Also, an initial assumption was made about influencing consumer choices at the point of purchase; hence steps two and three of the HSR were satisfied. In step four, the estimated HSR baseline points for plant and animal-based burgers were 7 and 19. The high value in the baseline score for the animal-based burger is attributed to the high saturated fat content of 11.8g per serving. Next, both products' HSR modifying scores of 42% and 38% corresponded to zero HSR protein points. With a dietary fiber content of 4.9g and 1g, respectively, an HSR fiber point of 5 and 1 was estimated for plant and animal-based burgers. It is important to mention that the higher the fiber points, the greater the tendency to obtain a lower HSR score which corresponds to a higher HSR rating of a product. Lastly, an HSR final score of 1 and 17 correlated to a 4-star and 1/2-star rating was computed using the category two food star rating. With the above HSR rating, a five-point nudge leveraging on a Likert scale was developed to which the plant-based burger and animal-based burger were declared "A better, healthier choice" and "a less healthy choice." Similarly, the FCS computed for the animal-based burger was 35, and that of the plant-based burger was 62. The associated nudges implemented during the study were "this type of food is not encouraged" and "this type of food is encouraged." The ratings, interpretation color code, and associated nudges developed for the HSR and FCS are presented in the Supplementary Document Tables SD20 and SD21.

Table 19: Health and nutritional composition of plant-based burgers and animal-based burgers

	Nutrient and energy	Unit	Plant-based burger	Animal-based burger
			Amount	
1	Energy	kcal	177	261
2	Protein	g	15.7	13.9
3	Saturated fat	g	6.3	11.8
4	Total sugars	g	1.07	4.85
5	Sodium	mg	569	508
6	Dietary fiber	g	4.9	1

7.4 Integration of environment and nutrition

So far, the study has presented the environmental impact, life cycle monetization of the respective impacts, and health and nutritional modeling of the two food products. This section integrates the scores for the environmental monetized cost and health and nutrition profiling of the plant and animal-based burger by deploying a coupled entropy-linear combination method. Figure 9 presents the entropy weights and degree of diversification scores for the evaluation index described in section 2.4. The entropy weight method adopted here is based on the evaluation criteria' information, thus supporting the objective evaluation of criteria. One advantage of the technique is that it eliminates human interference, avoiding subjective errors and human factors introduced when determining the weights of indicators. Figure 9 shows a high degree of dispersion between the indicators ranging from 0.68 to 0.95. Ecosystem cost had the highest dispersion, while resource scarcity obtained the least. A possible explanation for this might be the high ecosystem cost ($0.084) associated with the plant-based burger and the relatively low cost associated with the animal-based burger ($0.002). The higher the degree of dispersion value, the greater the potential of obtaining more information from the indicator weights. In addition, the high degree of dispersion between the criteria confirms their appropriateness in evaluating alternative food products. For example, the difference between ecosystem cost for plant-based burgers and animal-based was 98.05%, which shows the criterion is appropriate for evaluating the two food products. Similar observations were made across all criteria.

Nonetheless, if a lower difference had been observed, the criteria would have no relevance to qualifying the alternatives in the decision-making process. Subsequently, a higher degree of dispersion is correlated to higher weights. This is evident in Figure 9, as it can be seen that the highest weight is allocated to ecosystem cost (0.242), while the lowest weight is allocated to resource scarcity cost (0.174). The results imply that ecosystem cost, HSR, and human health cost weighed 0.242, 0.212, and 0.187, thus reflecting the importance of the indicators. These results corroborated the current narrative of increased consumer awareness and preference for environmentally friendly products.

The results were later translated into a four-point scale using a linear combination approach to obtain a novel Environmental-Nutrition Score (EnN score). The objective of this approach and the development of the EnN score was to provide the consumer with an easy label with the potential of persuading or perhaps encouraging sustainable food choices. An EnN score of 1.47 and 2.53 was obtained for animal-based and plant-based burgers. Equations 8 and 9 present the mathematical relations developed to derive the EnN score of the two products. However, to provide more appropriate and easy answer options for consumers, the score was transformed to a one-point interval of 2 and 3.

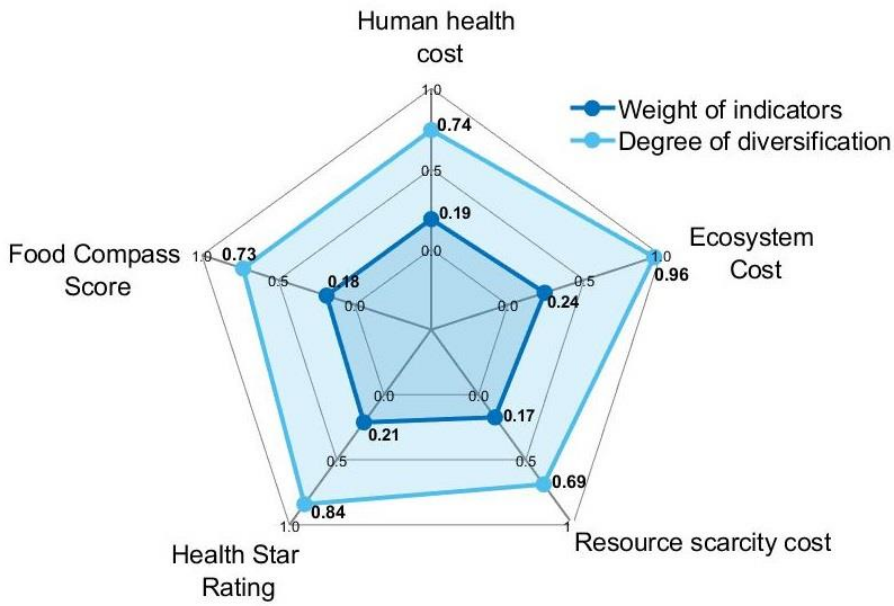


Figure 25: Weight index for the environmental-nutrition indicators

The EnN scores of 2 and 3 were associated with nudges of “This food is slightly healthy and unsustainable’ and “this food is moderately health and sustainable” and color code of orange and light green (See Supplementary Document Table S20 for the different color codes and their associated nudges).

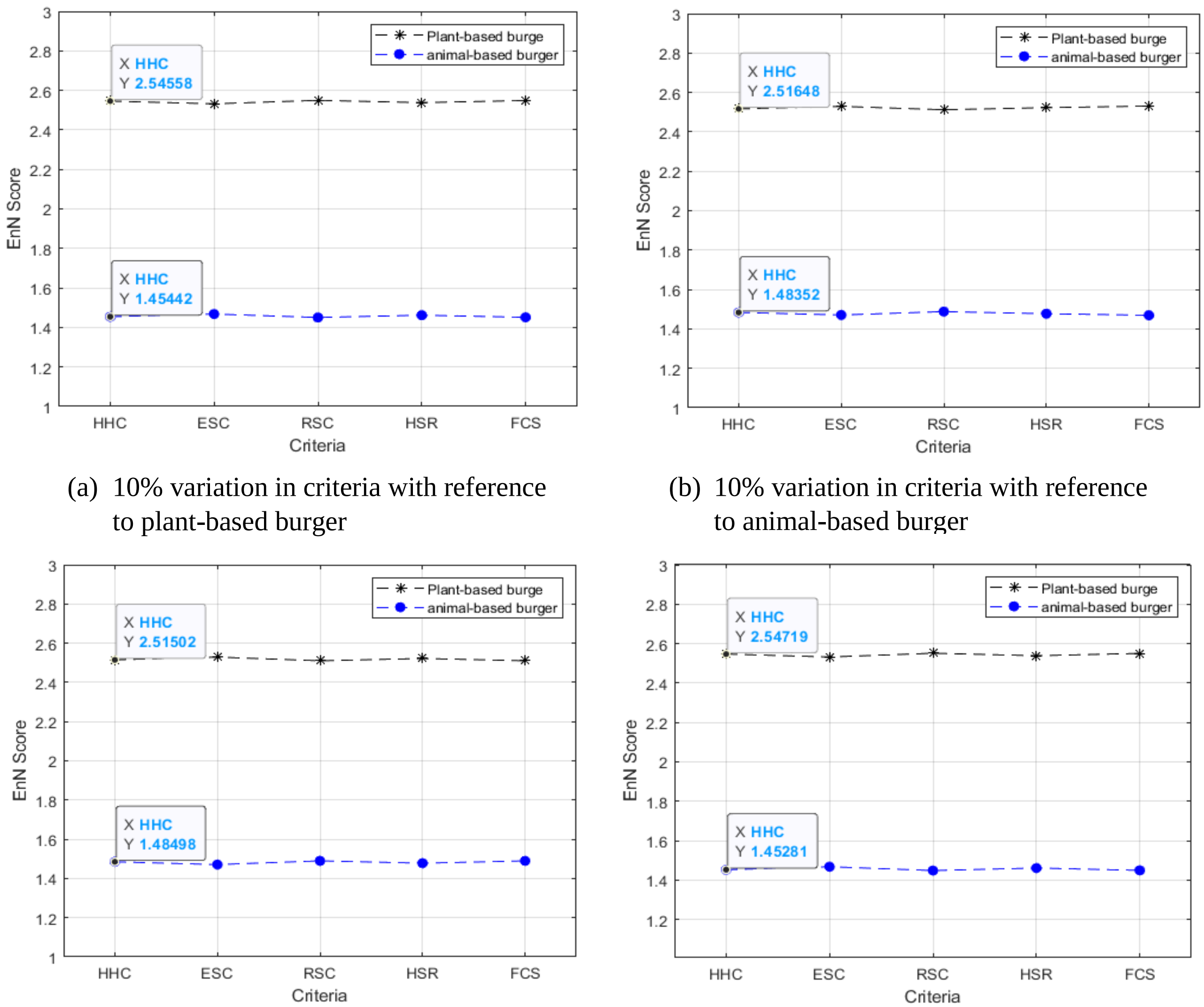
$$W_{ij} = \ w_i p_{ij} + \cdots + \ w_n p_{nj} \quad for\ i = 1 \ldots 5\ and\ j = 1,2. \qquad (8)$$

$$EnN_j = \frac{1}{n} \sum_{i=1,j=1}^{i=\ 5,j=\ 2} \frac{4.\,W_{ij}}{W_{ij} +\ W_{ij}} \qquad (9)$$

Where n is the number of criteria, W_{ij} is the normalized weighted matrix for each j alternative.

To confidently implement the novel EnN score, it was expedient to measure the robustness, strength, and stability through a sensitivity analysis. This was achieved by varying the exact value of each criterion by ±10% and then exploring its influence on the EnN score of the two products.

Figure 10 presents the sensitivity evaluation of the magnitude of EnN scores, assuming a ±10% in the magnitude of the criteria for developing it. Figure 10a shows variations in the EnN score ranging from 2.549 to 2.531 and 1.451 to 1.468 for plant-based and animal-based burgers, respectively. Figures 10a,b,c and d reveals a slight rate of change of +0.12%, +0.22%,-0.16%, +0.13% and -0.12%, -0.22%,+0.16%, -0.13% in EnN score plant-based burger and animal-based burger, respectively. Alternatively, a change in the EnN score of 0.69%, 0.73%, 0.75%, 0.76%, and 1.19%, 1.25%, 1.27%, 1.32% between the maximum and minimum scores attained for the plant-based burger is reasonably small and insignificant. The results imply that the criteria and the EnN score are insensitive to small variations in criteria magnitudes. It also provides further support for the robustness and guaranteed performance of the EnN score when comparing the two food products.



(a) 10% variation in criteria with reference to plant-based burger

(b) 10% variation in criteria with reference to animal-based burger

(c)-10% variation in criteria with reference to plant-based burger

(d) -10% variation in criteria with reference to animal-based burger

**Human health cost (HHC), Resource Scarcity Cost (RSC), Ecosystem cost (ESC)

Figure 26: Sensitivity evaluation of the EnN score for plant-based burgers and animal-based burgers

7.5 Novel decision support system

The environmental cost assessment and nutrient profile modeling show that plant-based burgers have a better overall cost and EnN score than animal-based burgers. However, to influence consumer behavior to embrace sustainability, we developed a DISH food choices simulator that can be used at the point of purchase. This web-based application allows consumers to select the two products and receive output on the nutrient and health profile, life cycle cost, EnN score, and associated nudges that stimulate consumer behavior. Figure 10 shows the five-step process of using the simulator.

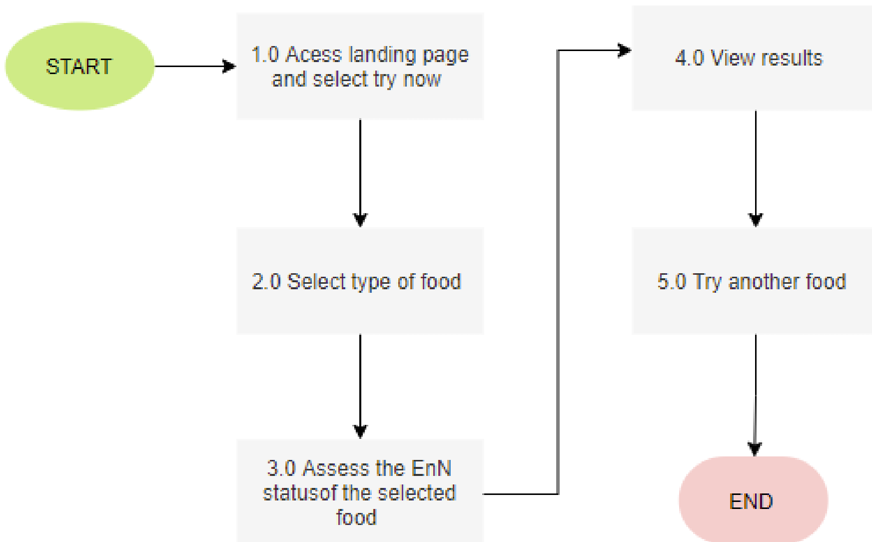


Figure 27: The five-step process for using the DISH food choice simulator

From Figure 10, the first step requires the user to access the simulator on this landing page. The page contains information on the number of total annual death-diet-related issues, how to use the simulator, who can use the simulator, and the potential health and environmental benefits of using the simulator. The objective was to present information that could inform the purchasing decision of consumers and guide consumers on how to use the simulator. To navigate to the environment of the simulator, the user or consumer, a call-to-action button is placed at three different sections of the landing page. Having had access to the simulator environment, the user can now select a type of food, confirm, or change the choice, and the process to assess the EnN status of the selected in step 3. Step 4 takes the user directly to the dashboard, which shows the results in three domains thus health and nutritional outlook, environmental impact cost, and overall sustainability. The user can then select another food and run through the same process. Figure 10a and b display the user interface of the DISH food choice simulator. It was designed for easy use and to enable rapid utilization and experimentation of the simulator by a consumer with easy access to the internet. A documentation module was also included to provide users with information on the scientific principles adopted by the creators of the simulator. The simulator was then tested through a consumer survey, presented in the next section. DISH draws practical attention to the nutritional implications of diet choices and how it contributes to healthy living at the point of food choice/decision-making, provides consumers environmental impact information of chosen foods (ecosystem quality and human health impact), and provides an interactive avenue for environmental-nutrition trade-off analysis and comparison of different choices to enable consumers make informed decision.

Figure 28: Interface of the DISH food choice simulator used deployed for consumer testing.

7.6 Survey data analysis

During the participant's survey, all questions were answered by individual participants; as such, Harman's one-factor test was used to test possible biases. The results from this test demonstrate that the most influencing factor, the nudges provided, represents 19.84% of the variance. Conversely, the least influencing factor is demography accounting for 2.93% of the variance. Additionally, the data from the survey were screened to identify outliers and normality of distribution using Cook's distance value. The analysis estimated a minimum, maximum, and mean Cook's distance values of 0.00, 0.237, and 0.010, which were less than one. This indicates the absence of outliers, conformity to distribution, and, more importantly, none of the residuals are poorly predicted. Furthermore, the analysis results indicated no significant deviation from a normal distribution with kurtosis and skewness values below the acceptable threshold of ten and three, respectively [50]. More importantly, a reliability and validity test was employed to assess the stability and consistency among the related variables. Finally, a multinomial logistic regression was employed to explore the factors influencing participants' choices.

The survey findings demonstrate that the nudges and the novel EnN score impacted participants' choices. Additional factors include: In this section, we present the socio-demographic background of the participants, burger consumption frequency, participant smartphone behavior, user experience on the simulator, purchasing frequency, and reviews, which will be adopted for future studies. Figure 13 presents a summary of the responses collated in the context of the survey questions and participants' exposure to the DISH simulator. Additionally, Figure 14 briefly describes the different factors that influence consumer decisions and feedback on their experience with the DISH simulator.

7.6.1 Reliability and validity of the analysis

Table 9 presents a reliability and validity test for the survey responses. Table 9 shows factor loading ranging between 0.173 to 0.575. A stringent threshold of 0.3 was set according to the recommendations of Tabachnick, Fidell [51]. Additionally, the Table shows that all variables had adequate reliability, with Cronbach's alpha ranging from 0.028 to 0.368. However, a lower alpha value is observed for mobile phone usage and demography, thus introducing internal inconsistency. Therefore, all factors with a factor loading less the 0.3 were removed to provide a better fit for further analysis.

Table 20: Reliability and validity test of the survey responses

S/N	Variables	Factor loading	Cronbach's alpha	Average variance
1	Recollection of nudge (ABB)	.305	0.368	19.839
2	Recollection of nudge (PBB)	.304	0.318	15.752
3	Mobile phone	.295	0.213	13.494
4	Dietary pattern	.575	0.098	11.036

5	Understanding og EnN Score	.354	0.100	9.491
6	Modules on DISH	.509	0.028	8.725
7	Awareness	.354	0.109	7.918
8	Correct recollection of EnN score (PBB)	.505	0.109	5.070
9	Correct recollection of EnN score (ABB)	.565	0.125	3.604
10	Demography	.173	0.060	2.923
11	Final choices	.435	0.075	2.150

7.6.2 Socio-demographic characteristics of participants

A total of 112 surveys were completed. The findings from the survey revealed that 53.6% of the participants were male, 42.9% were white, 29.5% were blacks/ African American, and the rest were either Asian, Hispanic, or Arabic. About 1.8% of the participants preferred not to disclose their racial background information. Also, many participants were between 18 and 24 years; thus, 53.6% were highly educated (46.4% graduate students, 45.5% undergraduate students, and 7.1 % workers from different companies). The sample demography characteristics reveal bias, as more whites and blacks/African Americans are overrepresented, and not every racial group is proportionally represented. Table SD22 of the Supplementary Document presents the socio-demographic characteristics of the survey participants.

7.6.3 Burger frequency consumption and Smart phone behavior, and familiarity

52.7% of the participants declared they did not adhere to any dietary pattern, while 30.4 % declared to adhere to a dietary pattern. Of the 30.4% that declared to adhere to a dietary pattern, 13.4% were omnivores, and 4.5% were flexitarian. Interestingly, 10.7% of the 30.4% of participants who declared to adhere to a dietary pattern are slow food eaters, no crustaceans, high protein diet consumers, and individuals who eat a single meal a day. Additionally, 21.4% of the participants eat burgers once or twice a week, while 30.4% eat burgers twice a month. Furthermore, 83.5% and 66.2% of participants had eaten animal-based or plant-based burgers before participating in the experiment. Proir to being exposed to the simulator, the initial test of participants' intent was conducted. Thus over 87% declared they would purchase animal-based burgers on any given day.

7.6.4 Smartphone usage and behavior

To determine the participants' digital product habits, the survey revealed that over 27.7% of the participants download onto their mobile phones once a month, while 58.9% download once/twice in six months. More interestingly, over 38.4% and 25.9% of the participants are either extremely comfortable or somewhat comfortable using mobile and web applications to purchase food. Several applications, such as Walmart, Target, Chick Fil A, and UberEATS were mentioned as the most frequently used for purchasing food. Aside from this, 25.9% use mobile applications to purchase food once or twice a week, while 33.9% use it once or twice a week. Only 2.7% of the participants use mobile applications daily to purchase food. The data for this is shown in Figure 12.

7.6.5 User experience on the DISH simulator

This section investigated the participant's experience using the DISH simulator when attempting to purchase a burger. First, the user experience of the simulator was measured across five indicators thus the user interface, navigation of pages, layout of pages, language used on the page, and information flow. Next, participants were asked to rate the simulator on a scale of 1 and 100 against the abovementioned indicators.

Table 21: Descriptive Statistics of user experience on the DISH simulator

Questionaire	N	Minimum	Maximum	Mean	Std. Dev
Q19_1 User interface	112	9	100	75.76	21.66
Q19_2 How was your experience navigating the simulator? - Navigation of pages	112	19	100	76.32	24.46
Q19_3 How was your experience navigating the simulator? - Layout of pages	112	40	100	80.00	18.77
Q19_4How was your experience navigating the simulator? - Language used on the page	112	5	100	82.51	23.25
Q19_5 How was your experience navigating the simulator? -Information flow on the page	112	26	100	80.57	18.77

Next, the participant's understanding of the modules of the DISH simulator was tested. The results indicate that 46.4% of participants understood the Nutrition and Health Outlook module, while 60.7% understood the simulator's environmental impact cost module. More strikingly, 84.9% of the participants recognized the meaning of the EnN score applied in the simulator. Also, 87.5% affirmed that the documentation page provided sufficient information about the different modules on the DISH dashboard.

Following this, the participants were tested to determine their awareness and recollection of the information presented on the DISH dashboard prior to making a purchase. To determine this, participants were asked to recall the information on the EnN score, the EnN score rating, and their respective nudges interventions for both food products. Once again, our results indicate that 78.6% of participants accurately recalled the EnN score associated with a plant-based burger. Unfortunately, however, a staggering 74.6% recalled the associated nudge wrongly. A possible explanation for this might be the Likert scale used to develop the nudges.

Nonetheless, 81.3% of the participants identified the nudge intervention associated with the plant-based burger. In much the same way, 76.8% of participants recalled the EnN score correlated to the plant-based burger. However, 63.4% of these participants could describe the corresponding nudge intervention. Despite the higher increase in response compared to the plant-based burger, participants' recall of the EnN score rating associated with the animal-based burger was low (56.3%). The results of the test statistics are displayed in Table 10.

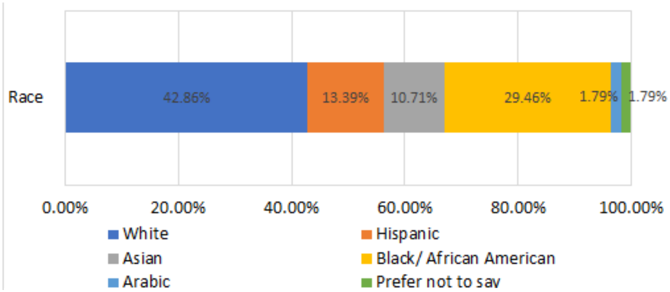
7.6.6 Purchase, simulator trust, and acceptance

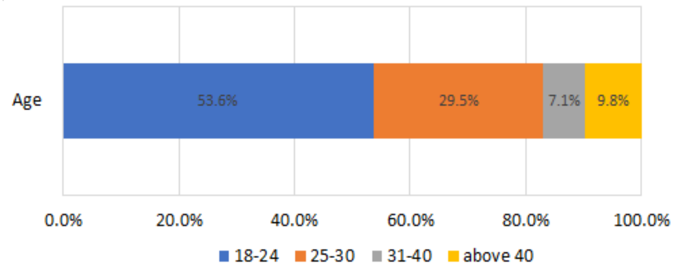
To determine the influence of the simulator and its respective nudges in stimulating consumers toward a healthy and sustainable diet choice, the final set of interview questions focused on exploring the purchasing decisions of the participants. The results indicate that 58% of participants purchased an animal-based burger after the experiment. Interestingly, 56.9% of participants who would have potentially purchased an animal-based resorted to purchasing a plant-based burger, and over 83% attributed their decision based on sufficient information presented on the simulator. Interestingly, 89.3% of participants referenced the DISH modules as having a substantial impact on their final decision. Among participants, 56.9% of participants who resorted to purchasing plant-based burgers, and 55.6% attributed the environmental module on DISH as influencing the decision. Likewise, 36.1% attributed the health benefits as influencing their final decision. The single most striking result to emerge was some socio-cultural and sensory factors that inexplicable predispose individuals toward a particular decision. For example, some participants revealed a strong affinity toward meat-based products and, despite their environmental claims, would still go in for such products. Other factors, such as taste, flavor, and health-related issues, such as increased estrogen (when consuming soy products), were external factors that influenced participants' choices.

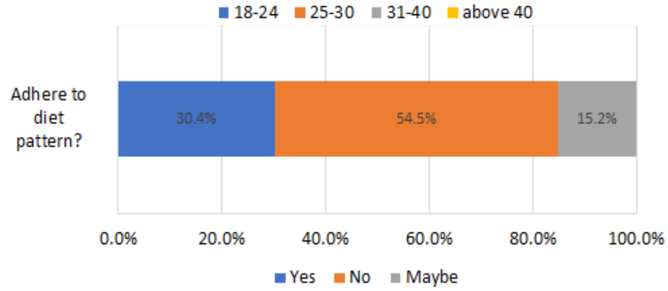
Generally, trust is an important indicator of consumer attitudes and behavior toward using a product. Therefore, our study focused on determining the participant's trust and belief in the information presented on the DISH simulator. The results revealed that a staggering 86.6% were confident about the information presented. In addition, 92% of the participant recommended that the simulator be translated into a web application with the addition of more foods. In the model implemented, independent covariates with

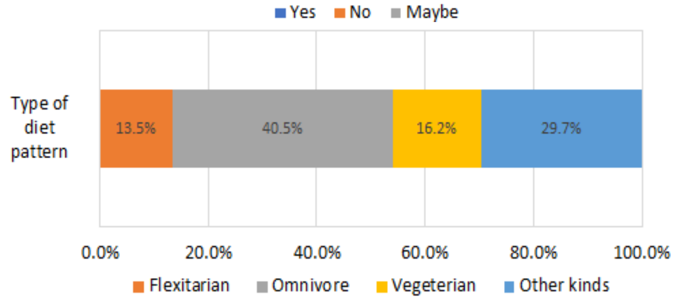
7.6.7 Factors influencing the consumer choices

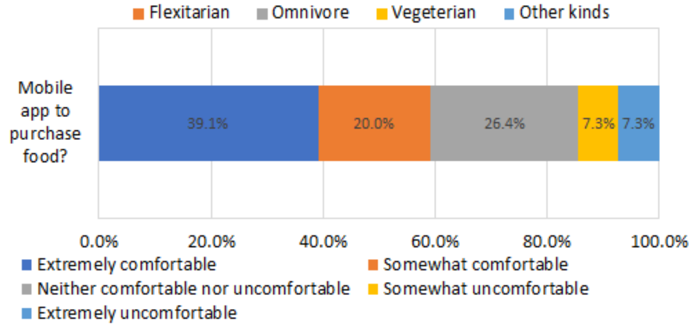
A multinomial logistic regression model was applied to ascertain the influence of different factors on final consumer choice. The final purchase choice was set as the dependent variable within the multinomial model. Variables such as understanding of EnN score, modules of the simulators (an aggregation of a health benefit claim, environmental impact claim, and nutritional claim), dietary pattern, smartphone usage, and recollection of nudges associated with both products, awareness, and participants racial demography were set as the covariates. Independent covariates with a significant chi-square value of <0.001 influenced final consumer choices. Table 10 presents the results of the multinomial logistic regression analysis. The results demonstrate that the modules of DISH, EnN score, and nudges associated with the two fast-food products considerably influence final consumer decisions with a chi-square significant value of <0.001.

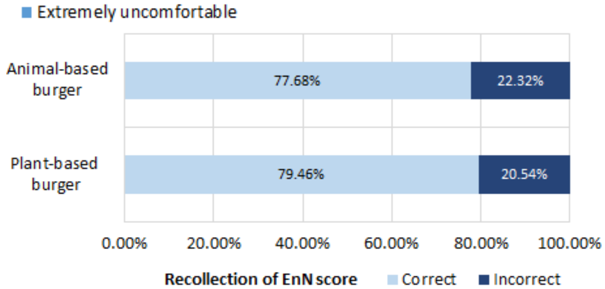

Race
42.86%
13.39%
10.71%
29.46%
1.79%
1.79%
0.00% 20.00% 40.00% 60.00% 80.00% 100.00%
White
Hispanic
Asian
Black/ African American
Arabic
Prefer not to say

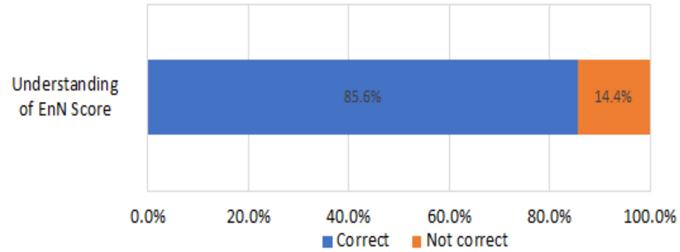

Age
53.6%
29.5%
7.1%
9.8%
0.0% 20.0% 40.0% 60.0% 80.0% 100.0%
18-24
25-30
31-40
above 40

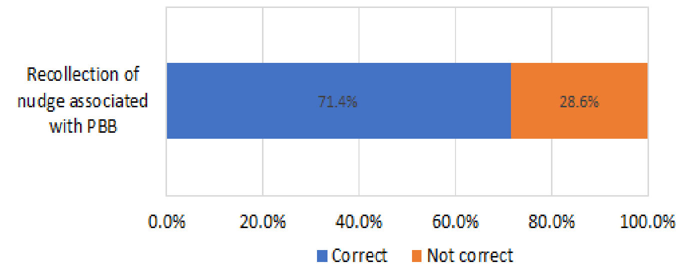

Adhere to diet pattern?
30.4%
54.5%
15.2%
0.0% 20.0% 40.0% 60.0% 80.0% 100.0%
Yes
No
Maybe

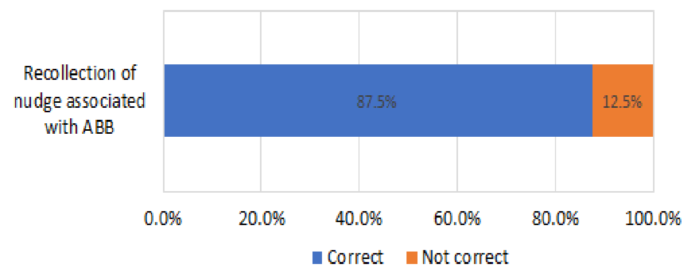

Type of diet pattern
13.5%
40.5%
16.2%
29.7%
0.0% 20.0% 40.0% 60.0% 80.0% 100.0%
Flexitarian
Omnivore
Vegeterian
Other kinds

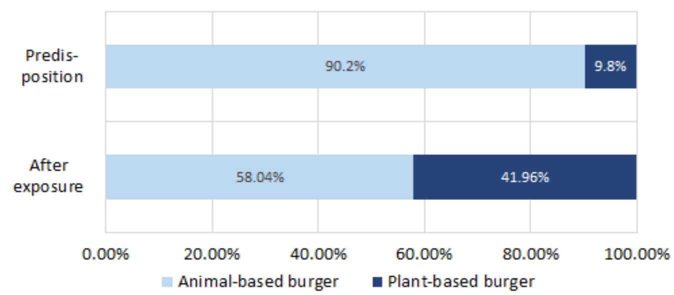

Mobile app to purchase food?
39.1%
20.0%
26.4%
7.3%
7.3%
0.0% 20.0% 40.0% 60.0% 80.0% 100.0%
Extremely comfortable
Somewhat comfortable
Neither comfortable nor uncomfortable
Somewhat uncomfortable
Extremely uncomfortable

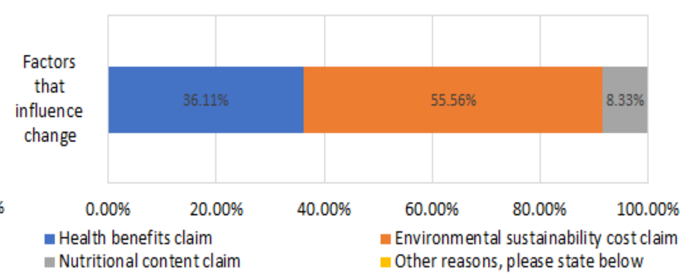

Animal-based burger
77.68%
22.32%
Plant-based burger
79.46%
20.54%
0.00% 20.00% 40.00% 60.00% 80.00% 100.00%
Recollection of EnN score
Correct
Incorrect


Understanding of EnN Score
85.6%
14.4%
0.0% 20.0% 40.0% 60.0% 80.0% 100.0%
Correct
Not correct


Recollection of nudge associated with PBB
71.4%
28.6%
0.0% 20.0% 40.0% 60.0% 80.0% 100.0%
Correct
Not correct


Recollection of nudge associated with ABB
87.5%
12.5%
0.0% 20.0% 40.0% 60.0% 80.0% 100.0%
Correct
Not correct


Predis-position
90.2%
9.8%
After exposure
58.04%
41.96%
0.00% 20.00% 40.00% 60.00% 80.00% 100.00%
Animal-based burger
Plant-based burger


Factors that influence change
36.11%
55.56%
8.33%
0.00% 20.00% 40.00% 60.00% 80.00% 100.00%
Health benefits claim
Environmental sustainability cost claim
Nutritional content claim
Other reasons, please state below

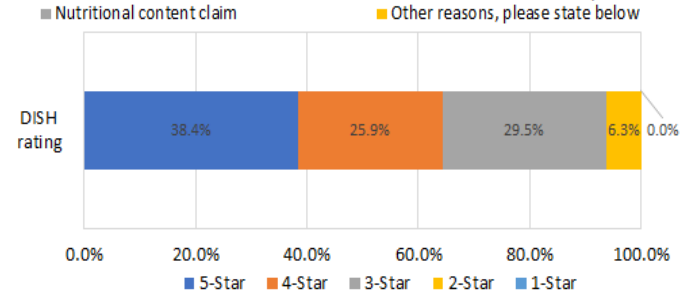

DISH rating
38.4%
25.9%
29.5%
6.3%
0.0%
0.0% 20.0% 40.0% 60.0% 80.0% 100.0%
5-Star
4-Star
3-Star
2-Star
1-Star

Figure 29: Percentage responses from the questionnaire administered.

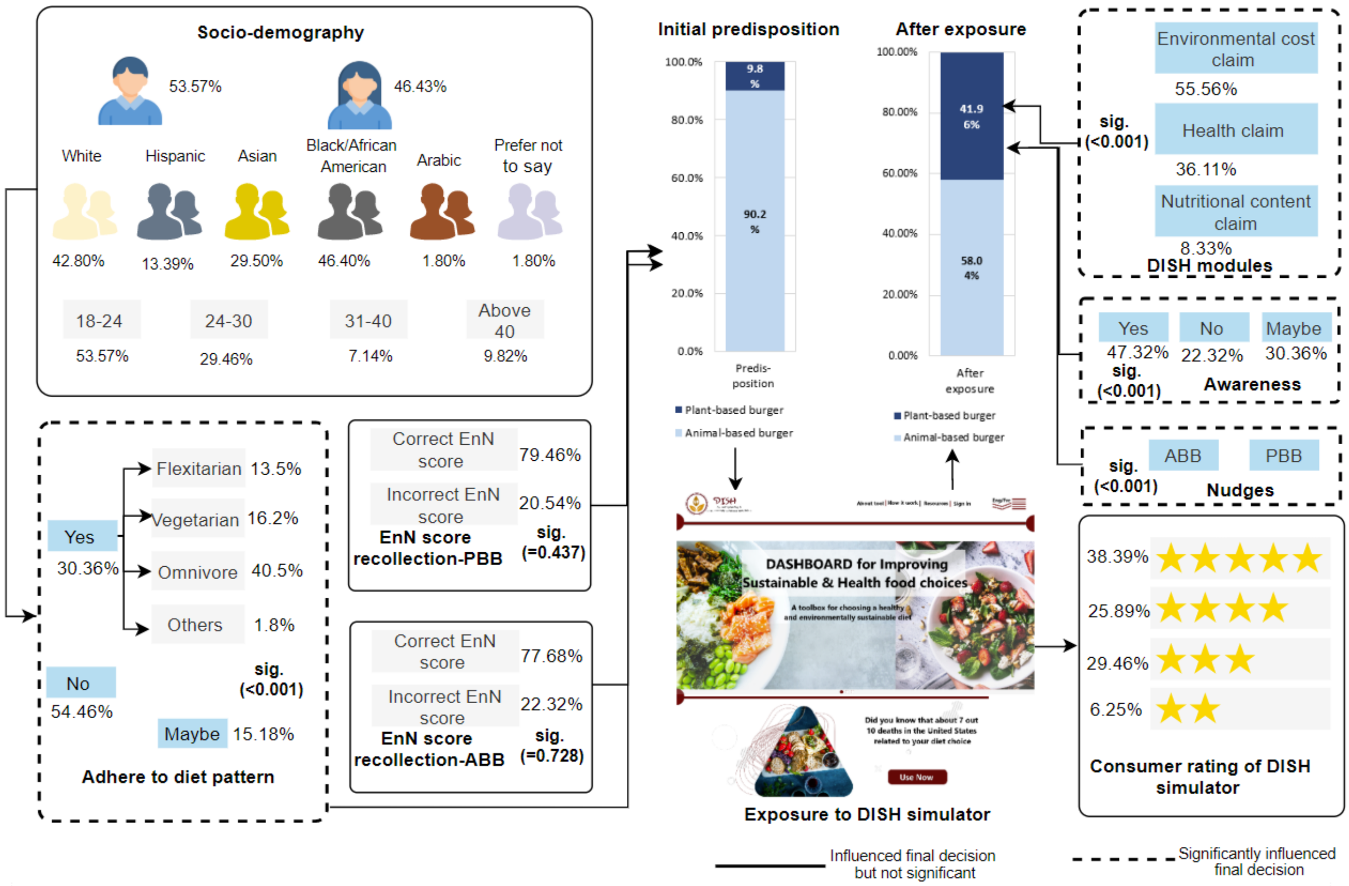


Figure 30: A brief description of the influence and feedback of the DISH simulator on consumer choices (values in the Figure are in percentage of responses from participants).

Table 22: Likelihood ratio tests

S/N		-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
1	Intercept	83.104	5.942	1	.015
2	Awareness	94.239	17.077	1	<.001
3	Modules of DISH	88.877	11.715	1	<.001
4	Understanding of EnN Score	79.879	2.717	1	.099
5	Dietary pattern	90.313	13.151	1	<.001
6	Recollection of nudges (PBB)	84.070	6.908	1	.002
7	Recollection of nudges (ABB)	87.659	10.497	1	<.001
8	Correct recollection of EnN score (PBB)	77.767	.605	1	.437
9	Correct recollection of EnN score (ABB)	77.283	.121	1	.728

7.7 Conclusion

Returning to the initial hypothesis stated at the beginning of this study, it is now possible to state that providing appropriate nudges, environmental impact, nutritional, and health implication information can significantly influence consumers' purchasing decisions. Other factors, such as novel Environmental-Nutrition Score of two fast-food products using a simulator, influenced consumer choices but not very significantly. The findings indicate that (1) at the level of environmental sustainability, an animal-based burger is associated with a higher environmental impact and external environmental cost compared to the plant-based burger, and (2) from a health and nutritional perspective, a plant-based burger has significantly higher HSR (4-stars), and FCS (62) thus associated with a healthier choice than the animal-based burger (1/2-star and an FCS (35), and (3) integrating both dimensions into a single novel EnN score, the plant-based burger had a higher EnN score (EnN score =3) which correlates to a healthier and more environmentally sustainable food compared to the animal-based burger (EnN score =2). Perhaps the most obvious finding to emerge from the study is that 64.3% of participants involved in the testing and evaluation of the simulator rated the novel DISH simulator either with a 5-star rating or a 4-star rating. Also, the data from the consumer survey suggests that 92% of participants recommended that the simulator be translated into a mobile application and that more foods should be added. However, the study raised important questions about including social-cultural and sensory factors when stimulating consumers toward sustainable and healthy decisions. A higher proportion of participants generally trust and accept the simulator firmly. Overall, this paper contributes to the recent debate and growing concern of consumers for a more sustainable and environmentally friendly product at the point of purchase. It also highlights the potential usefulness of translating the results to other fast-food products consumed frequently in America and to re-align how environmental-nutrition messages are reinforced among consumers to stimulate purchasing decisions. To the best of the authors' knowledge, this is the first study to integrate modeling approaches with nudges and digital technology to influence consumer choices at the point of purchase. One issue with the current study was the low number of participants. Broader research is needed in collaboration with different fast-food service providers in an uncontrolled environment to investigate the impact of DISH on their food choices.

7.8 Abbrevaitions and their meaning

FMPF	Fine particulate matter formation
FRS	Fossil resource scarcity
FEW	Freshwater ecotoxicity
FEW	Freshwater eutrophication

GWFE	Global warming, Freshwater ecosystems
GEHH	Global warming, Human health
GWTE	Global warming, Terrestrial ecosystems
HCT	Human carcinogenic toxicity
HNCT	Human non-carcinogenic toxicity
I.R.	Ionizing radiation
L.U.	Land use
ME	Marine ecotoxicity
MET	Marine eutrophication
MRS	Mineral resource scarcity
GHGE	Greenhouse gas emission
LCA	Life Cycle Assessment
HSR	Health Star Rating

7.9 Declaration of Competing Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

7.10 CRediT authorship contribution statement

Prince Agyemang: Conceptualization, Investigation and Survey, Methodology, Data curation, Writing (Initial draft) and Data Visualization. **Ebenezer M. Kwofie**: Conceptualization, Investigation and Survey, Resources, Writing (Review and Editing), Supervision. **Jamie Baum**: Conceptualization, Methodology, investigation and survey resources, Writing (Review and Editing). **Dongyi Wang:** Writing (Review and Editing).

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7.12 Ethics Statement

The study involving human participants was reviewed and approved by University of Arkansas Human Research Ethics Committee of Instituional Review Board with Protocol Number 2204398567. The participants provided their written informed consent to participate in this study.

7.13 Acknowledgements

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8 Supplementary Document

A food system sustainability compass: A case of a Dashboard for Improving Sustainable Healthy Food Choices for stimulating consumers toward healthy and environmentally sustainable diet choices.

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8.1 Inventory for Plant-based burger modeling

Table SD23: Feed production (Soybean)

Category	Components	Unit	Amount	Source
Soy cultivation	seeds (80% germination)	lb/acre	40.75	Arkansas Soybean Production Handbook
	Yield	lb/acre	3060	NASS STAT quick 2021
	Land, (acre planted)	acre	3250000	NASS STAT quick 2022
Fertilizer	Fertilizer (N)	lb/acre	15	NASS STAT quick 2020

	Fertilizer (P 2 O 5)	lb/acre	64	NASS STAT quick 2020
	Fertilizer (K 2 O)	lb/acre	103	NASS STAT quick 2020
	Sulfur	lb/acre	14	NASS STAT quick 2021
	Lime	lb/acre	94	Source 2
Pesticide	Pesticide (Acephate-103301)	lb/acre	0.948	NASS STAT quick 2020
	Herbicide (2,4 D, Dimethy Salt)	lb/acre	0.418	NASS STAT quick 2020
	Fungicide (Propiconazole)	lb/acre	0.027	NASS STAT quick 2020
Utilities	Electricity for irrigation	MJ/ha	131.68	Source 2
	Gasoline, all uses	MJ/ha	473.5	Source 2
	Diesel (farm tractor)	MJ/ha	1612.06	Source 2
	Natural gas	MJ/ha	159.17	Source 2
	Lubricant, all uses (road and ag)			
	Water (Total for irrigation)	Acre-feet/acre	1	NASS STAT quick 2018
Emissions	Emission (Direct N20)	kg/ha	2.814	IPCC model (Tier 1), 2019 update
	Emission (Indirect N2O)	kg/ha	0.660	IPCC model (Tier 1), 2019 update

Table SD24 Feed production (Wheat cultivation)

Category	**Components**	**Unit**	**Amount**	**Source**
Wheat cultivation	seeds	lb/acre	220	USDA
	Yield	lb/acre	4014	NASS STAT quick 2016
	Land, (acre planted)	acre	220000	NASS STAT quick 2022
Fertilizer	Fertilizer (N)	lb/acre	82	NASS STAT quick 2019
	Fertilizer (P 2 O 5)	lb/acre	39	NASS STAT quick 2019
	Fertilizer (K 2 O)	lb/acre	23	NASS STAT quick 2019
	Sulfur	lb/acre	11	NASS STAT quick 2019
	Lime	lb/acre		
Pesticide	Pesticide (Methyl-Parathion)	lb/acre	0.198	NASS STAT quick 2012
	Herbicide (MCPA, 2-Ethylhexyl=30564)	lb/acre	0.318	NASS STAT quick 2019
	Fungicide (Propiconazole=122101)	lb/acre	0.087	NASS STAT quick 2015
Utilities	Electricity for irrigation	MJ/ha	29836	Source 14
	Gasoline, all uses	MJ/ha	6822	Source 14
	Diesel (farm tractor)	MJ/ha	1290	Source 14
	Lubricant, all uses (road and ag)			

	Water (Total for irrigation)	Acre-feet/acre	0.5	NASS STAT quick 2018
Emissions	Emission (Direct N20)	kg/ha	3.304	IPCC model (Tier 1), 2019 update
	Emission (Indirect N2O)	kg/ha	0.770	IPCC model (Tier 1), 2019 update

Table SD25: Feed production (Black beans)

Category	**Components**	**Unit**	**Amount**	**Source**
black beans	seeds	lb/acre	80	
	Yield	lb/acre	2470	NASS STAT quick 2016
	Land, (acre planted)	acre	69700	NASS STAT quick 2020
Fertilizer	Fertilizer (N)	lb/acre	92	NASS STAT quick 2014
	Fertilizer (P 2 O 5)	lb/acre	107	NASS STAT quick 2014
	Fertilizer (K 2 O)	lb/acre	97	NASS STAT quick 2014
	Sulfur	lb/acre	31	NASS STAT quick 2014
	Lime	lb/acre		
Pesticide	Pesticide (Bifenthrin=128825)	lb/acre	0.105	NASS STAT quick 2016
	Herbicide (Clethodim)	lb/acre	0.114	NASS STAT quick 2016
	Fungicide (Vinclozolin=113201)	lb/acre	1.042	NASS STAT quick 2016
Utilities	Electricity for irrigation	MJ/ha	5040	Source 15
	Gasoline, all uses	MJ/ha		
	Diesel (farm tractor)	MJ/ha	4086	Source 15
	Lubricant, all uses (road and ag)			
	Water (Total for irrigation)	Acre-feet/acre	2.3	NASS STAT quick 2018
Emission	Emission (Direct N20)	kg/ha	4.700	IPCC model (Tier 1), 2019 update
	Emission (Indirect N2O)	kg/ha	1.084	IPCC model (Tier 1), 2019 update

Table SD26: Feed production (Rice cultivation)

Category	**Components**	**Unit**	**Amount**	**Source**
Rice	seeds	lb/acre	120	
	Yield	lb/acre	7630	NASS STAT quick 2016
	Land, (acre planted)	acre	1191000	NASS STAT quick 2020
Fertilizer	Fertiliser (N)	lb/acre	102	NASS STAT quick 2021
	Fertiliser (P 2 O 5)	lb/acre	78	NASS STAT quick 2021
	Fertiliser (K 2 O)	lb/acre	105	NASS STAT quick 2021
	Sulfur	lb/acre	44	NASS STAT quick 2021

	Lime	lb/acre		
Pesticide	Insecticide (Lambda-cyhalothrin=128897)	lb/acre	0.028	NASS STAT quick 2021
	Herbicide (Glyphosphate ISO salt)	lb/acre	1.034	NASS STAT quick 2021
	Fungicide (Azoxystrobin=113201)	lb/acre	0.173	NASS STAT quick 2021
	Other chemical (Sodium chlorate)	lb/acre	5	NASS STAT quick 2013
Utilities	Electricity for irrigation	kwh	282	Arkansas Rice Production manual
	Gasoline, all uses	MJ/ha		
	Diesel (farm tractor)	Liter	373	
	Water (Total for irrigation)	Acre-feet/acre	2.1	NASS STAT quick 2018
	Lubricant, all uses (road and ag)			
Emission	Emission (Direct N20)	kg/ha	5.765	IPCC model (Tier 1), 2019 update
	Emission (Indirect N2O)	kg/ha	1.324	IPCC model (Tier 1), 2019 update
	Methane	mg/m2	48.000	

Table SD27: Feed production (Corn)

Category	**Components**	**Unit**	**Amount**	**Source**
Corn	Seed	lb/acre	10.000	
	Land Use	acre	750000	NASS QuickSTAT 2021
	Yield	bu/acre	195.4	NASS QuickSTAT 2018
Fertilizer	Fertiliser (N)	lb/acre	54	NASS QuickSTAT 2021
	Fertiliser (P 2 O 5)	lb/acre	24	NASS QuickSTAT 2021
	Fertiliser (K 2 O)	lb/acre	12	NASS QuickSTAT 2021
	Sulfur	lb/acre	10	NASS QuickSTAT 2021
Pesticide	Insecticide (Bfentrhrin=128825)	lb/acre	8.70E-02	NASS QuickSTAT 2018
	Herbicide (Acetochlor=121601)	lb/acre	1.38E+00	NASS QuickSTAT 2018
	Fungicide (Metazachlor = 125619)	lb/acre	3.20E-02	NASS QuickSTAT 2016
	Other chemical (Chopyralid)	lb/acre	2.50E-02	
Utilities	Well water	liters	1.15E+03	BASF (2011)
	Electricity, irrigation	MJ	2.60E-01	BASF (1999)
	Natural Gas, irrigation wells	MJ	2.74	BASF (1999)
	Diesel, irrigation surface water, off road and road	MJ	8.81E-01	BASF (1999)

	Gasoline, all	MJ	4.98E-01	BASF (1999)
	Lubricant, all uses (road and ag)	MJ	6.06E-02	
	Renewables bio-based	MJ	5.07E+01	
Emisson	Emission (Direct N20)	kg/ha	0.889	IPCC model (Tier 1), 2019 update
	Emission (Indirect N2O)	kg/ha	0.226	IPCC model (Tier 1), 2019 update

Table SD28: Harvesting, during of feed for storage and transportation

Category	Components	Unit	Amount	Source
Harvesting	Combine harvesting (Total area for the crops)	m2		
	Drying of (corn)			
	Electricity	kWh/acre	31.811	NASS QuickSTAT 2015
	Propane	gal/acre	26.027	NASS QuickSTAT 2015
	Drying of (wheat)			
	Electricity	kWh/acre	618.156	
	Propane	gal/acre	505.764	
	Drying of (rice)			
	Electricity	kWh/acre	23.76	
	Propane	gal/acre	19.44	
	Transportation from farm to storage houses			

Table SD29: Packaging and transportation and manufacturing of burger pattie

Category	Components	Unit	Amount	Source
Packaging	bale loading (Assume for negligible)			
	Folding boxboard carton			
	Sacks/Bags			
Transportation	Transport of all raw material from farming to manufacturing Truck	miles	930	Morning Star Farm
Manufacturing	Production (pounds)	pounds	24541935	Morning Star Farm
	Electricity (kwh)	kwh	10461000	Morning Star Farm

Electricity Source	grid	grid	Morning Star Farm
Natural gas (MMBTU)	MMBTU	58536	Morning Star Farm
Water Use (gallons)	gallons	538887000	Morning Star Farm
Wastewater discharge (gallons)	gallons	45505891	Morning Star Farm
Waste used as animal feed (metric tonnes)	metric tonnes	661	Morning Star Farm
Waste incinerated (metric tonnes)	metric tonnes	125	Morning Star Farm
Waste recycled (metric tonnes)	metric tonnes	435	Morning Star Farm
Waste to landfill (metric tonnes	metric tonnes	1832	Morning Star Farm
GHG emissions (metric tonnes CO2 eq.)	metric tonnes CO2 eq.	7128	Morning Star Farm

Table SD30: Ingredients for burger patties production

Category	**Components**	**Unit**	**Amount**	**Source**
4 servings	Serving Size 1 Burger Pattie (284.6 g)			
Other ingredients	Water	tablespoon	2	Source 4
Patty ingredients	onions	slices	8	Souce 5
	cooked black beans (black beans, water)	cup	1	Source 10
	cooked brown rice (water, brown rice)	cup	2	Source 10
	corn (flour))	teaspooon	2	Source 6
	soy protein concentrate	cup	2	Source 8
	tomatoes	slices	2	
	wheat gluten	cup	0.5	Source 11
	onion powder	teaspoon	0.5	Source 5
	vegetable oil (corn, canola and/or sunflower oil)	teaspoon	1	Source 3
	green chiles	slices	8	
	soy protein isolate	cup	1	
	bulgur wheat	cups	2	source 10
	cornstarch	table spoon	2	Source 9

Contains 2% or less of	green peppers	cup	0.25	Source 4
	red bell peppers	cup	0.25	Source 4
	spices	teaspoon	1	Source 4
	tomato powder	cup	0.5	Source 8
	cilantro	cup	0.33	Source 10
	tomato juice	tablespoon	3	Source9
	salt	teaspoon	1	Source 5
	chipotle pepper (chilli powder)	teaspoon	1	Source 4
	methylcellulose (primary binder)	g	6	Source 9
	cooked onion and carrot juice concentrate (shredded)	large	1	Source 6
	jalapeno pepper	table spoon	1	Source 7
	carrageenan	table spoon	2	
	garlic powder	teaspoon	0.5	
	natural flavor	tablespoon	1	Source 12
	paprika	teaspoon	0.5	Source 4
	soy sauce powder (soybeans, wheat, salt)	tablespoon	1	Source 11
	gum arabic			
	vinegar	g	8	Source 8
	citric acid	g	15	Source 8
	red pepper (flakes)	teaspoon	0.5	
	green pepper juice	cups	1.5	Source 6
	turmeric	teaspoon	2	
	garlic juice (chilli garlic sauce)	tablespoon	3	
	lime juice	tablespoon	1	

Table SD31: Inventory for packaging and preparation of burger

Category	**Components**	**Unit**	**Amount**
Packaging			
	# of packages/ case		8
Spicy Black Bean Burgers, 12 count, 9.5oz	Weight of closure	g	2.183
Primary packaging	Weight of film (48-gauge Matte PET)	g	7.72
	Weight of case	g	167.8
Secondary packaging	Cardboard		
Distribution center	Transport from distribution center to retail store	miles	450
Grilling of buns	hamburger buns, split and toasted	hamburger buns	8

	heat (160 F)		
	Time	minutes	1
Other ingredients (Toppings)	Lettuce leaves	leaves	8
	Ketchup	tablespoon	2.5
	mustard	cup	0.5
	onion slices	Slices	8
	pickle slices	tablespoon	2
	sliced tomato	Slices	4
	cooked bacon strips	slices	8
	Cheese	Slice	4

8.2 Inventory for the animal-based burger

Table SD32: Inventory for feed cultivation (Corn silage)

Material / Resource	unit/CB	Amount	Source
Urea fertilizer (CH_4N_2O)	kg	6.33E-02	BASF (2005)
Glyphosate	kg	1.76E-04	BASF (1997)
Dimethylamine salt of dicamba	kg	5.73E-06	BASF (1999)
Dimethenamide pesticide	kg	3.65E-05	Ecoinvent 2.2
Atrazine	kg	3.20E-04	Ecoinvent 2.2
S-metolachlor	kg	1.72E-05	BASF (1997)
Acetochlor	kg	1.61E-04	BASF (2011)
Pyraclostrobin	kg	2.99E-06	BASF (2006)
Well water	liters	6.42E+02	BASF (2010)
Electricity, irrigation	MJ	1.45E-01	BASF (2011)
Natural Gas, irrigation wells	MJ	1.53	BASF (1999)
Diesel, irrigation surface water, off road and road	MJ	4.30E-01	BASF (1999)
Gasoline, all uses	MJ	2.78E-01	BASF (1999)
Lubricant, all uses (road and ag)	MJ	3.39E-02	BASF (1999)
Land Use	m^2	1.83	
Renewables bio-based	MJ	6.93E+01	

Table SD33: Inventory for feed cultivation (Corn grain)

Material / Resource	**unit/CB**	**Amount**	**Source**
Urea fertilizer (CH_4N_2O)	kg	8.81E-02	BASF (2005)
Glyphosate	kg	3.14E-04	BASF (1997)
Dimethylamine salt of dicamba	kg	2.25E-05	BASF (1999)
Dimethenamid	kg	1.54E-04	Ecoinvent 2.2
Atrazine	kg	5.73E-04	Ecoinvent 2.2
S-metalochlor	kg	3.07E-05	BASF (1997)

Acetochlor	kg	2.88E-04	BASF (2011)
Pyraclostrobin	kg	5.36E-06	BASF (2006)
Well water	liters	1.15E+03	BASF (2010)
Electricity, irrigation	MJ	2.60E-01	BASF (2011)
Natural Gas, irrigation wells	MJ	2.74	BASF (1999)
Diesel, irrigation surface water, off road and road	MJ	8.81E-01	BASF (1999)
Gasoline, all	MJ	4.98E-01	BASF (1999)
Lubricant, all uses (road and ag)	MJ	6.06E-02	BASF (1999)
Land Use	m²	3.27	
Renewables bio-based	MJ	5.07E+01	

Table 34: Inventory for animal feed cultivation (Alfalfa)

Material / Resource	unit/CB	Amount	Source
SSP (20% P_2O_5)	kg SSP	5.39E-02	BASF (1997)
Ammonium salt of imazethaphyr	kg	3.59E-06	BASF (1996)
Diesel, irrigation surface water, off road and road	MJ	8.48E-01	BASF (1999)
Gasoline, all	MJ	5.63E-01	BASF (1999)
Lubricant, all uses (road and ag)	MJ	6.85E-02	BASF (1999)
Land Use	m²	3.69	
Renewables bio-based	MJ	5.49E+01	

Table 35: Utilities for feed cultivation

Material / Resource	unit/CB	Amount	Source
Water Well	L	1.46E+03	BASF, 2010
Electricity, irrigation	MJ	3.31E-01	BASF, 2011
Natural Gas, irrigation wells	MJ	3.49	BASF, 1999
Diesel, irrigation surface water, off road and road	MJ	5.47E-02	BASF, 1999
Gasoline, all	MJ	1.90E-02	BASF, 1999
Lubricant, all uses (road and agriculture)	MJ	2.31E-03	BASF, 1999
Land Use†	m²	4.28E+01	
Renewables bio-based	MJ	2.27E+02	

Table SD36: Emissions from feed cultivation (Calculated using emission models)

Material / Resource	unit/CB	Amount
N-fertilizer direct N_2O	kg	2.76E-03
N-fertilizer, indirect N_2O	kg	9.51E-04
N-fertilizer, NH_3-emission	kg	2.28E-02
N-fertilizer, NOx-emission	kg	4.21E-03

N-fertilizer (urea), direct CO_2	kg	2.48E-01
N-fertilizer, water emission	kg	7.60E-03
P-fertilizer, water emissions	kg	1.04E-03
Heavy Metal: Cd	kg	1.57E-07
Heavy Metal: Zn	kg	1.12E-04
Heavy Meta: Pb	kg	6.71E-08
Heavy Metal: Ni	kg	1.36E-05
Heavy Metal: Hg	kg	7.75E-08
COD pesticides	kg	3.65E-03
VOC - silage/hay	kg	6.11E-02

Table SD37: Feed inventory (Pasture grass)

	Flow	**Unit**	**Amount**	**Source**
Pasture (grass)	Urea fertilizer (CH_4N_2O)	kg	1.87E-01	BASF (2005)
	Glyphosate	kg	2.97E-05	BASF (1997)
	Paraquat Dichloride	kg	8.74E-05	Ecoinvent 2.2
	Clopyralid	kg	3.79E-06	Ecoinvent 2.2
	2,4-D	kg	1.16E-04	Ecoinvent 2.2
	Dimethylamine salt of 2,4-D-Dichlorophenoxyacetic acid	kg	1.90E-04	Ecoinvent 2.2
	Picloram	kg	2.59E-05	Ecoinvent 2.2
	Carbaryl	kg/UB	3.00E-05	BASF, 2002

Table SD38: Inventory for supplementary feed for cattle production

	Material/resources	Unit	Value	Source
Supplementary Feed	Corn	kg	4.56E-03	
	Copper Chloride	kg	6.15E-05	BASF (1998)
	Dicalcium phosphate	kg	1.01E-02	BASF (2003)
	Iodine	kg	5.71E-04	BASF (2006)
	Limestone (Calcium Carbonate)	kg	3.02E-02	BASF (1997)
	Magnesium oxide	kg	1.04E-03	Boustead (1996)
	Molasses	kg	2.08E-04	BASF (2000)
	Potassium fertilizer	kg	1.64E-03	BASF (1997)
	Sodium chloride	kg	8.33E-03	Boustead (1996)
	Sodium Selenite	kg	5.95E-07	BASF (2003)

	Thiamine Mononitrate	kg	1.98E-07	BASF (2003)
	Urea	kg	1.30E-02	BASF (2005)
	Zinc Sulfate	kg	3.11E-04	BASF (2003)
	Livestock waterers	liters	1.81E+01	IFSM
	Electricity, pole sheds	kwh	1.15E-01	BASF (2011)
Utilities	Diesel, road	MJ	1.08	BASF (1999)
	Gasoline, all	MJ	6.64E-01	BASF (1999)
	Land Use Feedlot	m²	3.45E-01	IFSM
	Lubricant	MJ	4.46E-03	BASF (1999)
Transport	Cows / Calves	ton km	5.62E-03	US LCI (2011)[1]
Air Emission	CH_4	kg	6.94E-02	IFSM
	N_2O	kg	3.51E-03	IFSM
	NH_3	kg	5.00E-02	IFSM

Table SD39: Invenory for cattle slaughter and chilling

Component	Flow	Unit	Amount	Source
Input	Agricultural spreading, digestive tract	kg	0.103	Ecoinvent
	Disposal, animal byproduct to incineration	kg	0.15	Ecoinvent
	Transport, frieght, lorry (16-32 metric tons)	kg.ton	76.44	Ecoinvent
				Ecoinvent
				Ecoinvent
	Slaughtering and chilling; of beef, industrial production; French production mix, at plant;1 kg of animal by-products C3 for PAP, for processing (POUi)/FR U			Ecoinvent
Output	Slaughtering and chilling; of beef, industrial production; French production mix, at plant;1 kg of beef carcass, for processing (POUi)/FR U	kg	1	Ecoinvent
	Slaughtering and chilling; of beef, industrial production; French production mix, at plant;1 kg of blood PAP C3, for processing (POUi)/FR U	kg	0.0425	Ecoinvent
	Slaughtering and chilling; of beef, industrial production; French production mix, at plant;1 kg of edible offal, for processing (POUi)/FR U	kg	0.0847	Ecoinvent
	Slaughtering and chilling; of beef, industrial production; French production mix, at plant;1 kg of Fat C3, for processing (POUi)/FR U	kg	0.111	Ecoinvent
	Slaughtering and chilling; of beef, industrial production; French production mix, at plant;1 kg of hide, for processing (POUi)/FR U	kg	0.107	Ecoinvent
Emissions	Ammonia	kg	13.46	Ecoinvent

Table SD40: Inventory Fresh ground beef production

Component	Flow	Unit	Amount	Source
Input	Building hall	m2	4.57E-07	Ecoinvent
	Deboning of beef quarter	kg	1.00242	Ecoinvent
	Fresh product storage	kg	1	Ecoinvent
	Fresh trimming storage	kg	1.00242	Ecoinvent
	Grinding, forming and packaging	kg	1	Ecoinvent
	Occupation, industrial area	m2.a	0.00015	Ecoinvent
	Quarter storage, beef quarter	kg	1.38787	Ecoinvent
	slaughtering and chilling of beef	kg	1.38787	Ecoinvent
Output				
	Fresh ground beef production	kg	1	

Table 41: Inventory for packaging of slaughtered cattle

Component	Flow	Unit	Amount	Source
Packaging for slaughter	Aluminum Alloy	kg	2.04E-05	BASF (1996)
	Cardboard, recycled	kg	3.05E-03	Ecoinvent 2.2
	Cardboard, virgin	kg	1.84E-02	Ecoinvent 2.2
	HDPE	kg	4.47E-05	BASF (2007)
	Label, paper	kg	4.27E-05	Ecoinvent 2.2
	Latex		2.79E-05	Ecoinvent 2.2
	LDPE	kg	1.30E-02	BASF (2005)
	Polypropylene	kg	8.07E-05	BASF (1996)
	Wood pallets	kg	1.41E-03	Ecoinvent 2.2
Consumables	Cotton	kg	1.94E-05	BASF (2003)
	HDPE	kg	7.18E-07	BASF (2007)
	Iron	kg	6.67E-07	BASF (1999)
	Nylon	kg	4.48E-07	BASF (2002)
	PVC	kg	3.97E-06	BASF (1996)
	Steel	kg	8.34E-06	BASF (2010)
	Uniform Laundering	l	2.01E-01	BASF (2005)
Utilities	Biogas (on site generation & use)	MJ	6.14E-03	Ecoinvent 2.2
	Diesel	MJ	1.79E-03	BASF (1999)
	Electricity (Purchased)	MJ	2.55E-01	BASF (2011)
	Gasoline	MJ	7.18E-05	BASF (1999)
	Land footprint of building	m²	3.77E-05	
	Land footprint of landscaped area surrounding building	m²	1.29E-04	
	LPG Butane Propane (liquid)	MJ	3.93E-04	Boustead (1996)
	Lubricant Oil	MJ	2.33E-04	BASF (1999)

	Natural Gas	MJ	5.84E-02	BASF (1999)
	Municipal water	l	5.02	BASF (2010)
	Refrigerant Gas		9.26E-06	Ecoinvent 2.2
	Road	m^2	1.44E-04	
	Water Well	l	1.34E-01	BASF (2010)
Transport	Cardboard	ton.km	1.47E-02	US LCI (2011)
	Cattle	ton.km	2.04E-01	US LCI (2011)
	CO_2	ton.km	4.01E-04	US LCI (2011)
	Harvesting to case-ready	ton-km	2.08E-01	US LCI (2011)
	Plastic	ton.km	5.95E-03	US LCI (2011)
	Waste	ton.km	9.63E-05	US LCI (2011)
	Average for all other material inputs	ton.km	2.55E-03	US LCI (2011)
Emissions†	CH_4	mg	1.14E-01	
	Chloride	mg	5.40E+01	
	COD	mg	3.54E-02	
	Landfill	kg	9.01E-03	Ecoinvent 2.2
	N_2O	mg	1.64E-02	
	NH_3	mg	1.08E-01	
	NO_X	mg	1.47	
	N-total	mg	6.38	
	Organic Compounds (VOC) including Hexane	mg	1.73E-01	
	PO_4 as P	mg	2.4	
	SO_X	mg	5.11	
	Sulfate	mg	4.23E+01	

Table SD42: Ingredients for animal burger production

Component 4 servings (268 g per serving)	Flow	Conventional	Unit	Source
Grilling of beef (patty)	Ground Beef	oz	32	USDA
	chopped onion	tablespoons	2	Source 2
	sour cream	cup	0.5	Source 2
	dried parsley flakes	teaspoons	4	Source 2
	salt	teaspoon	0.5	Source 2
	pepper	teaspoon	0.5	Source 2
	dried thyme	teaspoon	1	
	preheated gas grill (medium heat (160F)			
	Time to grill	minutes	7 to 9	
Grilling of buns	hamburger buns, split and toasted	hamburger buns	8	
	heat (160 F)			
	Time	minutes	1	

Other ingredients (Toppings)	Lettuce leaves	leaves	8
	Ketchup	tablespoon	2.5
	mustard	cup	0.5
	onion slices	Slices	8
	pickle slices	tablespoon	2
	sliced tomato	Slices	4
	cooked bacon strips	slices	4
	Cheese	Slice	4

Dressing percentage represents the portion of the live animal weight that transfers to the hot carcass weight.

An average cow of 1200 lb will consume 27 lb of feed , Corn silage is 28.5 lb. per head per day (18.5 lb. is water and 10 lb. is silage). Corn silage is 35% dry matter and 65% moisture.

2.07 lb to 2.24 lb of corn per lb of finished animal.

The weight of cattle is 1250 lb slaughter weight. Carcas

Hay wastage was assumed to be 6% to 20%

8.3 IPCC method for estimating the direct and indirect N_2O emissions for agricultural production

Tier 1

In its most basic form, direct N_2O emissions from managed soils are estimated using Equation 11.1 as follows:

EQUATION 11.1
DIRECT N_2O EMISSIONS FROM MANAGED SOILS (TIER 1)

$$N_2O_{Direct}\text{–}N = N_2O\text{–}N_{N\,inputs} + N_2O\text{–}N_{OS} + N_2O\text{–}N_{PRP}$$

Where:

$$N_2O\text{–}N_{N\,inputs} = \begin{bmatrix} \left[(F_{SN} + F_{ON} + F_{CR} + F_{SOM}) \bullet EF_1 \right] + \\ \left[(F_{SN} + F_{ON} + F_{CR} + F_{SOM})_{FR} \bullet EF_{1FR} \right] \end{bmatrix}$$

$$N_2O\text{–}N_{OS} = \begin{bmatrix} \left(F_{OS,CG,Temp} \bullet EF_{2CG,Temp}\right) + \left(F_{OS,CG,Trop} \bullet EF_{2CG,Trop}\right) + \\ \left(F_{OS,F,Temp,NR} \bullet EF_{2F,Temp,NR}\right) + \left(F_{OS,F,Temp,NP} \bullet EF_{2F,Temp,NP}\right) + \\ \left(F_{OS,F,Trop} \bullet EF_{2F,Trop}\right) \end{bmatrix}$$

$$N_2O\text{–}N_{PRP} = \left[\left(F_{PRP,CPP} \bullet EF_{3PRP,CPP}\right) + \left(F_{PRP,SO} \bullet EF_{3PRP,SO}\right) \right]$$

Where:

$N_2O_{Direct}\text{–}N$ = annual direct N_2O–N emissions produced from managed soils, kg N_2O–N yr^{-1}

$N_2O\text{–}N_{N\,inputs}$ = annual direct N_2O–N emissions from N inputs to managed soils, kg N_2O–N yr^{-1}

$N_2O\text{–}N_{OS}$ = annual direct N_2O–N emissions from managed organic soils, kg N_2O–N yr^{-1}

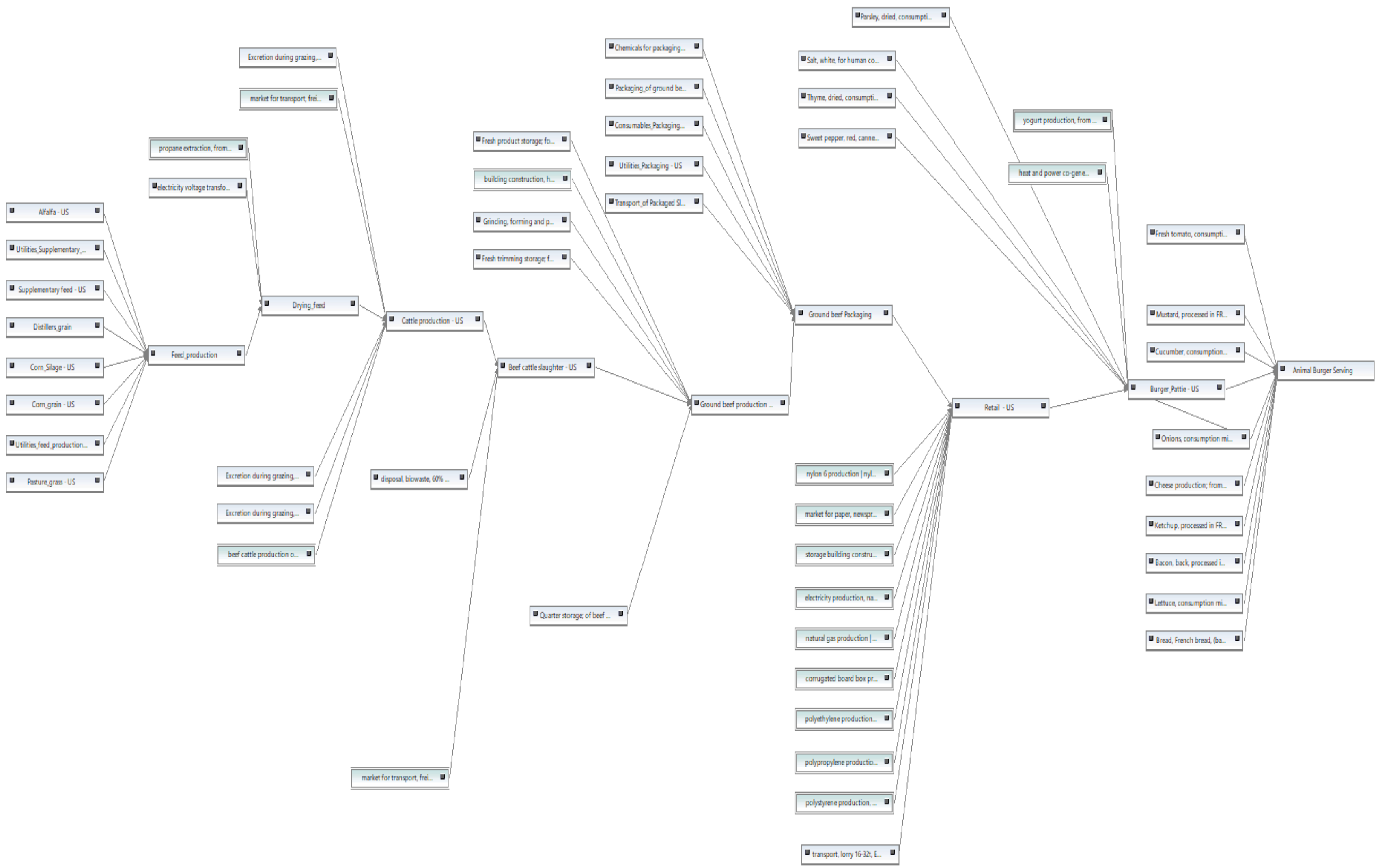

Figure SD31:Open LCA model for the production of beef burger

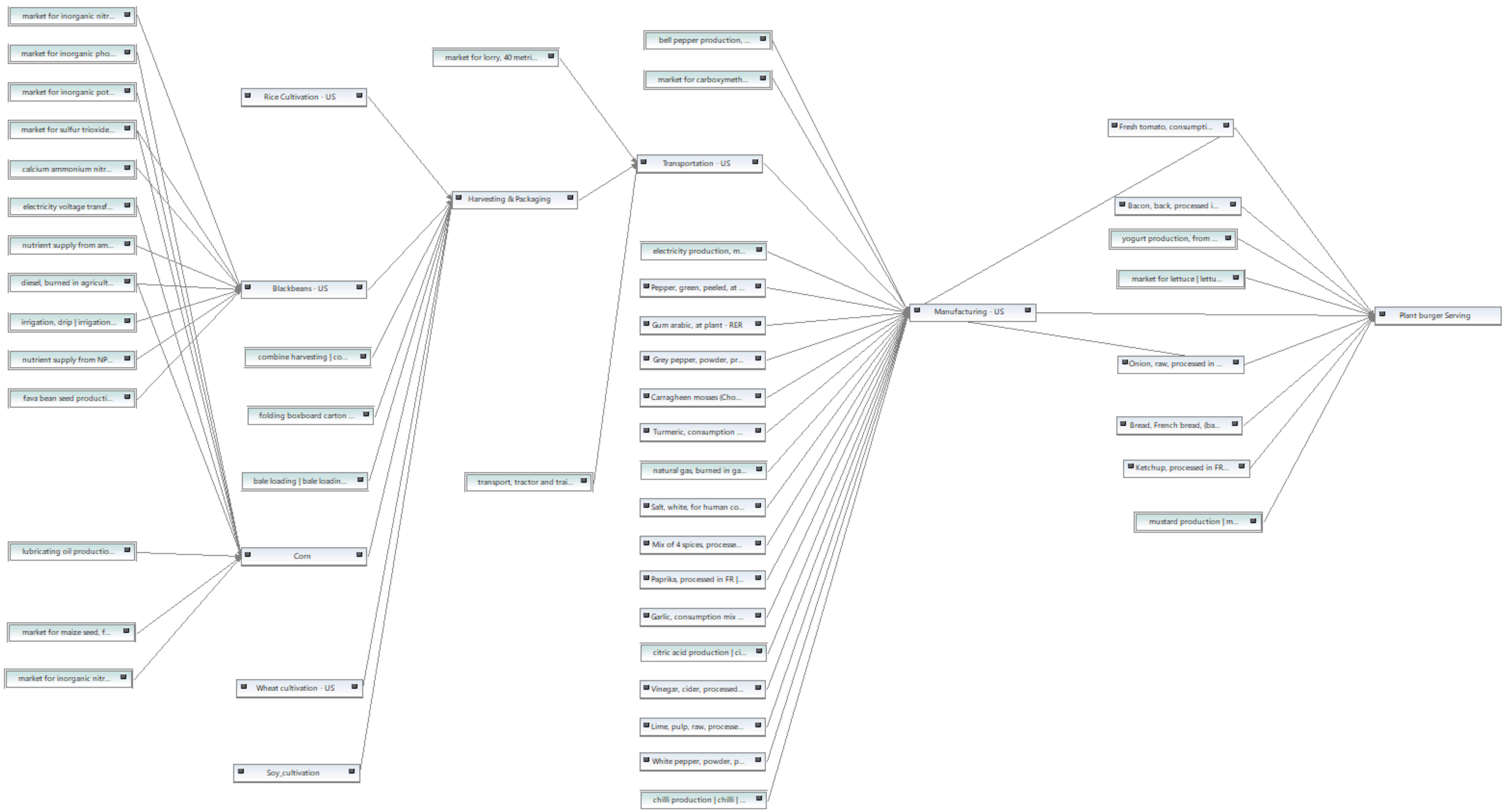

Figure SD32; OpenLCA model graph for LCA of plant-burger per serving

Table SD43: Midpoint environmental impact results for plant-based burger

Impact category	Reference unit	Result	Normalized	Result	Normalized
		Plant-based burger		Animal-based burger	
Fine particulate matter formation	kg PM2.5 eq	5.347165	0.20907415	14.82152	0.579521378
Fossil resource scarcity	kg oil eq	5772.36	5.887807351	3375.956	3.443474969
Freshwater ecotoxicity	kg 1,4-DCB	125.1021	101.9582082	2935.161	2392.156055
Freshwater eutrophication	kg P eq	0.396766	0.611019191	5.137697	7.912053015
Global warming	kg CO2 eq	12471.22	1.561396634	15417.12	1.930223951
Human carcinogenic toxicity	kg 1,4-DCB	294.4106	106.2822415	697.5562	251.8178041
Human non-carcinogenic toxicity	kg 1,4-DCB	2001.368	13.42917649	695305.8	4665.501749
Ionizing radiation	kBq Co-60 eq	86.91139	0.180775684	156.9028	0.326357782
Land use	m2a crop eq	198.7333	0.032194795	52287.82	8.470627056
Marine ecotoxicity	kg 1,4-DCB	164.0694	158.9832713	1120.483	1085.748168
Marine eutrophication	kg N eq	0.082373	0.017875004	14.9434	3.242716866
Mineral resource scarcity	kg Cu eq	11.91794	9.92765E-05	30.75968	0.000256228
Ozone formation, Human health	kg NOx eq	8.2831	0.402558683	25.32369	1.23073157
Ozone formation, Terrestrial ecosystems	kg NOx eq	9.093558	0.511967312	26.13362	1.471322764
Stratospheric ozone depletion	kg CFC11 eq	0.001353	0.022596171	0.075366	1.258606897
Terrestrial acidification	kg SO2 eq	15.93718	0.388867258	51.33331	1.252532721

Terrestrial ecotoxicity	kg 1,4-DCB	3346.691	3.229557043	9951642	9603.334912
Water consumption	m3	1108.068	4.155253782	5418.672	20.32001955

Table SD44: Environmental impact metrics quantified in the LCA of beef-burger production

	Full burger	Burger patties	Retail	Complete packaging	Cattle slaughter	Cattle production	Drying of feed	Feed production
Fine particulate matter formation, kg PM2.5 eq	9.42E-03	3.27E-03	5.30E-02	3.84E-03	5.74E-03	4.72E-02	3.07E-02	1.21E-01
Fossil resource scarcity, kg oil eq	4.06E-01	3.47E-01	3.35E+00	5.02E-01	5.35E-01	5.48E-01	7.96E+00	1.94E+01
Freshwater ecotoxicity, kg 1,4-DCB	8.97E-02	4.42E-02	1.09E+00	1.41E-01	1.81E-01	1.12E-01	6.96E-02	1.17E+01
Freshwater eutrophication, kg P eq	1.55E-03	4.33E-04	6.53E-03	7.81E-04	2.25E-02	1.90E-03	1.44E-03	2.59E-02
Global warming, kg CO2 eq	3.89E+00	2.20E+00	1.84E+01	1.76E+00	2.12E+00	3.56E+01	9.88E+00	5.98E+01
Human carcinogenic toxicity, kg 1,4-DCB	1.53E-01	1.90E-01	1.34E+01	2.46E-01	5.10E-01	3.17E-01	6.61E-01	1.09E+01
Human non-carcinogenic toxicity, kg 1,4-DCB	1.03E+00	1.97E-01	7.67E+00	1.46E+00	5.20E-01	3.22E+00	6.46E-01	1.26E+02
Ionizing radiation, kBq Co-60 eq	3.08E+00	1.46E-01	1.71E+00	7.00E-01	3.24E-01	2.54E+00	8.51E-01	3.20E+00
Land use, m2a crop eq	4.03E+00	3.47E+00	2.99E+00	5.31E-01	5.78E-02	1.54E+01	3.86E-02	1.01E+00
Marine ecotoxicity, kg 1,4-DCB	2.12E-01	1.29E-01	3.31E+00	1.90E-01	3.38E-01	3.40E-01	2.77E-01	1.22E+01
Marine eutrophication, kg N eq	2.07E-03	4.63E-04	3.00E-04	7.07E-05	9.33E-05	3.40E-03	3.08E-05	2.63E-03
Mineral resource scarcity, kg Cu eq	3.52E-02	6.01E-03	3.71E-01	6.73E-03	1.22E-02	1.64E-01	1.01E-02	2.93E-01
Ozone formation, Human health, kg NOx eq	9.45E-03	3.96E-03	7.07E-02	5.22E-03	5.09E-03	3.13E-02	3.60E-02	1.71E-01
Ozone formation, Terrestrial ecosystems kg NOx eq	9.49E-03	3.96E-03	7.16E-02	5.29E-03	5.08E-03	3.10E-02	3.67E-02	1.76E-01
Stratospheric ozone depletion kg CFC11 eq	7.18E-06	2.29E-06	1.67E-06	6.82E-07	1.48E-06	4.50E-05	2.84E-06	5.03E-06
Terrestrial acidification kg SO2 eq	2.08E-02	5.96E-03	7.38E-02	5.45E-03	5.64E-03	1.48E-01	4.06E-02	1.58E-01
Terrestrial ecotoxicity kg 1,4-DCB	5.09E-02	0.00E+00	3.31E-01	2.57E+00	2.54E-02	5.09E-02	2.04E-01	2.51E+02

Water consumption m3	3.23E-02	1.84E-02	5.50E-02	9.92E-02	1.67E-02	4.53E-02	8.17E-03	1.58E+00

Table SD45; Environmental impact metrics quantified in the LCA for plant-based-burger production

Impact category	Full burger	Retail	Packaging & transport of patties	Manufacturing	Packaging & transportation	Harvesting & processing	Feed production
Fine particulate matter formation, kg PM2.5 eq	5.52E-03	8.78E-02	1.73E-03	3.40E-03	9.88E-04	3.26E-02	1.42E-01
Fossil resource scarcity, kg oil eq	6.61E-01	4.07E+00	2.35E-01	1.08E+00	8.26E-02	1.97E+01	7.21E+00
Freshwater ecotoxicity, kg 1,4-DCB	2.69E-01	4.59E+00	9.11E-02	3.35E-02	4.15E-02	7.75E-01	7.59E+00
Freshwater eutrophication, kg P eq	1.22E-05	2.20E-02	6.65E-04	3.05E-04	4.21E-04	3.56E-03	3.23E-02
Global warming, kg CO2 eq	4.01E+00	6.41E-01	5.35E-02	2.41E-01	2.67E-02	1.19E+00	1.31E+02
Human carcinogenic toxicity, kg 1,4-DCB	1.06E+00	1.57E+01	8.72E-02	1.37E-01	5.02E-02	1.44E+00	7.98E+00
Human non-carcinogenic toxicity, kg 1,4-DCB	2.11E+00	3.64E+01	1.17E+00	2.95E-01	4.36E-01	7.98E+00	9.22E+01
Ionizing radiation, kBq Co-60 eq	7.53E-03	3.75E+00	3.35E-01	3.73E-01	1.41E-01	2.07E+00	5.88E+00
Land use, m2a crop eq	7.71E-02	1.09E+01	3.64E-01	1.93E-02	1.90E-01	1.49E-01	1.59E+01
Marine ecotoxicity, kg 1,4-DCB	4.59E-01	2.73E+00	6.63E-02	2.89E-02	2.89E-02	5.01E-01	1.32E+01
Marine eutrophication, kg N eq	1.99E-05	1.21E-03	2.08E-05	3.72E-05	2.90E-05	4.19E-04	7.33E-03
Mineral resource scarcity, kg Cu eq	8.97E-05	4.06E-01	4.85E-03	2.06E-03	1.97E-03	1.97E-02	4.63E-01
Ozone formation, Human health, kg NOx eq	1.18E-02	2.90E-02	3.09E-03	3.49E-03	1.03E-03	2.08E-02	2.63E-01
Ozone formation, Terrestrial ecosystems kg NOx eq	4.57E-03	3.52E-02	2.98E-03	3.42E-03	9.83E-04	2.26E-02	2.69E-01
Stratospheric ozone depletion kg CFC11 eq	3.97E-08	3.56E-06	5.63E-07	1.09E-06	1.85E-07	3.84E-06	5.70E-05
Terrestrial acidification kg SO2 eq	9.17E-05	1.21E-01	3.80E-03	8.39E-03	1.56E-03	8.18E-02	2.41E-01

Terrestrial ecotoxicity kg 1,4-DCB	2.54E-02	6.61E+01	6.56E+00	1.73E+00	1.88E+00	5.62E+00	1.72E+02
Water consumption m3	3.71E-02	8.91E-03	3.71E-04	2.45E-01	1.86E-04	8.17E-03	1.56E+00

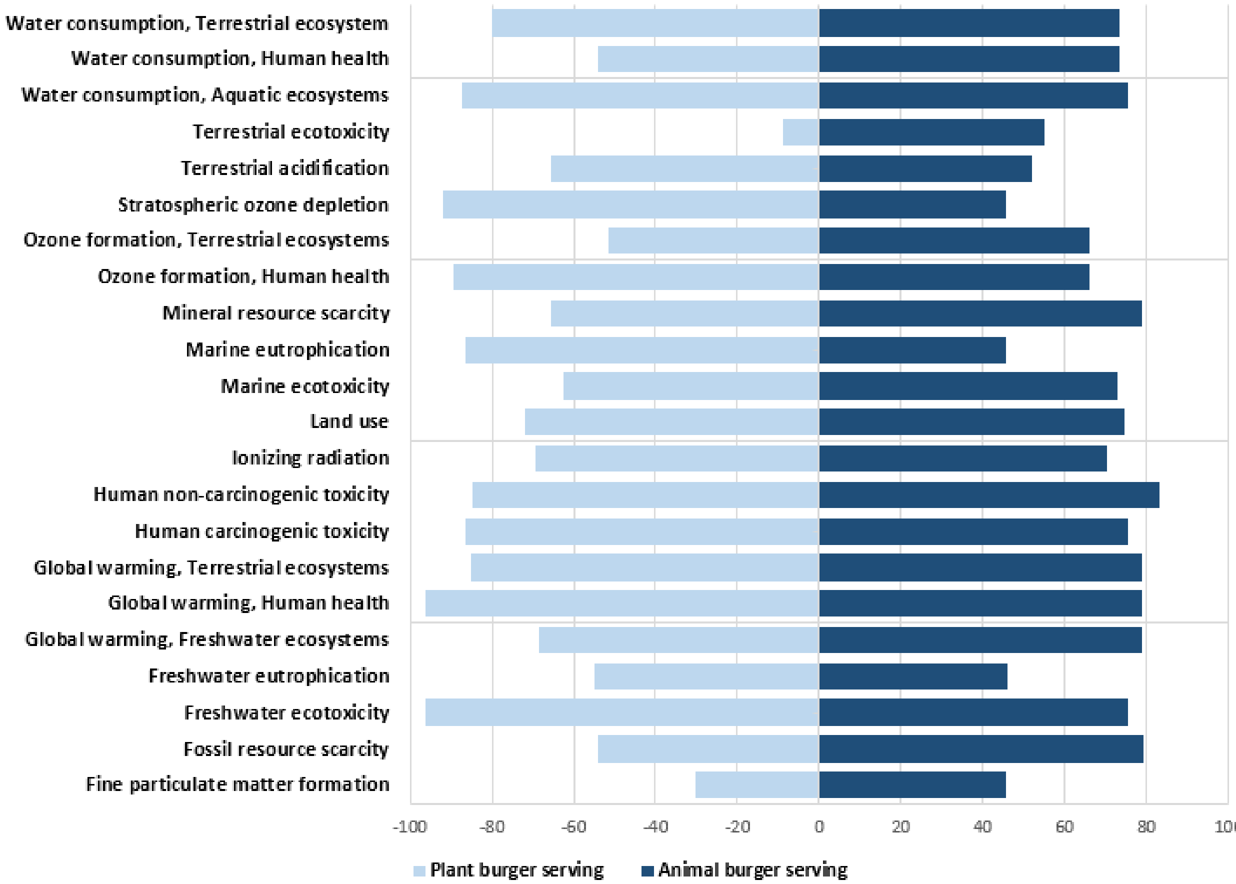

Figure SD33

Calculate final HSR score:
HSR baseline points – V points – P points – F points

Category 3D products must score	
≤ 24	5 stars
25 to 26	4½ stars
27 to 28	4 stars
29 to 30	3½ stars
31	3 stars
32 to 33	2½ stars
34 to 35	2 stars
35 to 36	1½ stars
38 to 39	1 star
≥ 40	½ star

Category 2D products must score	
≤ -2	5 stars
-1 to 0	4½ stars
1 to 2	4 stars
3	3½ stars
4 to 5	3 stars
6 to 7	2½ stars
8	2 stars
9 to 10	1½ stars
11 to 12	1 star
≥ 13	½ star

Category 1D beverages must score	
≤ -2	5 stars
-1	4 ½ stars
0	4 stars
1	3 ½ stars
2	3 stars
3	2 ½ stars
4	2 stars
5	1 ½ stars
6	1 star
≥7	½ star

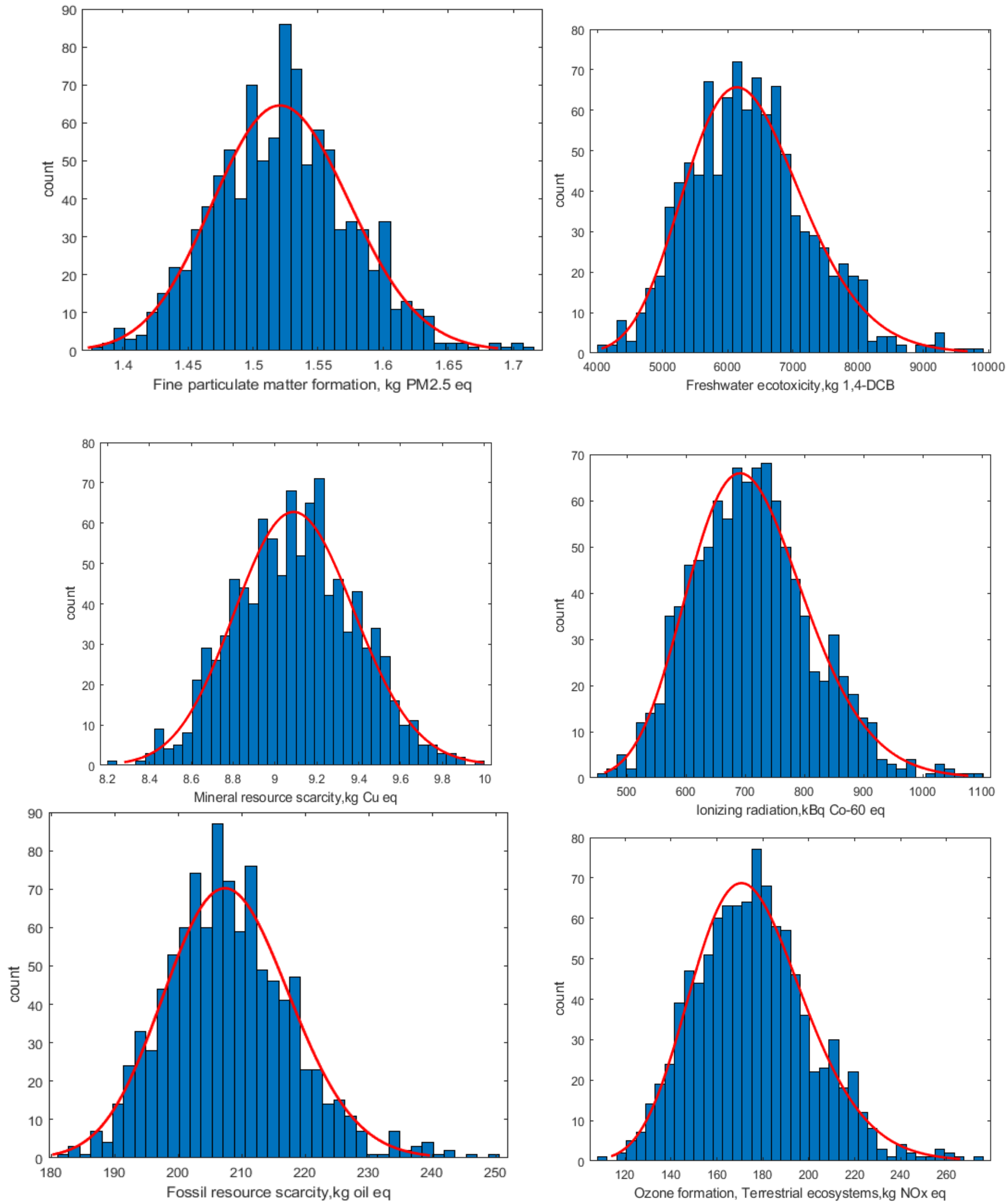

Figure SD34: Probability distribution for LCIA of plant-based burger model

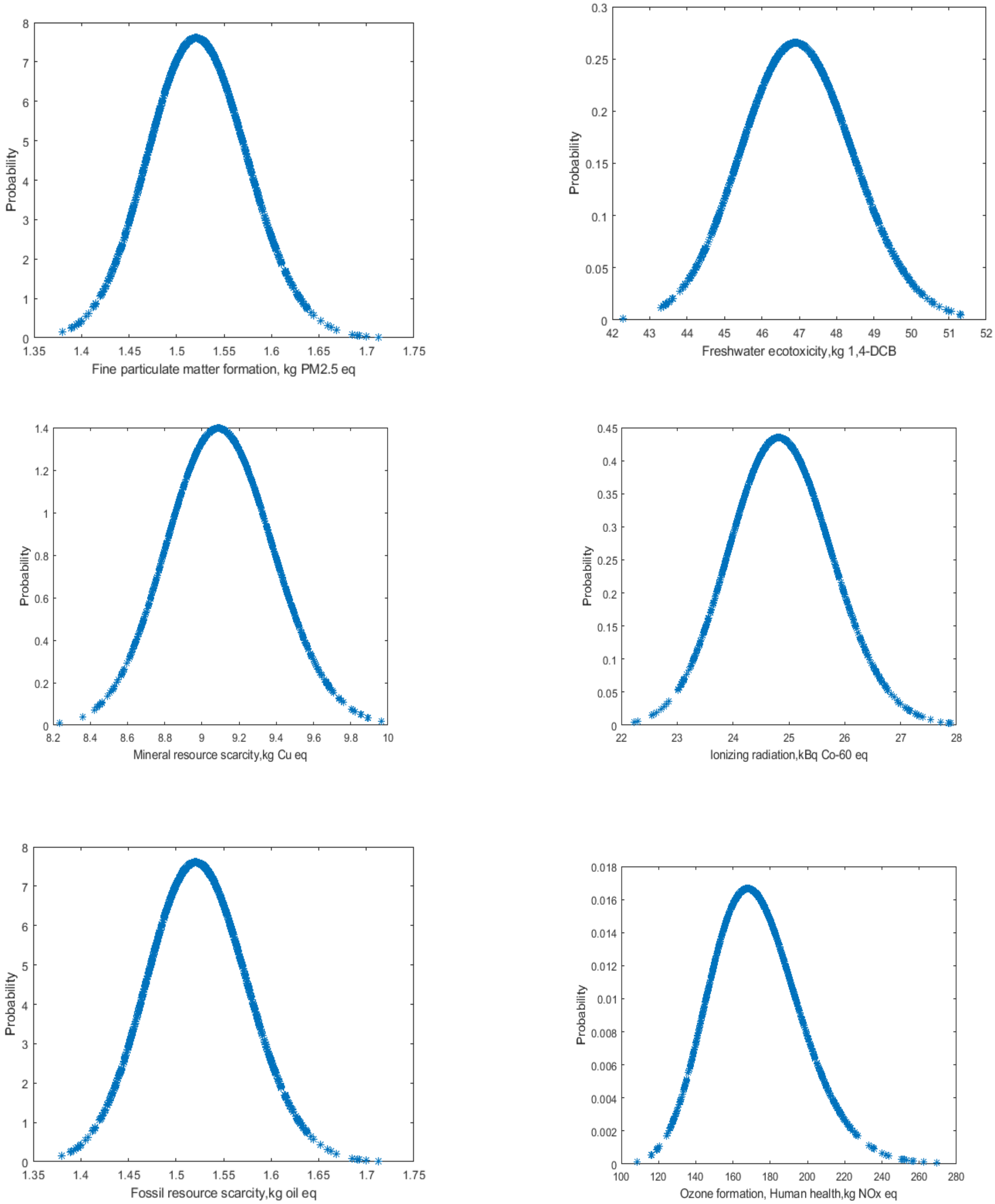

Figure SD35 Probability profile for the LCAI considering the plant-based burger model

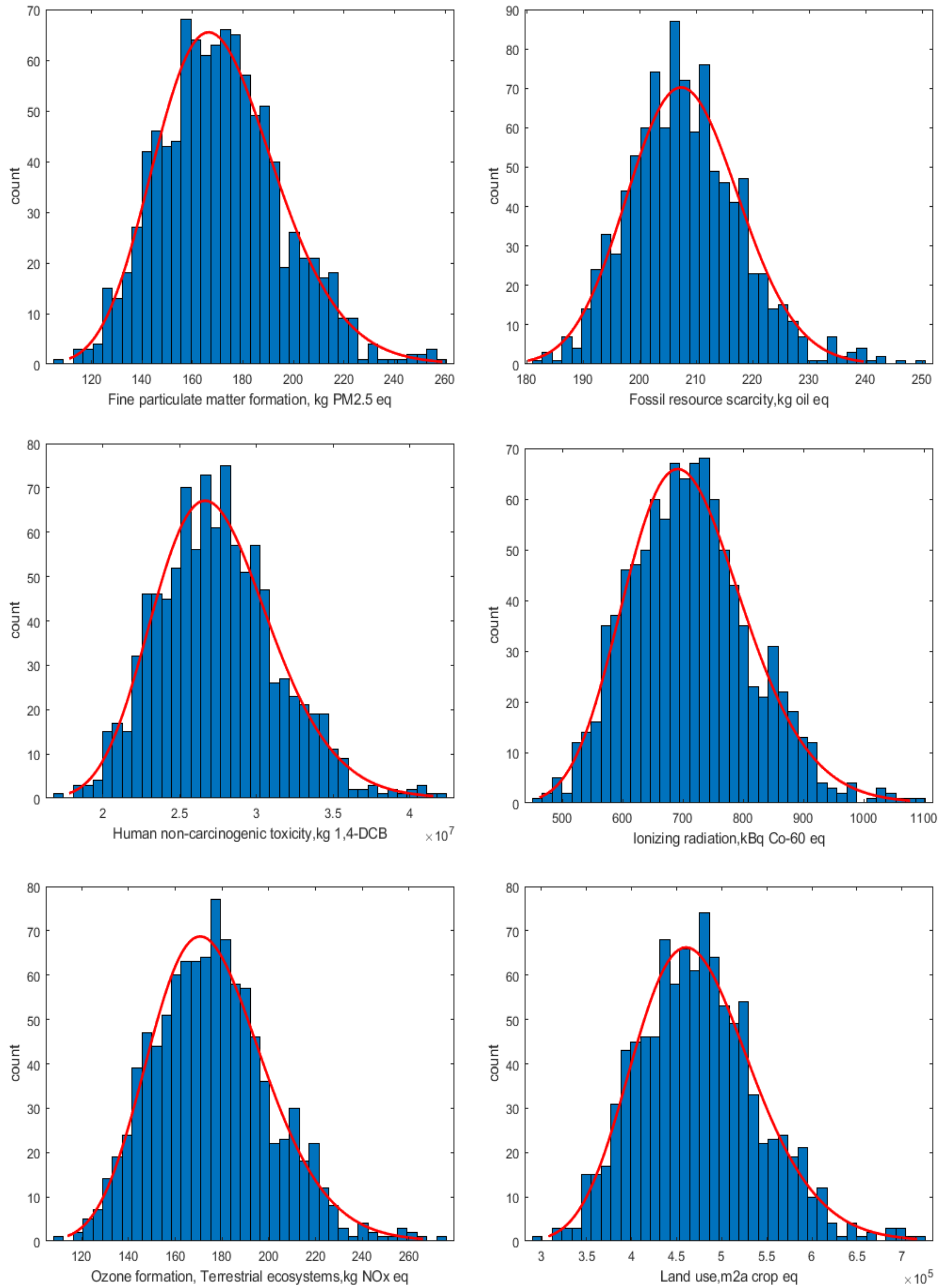

Figure SD36: Probability distribution function of LCIA of the animal-based burger LCA model

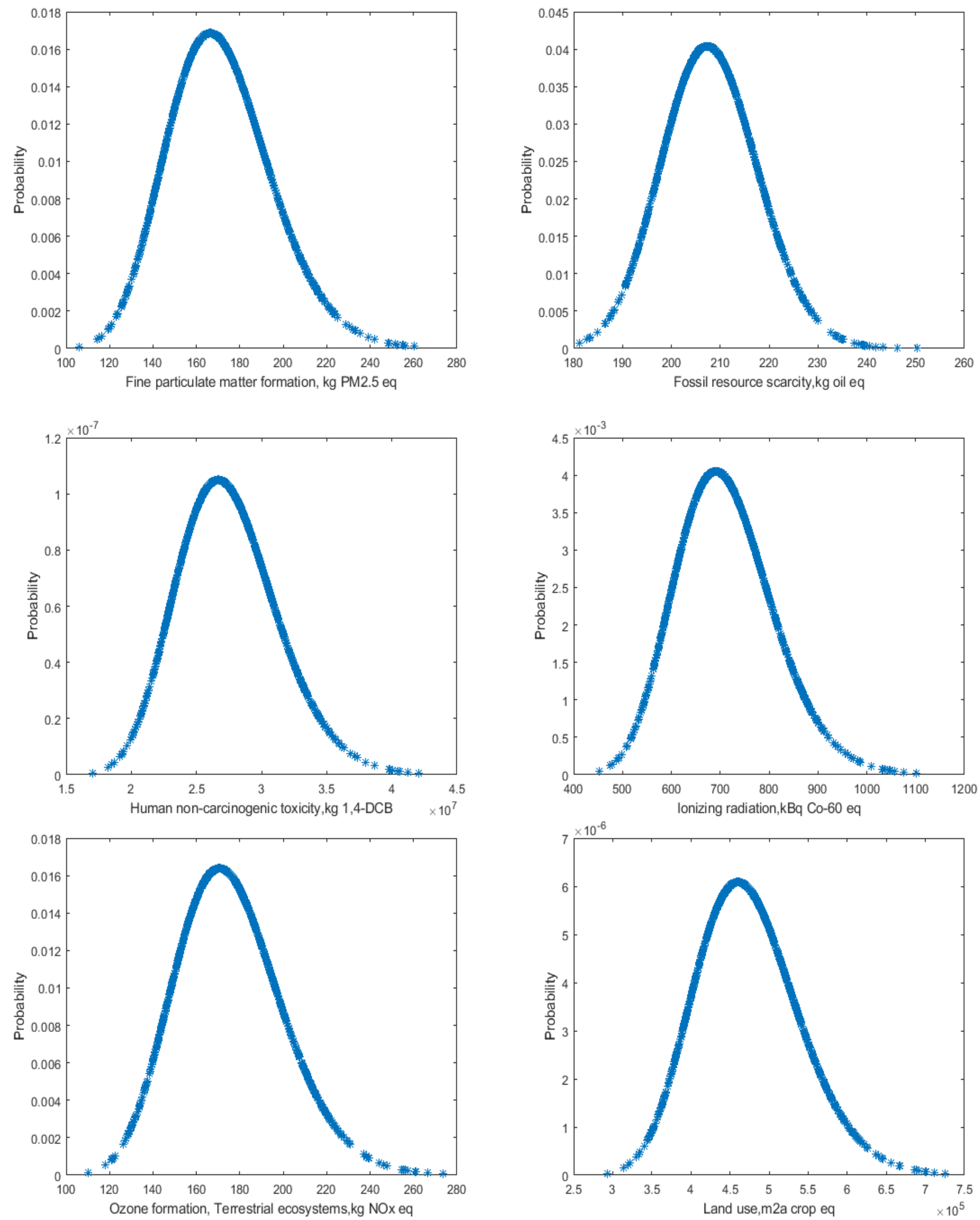

Figure SD37: Probability profile for the LCAI of the animal-based burger model

Table SD46: Health star rating and its associated nudges to influence consumer choices

S/N	Star rating	Associated nudge
1	1 star	Not a healthy choice
2	2 stars	Less healthy choice
3	3 stars	Neutral healthy choice
4	4 stars	More healthier choice
5	5 stars	Healthier choice

Table SD47

S/N	Food compass score range	Interpretation	Color code	Associated nudge
1	0 to 20	Least healthy		This type of food is not encouraged!
2	20 to 40	Less healthy		
3	40 to 60	Neutral healthy		
4	60 to 80	More healthy		
5	80 to 100	Most healthy		This type of food is encouraged!!

Table SD48: Sustainability score

S/N	Overall sustainability Performance score	EnN score rating	Color code	Associated nudge
1	0 to 0.25	1		This food is unhealthy and unsustainable
2	0.25 to 0.50	2		This food is slightly healthy and unsustainable
3	0.50 to 0.75	3		This food is moderately healthy and sustainable
4	0.75 to 1	4		This food is healthy and sustainable

8.4 Statistical analysis of Survey data

Table SD49

Socio-demographic details

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-24	60	53.6	53.6	53.6
	25-30	33	29.5	29.5	83.0
	31-40	8	7.1	7.1	90.2
	above 40	11	9.8	9.8	100.0

	Total	112	100.0	100.0	

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	52	46.4	46.4	46.4
	Male	60	53.6	53.6	100.0
	Total	112	100.0	100.0	

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Arabic	2	1.8	1.8	1.8
	Asian	12	10.7	10.7	12.5
	Black/ African American	33	29.5	29.5	42.0
	Hispanic	15	13.4	13.4	55.4
	Prefer not to say	2	1.8	1.8	57.1
	White	48	42.9	42.9	100.0

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		1	.9	.9	.9
	Graduate student	52	46.4	46.4	47.3
	Staff/Faculty	8	7.1	7.1	54.5
	Undergraduate student	51	45.5	45.5	100.0

Q8Do you adhere to any dietary pattern?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		2	1.8	1.8	1.8
	Maybe	17	15.2	15.2	17.0
	No	59	52.7	52.7	69.6
	Yes	34	30.4	30.4	100.0
	Total	112	100.0	100.0	

Q9If yes, which dietary pattern? - Selected Choice

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		74	66.1	66.1	66.1
	Flexitarian	5	4.5	4.5	70.5
	Omnivore diet	15	13.4	13.4	83.9
	Others, kindly list below	12	10.7	10.7	94.6
	Vegetarian	6	5.4	5.4	100.0
	Total	112	100.0	100.0	

Q9_5_TEXT If yes, which dietary pattern? - Others, kindly list below - Text

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		100	89.3	89.3	89.3
	Fasting, I only eat one meal a day	3	2.7	2.7	92.0
	high protien diet	1	.9	.9	92.9
	I think I was confused on the previous question. I just try to limit dairy products.	1	.9	.9	93.8
	No crustaceans	2	1.8	1.8	95.5
	No specific pattern	2	1.8	1.8	97.3
	Slow food	3	2.7	2.7	100.0
	Total	112	100.0	100.0	

Q10How often do you eat burgers?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		1	.9	.9	.9
	Once /twice a week	24	21.4	21.4	22.3
	Once a month	53	47.3	47.3	69.6
	two/three times in a month	34	30.4	30.4	100.0
	Total	112	100.0	100.0	

Q11Have you eaten any animal-based burgers over the last month?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		1	.9	.9	.9
	Definitely not	10	8.9	8.9	9.8
	Definitely yes	71	63.4	63.4	73.2
	Might or might not	5	4.5	4.5	77.7
	Probably not	10	8.9	8.9	86.6
	Probably yes	15	13.4	13.4	100.0
	Total	112	100.0	100.0	

Q12Have you eaten any plant-based burgers over the last month?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		1	.9	.9	.9
	Definitely not	37	33.0	33.0	33.9
	Definitely yes	19	17.0	17.0	50.9
	Might or might not	5	4.5	4.5	55.4
	Probably not	32	28.6	28.6	83.9
	Probably yes	18	16.1	16.1	100.0
	Total	112	100.0	100.0	

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	88.863	38	<.001
Deviance	84.997	38	<.001

Figure 38: A pair plot of participants who choices and different factors based on gender.

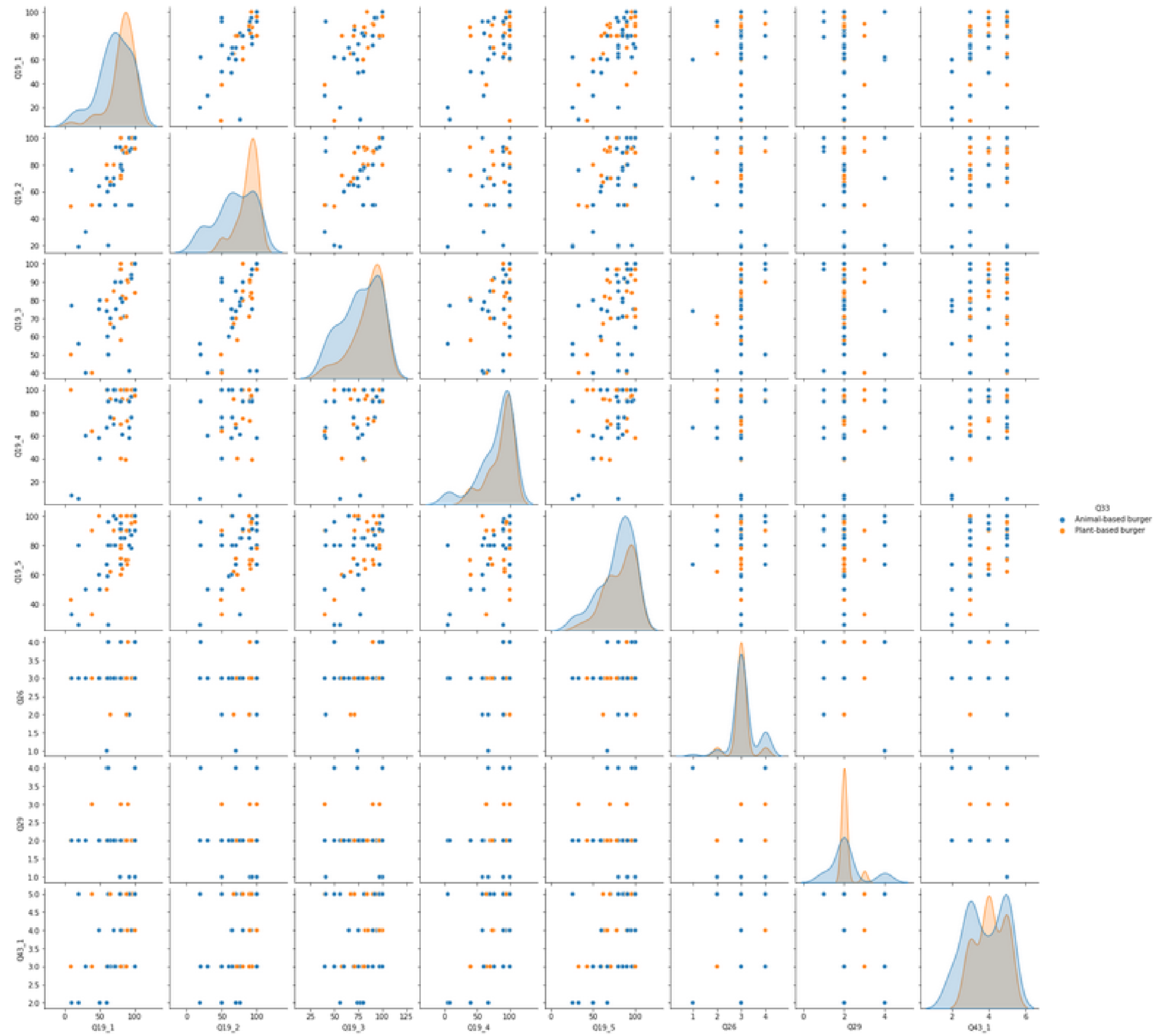

Figure 39: A pair plot of participants who chose plant-based burger vs animal-based burger against all numerical data collected

8.5 Questionnaire Design

Consumer testing

Objective: Consumer perception of FCOD burger simulator

- Consumers must see the two different burgers
- Having seen the two types and their health and environmental outcomes, which one would you

Hypothesis: We hypothesize that the nudges provided will positively influence consumer choice of purchasing.

Brief background information about the experiment

Chronological order of the survey

- Sample demographic
- Participants' burger consumption behavior and predisposition
- Participants' smartphone using behavior
- Simulator/Technology testing
- Purchasing testing
- Participants' trust and recommendations

Demographic

Objective: The objective is to avoid making assumptions about the participants and provide context analysis of different groups' preferences.

(1) What age group are you in?
  (a) Below 18 (b) 18-24, (c) 25-30, (d) 31-40, (e) above 40.
(2) How do you describe your gender?
  (a) Male, (b) female, (c) non-binary/third gender (d) Prefer not to say
(3) Which race do you belong to?
  (a) White (b) Black/African American (c) Asian (d) Hispanic (e) Prefer not to say
(4) Are you affiliated to the University of Arkansas?
  (a) Yes (b) No
  If No, Kindly state your institution of affiliation …………………..
(5) Which college are you affiliated with?
  (a) Dale Bumpers College of Agricultural, Food and Life Sciences
  (b) Fay Jones School of Architecture and Design
  (c) Fulbright College of Arts and Sciences
  (d) Sam M. Walton College of Business
  (e) College of Education and Health Professions,
  (f) College of Engineering
  (g) Others, then kindly list below…………….

(6) Which of the following do you relate to?
  (a) Undergraduate (b) Graduate (c) Staff/Faculty

Burger consumption testing

Objective: To test the frequency to which participants consume animal and plant-based burger

(1) Do you adhere to any dietary patterns?
 (a) Yes (b) No (c) Maybe
(2) If yes, which dietary pattern?
 (a) Flexitarian (b) Vegetarian (c) Vegan
 (d) Omnivore diet (e) Others, kindly list below
(3) How often do you eat burgers?
 (a) Every day, (b) Once/twice a week, (c) Once a month
(4) Have you eaten any animal-based burgers over the last month?
 (a) Definitely not (b) Probably not (c) Might or might not
 (d) Probably yes (e) Definitely yes
(5) Have you eaten any plant-based burgers over the last month?
 (a) Definitely not (b) Probably not (c) Might or might not
 (d) Probably yes (e) Definitely yes
(6) On any given which type of burger will you purchase?
 (a) Animal-based burger (made of beef) (b)Plant-based burger (made of black beans, soy etc)

Participants' smartphone behavior:

Objective: To determine consumer digital product habits

(1) How often do you use mobile applications when purchasing food?
 (a) Every day (b) Once/twice a week (c) Once in a month
 (d) More than once in a month (e) Not at all
(2) How experienced/comfortable are you using an application to purchase food?
 (a) Extremely uncomfortable (b) Somewhat uncomfortable
 (c) Neither confrtable nor uncomfortable (d) Somewhat comfortable
 (e) Extremely comfortable
(3) On average, how often do you download a new application onto your smartphone?
 (a) once a week, (b) twice a week, (c) once a month,
 (d) more than once a month
(4) Can you list any applications you've used in the last month to purchase food?

Technology testing

In the upcoming task, you will explore a Food Choices Overview Dashboard Simulator. This is a simulator designed to guide you to make sustainable food choices at the point of purchase. Assume that you are buying a burger made with two patties of 8oz in total for your lunch. There are two types of burgers, one labeled "animal-based burger" and the second labeled "plant-based burger". The simulator will attempt to guide you in making a sustainable decision by providing a series of indicators peculiar to the two products. After exploring both products on the simulator, you will be asked some questions about your experience with the simulator.

Please click on the link below to explore the Food Choices Overview Dashboard Simulator

FCOD -Burger Simulator

Technology Testing Part 1a:

Objective: to test the ease and usability of the technology

(1) How was your experience navigating the simulator?

S/N	Features	Select from a scale of 1 to 1000
1	User interfaces	
2	Navigation of pages	
3	Layout of pages	
4	The language used on the page	
5	Explanation of indicators	
6	Information flow on the page	

Technology Testing Part 1b:

Objective: to test the consumer level of understanding of specific indicators presented on the simulator

(1) What is the meaning of the term nutritional and health outlook used in the simulator?
  (a) Its a module that combines three health indicators to provide a nutritional and health label for food
  (b) It's a module that combines two health indicators to provide a nutrition and health label for food.
  (c) It's a module that combines four health indicators to provide a nutrition and health label for food.
(2) What is the term environmental impact cost as used in the simulator?
  (a) It's a module that displays the monetary burden of the environmental impact of food
  (b) Its a module that measures the environmental impact of food.
  (c) It's a module that provides an environmental-nutrition score for food
(3) What is the term overall sustainability scoring as used in the simulator?

(4) What is the term EnN score as used in the simulator?
  (a) It's a nutritional score

(b) It's an environmental score
(c) It's an environmental-nutritional score

(5) Did the documentation panel on the simulator provide sufficient information about the terms used and mentioned above?
(a) Yes (b) No (c) Maybe

Technology Testing Part 2:

Objective: To test consumer recollection of results represented by the simulator.

(1) What is the overall sustainability score of the food in the simulator for plant-based burgers?
(a) 1 (b) 2 (c) 3 (d) 4.

(2) What was the advisory/nudge associated with the plant-based burger's overall sustainability score in the simulator?
(b) This food is unhealthy and unsustainable
(c) This food is slightly healthy and unsustainable
(d) This food is healthy and sustainable
(e) This food is moderately healthy and sustainable

(3) What was the rating associated with the plant-based burger's overall sustainability scoring in the simulator?
(a) Very good (b) Good (c) Average (d) Poor

(4) For animal-based burgers, what is the overall sustainability score of the food in the simulator?
(a) 1 (b) 2 (c) 3 (d) 4..

(5) What was the advisory/nudge associated with the animal-based burger's overall sustainability score in the simulator?
a. This food is unhealthy and unsustainable
b. This food is slightly healthy and unsustainable
c. This food is healthy and sustainable
d. This food is moderately healthy and sustainable

(6) What was the rating associated with the animal-based burger's overall sustainability score in the simulator?
(a) Very good
(b) Good
(c) Average
(d) Poor

(7) Before this simulator, were you aware of different burgers' environmental costs and health?
(a) Yes (b) No (c) Maybe

Purchasing testing

Objective: To test which type of burger consumers will purchase

(1) Which burger will you buy?
    (a) Plant-based burger   (b) Animal-based burger
(2) Was the content provided on the simulator sufficient to guide your final decision?
    (a) Yes   (b) No   (c) Somehow
(3) Which of these factors on the simulator/experiment influenced your final decision to purchase a burger?
    (a) Nutritional content claim
    (b) environmental sustainability cost claim
    (c) health and nutritional benefits claim
(4) Would the cost of both products have influenced your final decision?
    (a) Yes   (b) No   (c) Maybe

Participants' Trusts and recommendations (Product review)

Objective: To test the participant's level of trust in the information presented

(1) Do you trust the information presented on the simulator?
    (a) Definitely not   (b) Probably not   (c) Might or might not
    (d) Probably yes   (e) Definitely yes
(2) Would you recommend translating this simulator into a mobile application to guide your sustainable decisions in the future?
    (a) Yes   (b) Maybe   (c) No
(3) Would you recommend that more food should be added to the simulator?

    (a) Yes   (b) Maybe   (c) No

(4) Have you used any simulator similar to this?
    (a) Definitely not   (b) Probably not   (c) Might or might not
    (d) Probably yes   (e) Definitely yes
(5) Which areas do you think the application can improve to give a better user experience?
    Space provided
(6) Overall, how will you rate this simulator?
    (a) 5   (b) 4   (c) 3   (d) 2   (e) 1
(7) Do you have any reviews or comments for the researchers involved in this project?

9 CONCLUSION

The main goal of the current project was to enhance the capacity of policymakers and consumers to make decisions about food production, supply, and consumption by simultaneously considering nutritional quality, contribution to health, and environmental sustainability. This was achieved by (a) assessing and articulate sustainable consumer dietary patterns and their correlation with human health, the environment and the socio-economic dimension of sustainability, (b) multi-objectively modeling the risk to health and environmental impact under stringent mitigation policies leveraging on machine learning and finally (c) developing a sustainable healthy food choice platform that provides consumers numerical and pictorial data on nutritional quality, contribution to healthy living, environmental impact, and cost. Through the application of mathematical modeling (AHP-TOPSIS) and a set of environmental, health and socio-economic indicators, the findings of the study suggest that vegetarian, vegan and provegetarian diet concepts are more beneficial to the environmental and population's health as compared to the national Healthy US-style diet concept which has an average overall lower GHGE impact of 2% (reduction), water consumption of 14% (reduction), and an increase in energy consumption of 17% compared to other diet concepts. However, the implementation and wider adoption of sustainable diet concepts is hindered by intrinsic socio-economic, cultural and behavioral barriers. These include a lack of understanding, limited access to food ingredients, and unfamiliarity with sustainable diet menu. As such the study proposed an optimized diet concepts that leverages on system thinking approach to promote the adoption and implementation of such diet concepts among the American population. Evidence from the study also suggest that providing appropriate nudges, environmental impact, nutritional, and health implication information can significantly influence consumers' purchasing decisions. Other factors, such as novel Environmental-Nutrition Score developed on the DISH simulator for the two fast-food products influenced consumer choices but not very significantly. The findings indicate that (1) at the level of environmental sustainability, an animal-based burger is associated with a higher environmental impact and external environmental cost compared to the plant-based burger, and (2) from a health and nutritional perspective, a plant-based burger has significantly higher HSR (4-stars), and FCS (62) thus associated with a healthier choice than the animal-based burger (1/2-star and an FCS (35), and (3) integrating both dimensions into a single novel EnN score, the plant-based burger had a higher EnN score (EnN score =3) which correlates to a healthier and more environmentally sustainable food compared to the animal-based burger (EnN score =2). Perhaps the most obvious finding to emerge from the study is that 64.3% of participants who explored the DISH simulator rated it either with a 5-star rating or a 4-star. Finally, the results of the second object suggest that substituting meat and beef production with a more resource-efficient agricultural product such as peas could reduce anticipated GHGE emission impact by 5-7% while reducing health impacts by 19-41% for the short-term goal of 2030. However, these high-impact reductions can be achieved depending on the kind of substitution. Future studies can focus on translating the DISH simulator to other fast-food in America. The novel FS-ROAS can also be extended to include other countries since similar data for different countries do exist.