THE APPLICATION OF MATHEMATICAL MODELLING AS A DESIGN SOLUTION FOR AFFORDABLE NUTRITION

BY

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DECLARATION

In presenting this dissertation titled "**The Application of Mathematical Modelling as a Design Solution for Affordable Nutrition**," I, Leticia Donkor, affirm that this study is the result of my independent research conducted under the guidance of Professor Firibu K. Saalia, Professor Nicole S. Affrifah, Dr. and Emmanuel Essien. This work has not been previously submitted, in whole or in part, for any other degree or qualification at any other institution. I confirm that all sources utilised or referenced in this thesis are appropriately cited and acknowledged, following academic standards.

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GENERAL ABSTRACT

Optimal nutrition is critical across all demographic groups and at different stages of life, from infancy to adolescence and adulthood. It is also an important component of sustainable diets. Sustainable diets are defined as diets with four main dimensions: affordability, nutrition, acceptability, and environment. However, access to sustainable diets is often constrained by cost factors and a lack of tools to make informed decisions.

The study aimed to investigate the complex challenge of achieving sustainable diets that address affordability, cultural acceptability, nutritional adequacy, and environmental impact across different demographics and within the food product development industry from locally available foods in Ghana.

Adolescent nutrition is crucial as it directly influences their health and long-term well-being, thus, the study initially designed affordable and culturally acceptable food baskets for adolescents in Ghana, addressing the economic (cost) constraints that hinder access to nutritious diets. Using a linear programming approach, subject to nutritional and cultural acceptability constraints, the study identified locally available ingredients that met nutritional requirements at minimal costs. The estimated cost of the optimised food baskets for adolescent males and females was GHS 15.70 and 15.57, respectively, for the day. They included fifteen food items each and fulfilled nutrient requirements recommended by the FAO & WHO and the Institute of Medicines.

The study also considered the nutritional needs of pregnant and lactating women within the context of environmentally sustainable diets. Linear programming was employed to design nutritionally adequate diets with low greenhouse gas emissions (GHGEs). The optimised diets for pregnant and lactating women, comprising 19 and 21 food items respectively, achieved nutrient adequacy with

GHGE values of 1.06 and 1.48 kg CO_2 eq./day. The diets highlighted a shift towards plant-based foods, legumes, seeds, and nuts, reducing reliance on staples and red meat.

Utilising a bi-objective optimisation method, the epsilon constraint technique was adopted to minimise cost and GHGE simultaneously in recognition of the significant contribution of food systems to global greenhouse gas emissions. The target consumers were adult males and females. The study aimed to simultaneously balance cost and environmental impact while ensuring nutritional and cultural acceptability. Results indicated a strong negative correlation between cost and GHGE, with correlation values of -0.93 and -0.95 for adult males and females respectively. The study also noted that achieving optimal diets requires a mix of nutrient-rich and environmentally friendly food choices, highlighting the need for dietary adjustments to balance economic and environmental goals.

To facilitate sustainable food product development, the study developed the "*NourishCraft* Graphical User Interface (GUI)," a user-friendly interface designed to aid sustainable product formulation. Leveraging Streamlit and Python libraries, the interface allows users to formulate nutritious food products considering affordability, nutrition, cultural preferences, and environmental impact. Users can choose to prioritise minimal cost, minimal greenhouse gas emissions, or a balanced approach, and define constraints for preferred nutritional parameters. The interface provides a list of ingredients that meet the defined nutritional parameters at the minimum objective value (cost, GHGE, and/ or both). Additional outputs include tables and figures, making it a practical tool for product developers to integrate sustainability into their processes.

To validate the *NourishCraft* interface, it was used to formulate a product, using one-third of the recommended dietary allowance (RDA) for adolescents 10 to 18 years, setting energy, carbohydrate, protein, and iron as the parameters. This formulation was set to measure the dimensions of affordability, nutrition, and acceptability because GHGE could not be assessed due to limited data. The ingredients from the formulation were purchased for cost assessment, and acceptability was evaluated by a consumer sensory test. The interface proposed output of cassava, coconut, millet, and Bambara beans in proportions of 27.64%, 14.2%, 24.44% and 32.71%, respectively at GHS 0.67. The drum-dried composite developed from the formulation contained 300 kcal of energy, 45 g carbohydrates, 10 g protein, and 4.29 mg of iron. The model predicted between 61.02% - 123.63% of the nutrient parameters. However, the actual cost of the ingredients purchased from the market amounted to GHS 1.48, showing a 45.27% prediction of the formulated cost by the interface. The product was well accepted with an overall likeness score of 7.82 ± 1.21. The results indicated that the *NourishCraft* graphical user interface has the potential to support nutritious and affordable food formulations.

The findings from these studies hold significant implications for policymakers, individuals, researchers, and the food industry. Policymakers can develop programs that promote affordable, nutritious, and sustainable food practices. Individuals can make informed dietary choices that prioritise health and environmental well-being. Researchers can further explore the complexities of sustainable food systems, and the food industry can utilise the "*NourishCraft* GUI" to aid in designing sustainable products. By integrating these considerations, stakeholders across the food system can contribute to a future where healthy and sustainable diets are accessible to all.

DEDICATION

To God be the glory for the great things He has done.

I dedicate this work to the memory of my mother, Mrs. Margaret Yankson Donkor, whose wise counsel, prayers, and love guided me through this journey. Though she has departed to be with our Maker, her presence remains with me every step of the way. Mama, I made you proud, and I pray the Lord holds you in His care until we meet again.

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TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AML – Algebraic modelling language

CDC – Centre for disease control and prevention

CH_4 – Methane

$CO_{2\ (eq.)}$ – Carbon dioxide (equivalent)

COVID-19 – Coronavirus disease of 2019

CVDs – cardiovascular diseases

DALY – Disability-adjusted life years

DM – Decision maker

DRI – Dietary reference intake

EAR – Estimated average requirement

FAO – Food and Agriculture Organisation

FB(s) – Food Basket(s)

GAMS – General Algebraic Modelling System

GHGE(s) – Green-house gas emission(s)

GP – Goal programming

GSA – Ghana Standards Authority

GUI – Graphical user interface

GWP – Global warming potential

HCFCs – Hydrofluorocarbons

HCI – human-computer interaction

IFPRI – International Food Policy Research Institute

LCA – Lifecycle assessment

LP – Linear programming

MoFA – Ministry of Food and Agriculture

MDG – Malaysian dietary guidelines

MOO(P) – Multi-objective optimisation (problem)

NCDs – Non-communicable diseases

N_2O – Nitrous oxide

RDA – Recommended dietary allowance

RUTFs – Ready-to-use therapeutic foods

SPSS – Statistical products and services solution

UL – Tolerable upper-level intake

UNICEF – United Nations Children's Fund

UI – User interface

UK – United Kingdom

UGSPH - University of Ghana School of Public Health

WHO – World Health Organisation

WCRF/AICR – World Cancer Research Fund/ American Institute for Cancer Research

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background

Good nutrition is one of the most critical components of good health. This is achieved when consumers have access to healthy diets. A diet refers to the variety of foods people consume, chosen from what is available in the food system. Diets, therefore, serve as the overall food demand, which drives and directs the food systems (Meybeck & Gitz, 2017). Chronic diseases (cardiovascular, obesity, etc.) can be significantly reduced by consuming healthy diets, which directly means that a population that achieves a healthy diet reduces the burden of malnutrition and its related diseases (Rao *et al.,* 2013). However, access to nutritious and healthy diets is constrained by a cost factor, especially for low-income earners (Nykänen *et al.,* 2018). The economically challenged in society will likely have poor health status due to poor diet consumption (Gavin & Kavanagh, 2016). Thus, socioeconomic status affects food choices and dietary quality (Bowman, 2006; Dijkstra *et al.,* 2014; Faksová *et al.,* 2019). A positive correlation has been observed between healthy diets and the cost of these diets (Mackanbach *et al.,* 2019). Parlesak *et al.* (2016) stated that when food must be purchased, many essential drivers in addition to cost, including taste, availability or access, and habit are considered.

A few studies have also suggested that some consumers, especially low-income earners, tend to purchase energy-dense foods because they are inexpensive sources of energy, as compared to less energy-dense (but nutrient-dense) foods (Gazan *et al.,* 2018; Nykänen *et al.,* 2018; Dizon *et al.,* 2019). Drewnowski (2009) linked the growing obesity rates in the population to increased consumption of energy-dense foods and sweetened beverages. This, therefore, poses dietary problems that need to be addressed to lessen the burden of malnutrition on the population.

Diet optimisation has been identified as one of the best approaches to address dietary problems and ensure that sustainable diets are achieved for individuals or groups based on local and culturally specific foods (dos Santos *et al.,* 2017; Wilson *et al.,* 2019). The FAO defines a sustainable diet as "a diet that has a low environmental impact, nutritionally adequate, accessible, economically fair and affordable, safe and healthy" (FAO, 2010). The concept of a sustainable diet is constantly gaining international recognition. It is incorporated into the Sustainable Development Goals because it promotes food security and addresses climate change by fostering food systems that reduce environmental impact (Meybeck & Gitz, 2017). MacDiarmid (2013) suggested that there is a need to define the elements of a sustainable diet being addressed by a study. Consequently, in the context of this study, a sustainable diet can be defined as an affordable diet that meets specified nutritional needs, is culturally acceptable, and has reduced greenhouse gas emissions (GHGE). The relationship between health, environment, economic access, and consumer dietary patterns is captured in the operative definition of sustainable diet for this research.

Mathematical diet optimisation models are used to create food plans that best resemble the eating habits of a defined population while meeting pre-specified nutrition and cost constraints (Masset *et al.,* 2009). However, diet optimisation goes beyond nutrition and cost; it includes acceptability and environmental friendliness and incorporates all constraints defined for diet optimisation by the World Health Organisation (WHO). According to Okubo *et al.* (2015), in diet optimisation, nutrient-based recommendations are translated into realistic nutritious-optimal food combinations that incorporate local and culture-specific foods.

Mathematical diet optimisation techniques can be a better solution to dietary problems than the rigorous trial-and-error methods that have always been used in product development for nutritionally adequate products (Westrich *et al.,* 1994). According to Kanellopoulos *et al.* (2020), designing healthy diets can be tedious and complex because of all the considerations and constraints. As such, mathematical diet models can be used to address the complexities associated with nutritious ingredient formulation. Computational models, mainly linear programming (LP), under different settings, have been extensively applied in diet optimisation. According to Beheshti *et al.* (2017), these mathematical tools can simulate different scenarios to formulate different diets for dietary problems such as least-cost diets, and other diet optimisation problems at minimal risk.

Diet optimisation models have been developed for different nutrient needs and for different age groups to satisfy various constraints. The approach to diet optimisation can be the application of linear programming, a mathematical approach that makes it possible to obtain ideal solutions simultaneously while satisfying several constraints. This ideal solution, which is termed the objective function, is either maximised or minimised under defined decision variables that can be controlled, within a set of constraints (Briend *et al.,* 2003; Karloff, 2009; Jones & Tamiz, 2010; Gazan *et al.,* 2018; van Dooren, 2018).

Nykänen *et al.* (2018) used linear programming to calculate the food basket (FB) for a low-income Ghanaian family of four in rural and urban settings. The FB fulfilled energy and nutrient recommendations. Also, linear programming was used to determine a predefined food group, the optimal number and size of servings of commonly consumed foods in Benin (Levesque *et al.,* 2021).

Mamat *et al.* (2011) used fuzzy linear programming to solve a diet problem low in fat and carbohydrate, with minimum cost. By using the probabilistic and linear membership approaches, diets that satisfy the nutrient requirements for sedentary females aged 30 years were achieved at a low cost.

The goal programming model approach was used to solve a joint minimization of diet costs and emission of methane from lactating dairy cows (Moraes *et al.*, 2015). The three-step approach first predicted the emissions from the lactating dairy cows and then used linear programming models developed to solve a minimised diet cost and methane emission individually. Goal programming was used to obtain a weighted set of solutions (Moraes *et al.,* 2015).

1.2 Problem Statement & Justification

Food purchase decisions of most consumers are made based on price rather than considerations of nutritional content. This is because of the perception that nutritious foods are more expensive and, therefore, not affordable by low-income groups. This indirectly impacts the health of consumers, increasing the rate of malnutrition across the globe. Hence, there is a need for food that provides adequate nutrients, is affordable to all consumers, and delivers the expected consumer satisfaction. Also, the changing trends in the consumption of food necessitate the consideration of all aspects of a sustainable diet. In addition, there is an increasing change in diet composition patterns as the world continues to skew towards more urban diets (more processed and packaged foods, higher animal-based foods) than rural diets (Wiskerke, 2015). Furthermore, the impact of the global pandemic (COVID-19) intensified food insecurity around the globe. A 2021 report by the International Food Policy Research Institute (IFPRI) indicated that cases of food insecurity have been on the rise since the pandemic (IFPRI, 2021). This has negatively impacted the quality and diversity of diet, especially for low-income earners who have felt the impact the most. According to the IFPRI, the pandemic has a long-term effect because of the loss of livelihoods, leading to increased malnutrition. Steenson & Buttriss (2021) suggested increased studies in low- and medium-income countries where their populations face food/nutrition insecurity.

Globally, food systems are challenged with changes in dietary consumption patterns that make current patterns unhealthy due to the consumption of more energy-dense products. Also, access to and consumption of adequate foods that are culturally acceptable, affordable, and nutritious is even more challenging (Fanzo *et al.*, 2012; Fanzo, 2019). Furthermore, designing healthy diets that are also classified as sustainable using trial-and-error methods can be complex and time-consuming. In addition to these constraints, there is little to no literature on promoting sustainable eating patterns/habits (Verly-Jr *et al.,* 2021). Steenson & Buttriss (2020) highlighted that there is more room for learning and research on integrating all aspects of a sustainable diet, especially when nutritional recommendations must be made. Developing a new product could be tedious, following rigorous trial and error methods. More so, it could be complex if all aspects of a sustainable diet are considered. Complex diet optimisation problems can be solved using computational models. Virtual tools, which are considered computational models, can be used to reduce the overall time needed to develop, design, and validate processes, products, and equipment, as well as reduce the costs involved in the production of different types of products while meeting the demands of the market (Chua *et al.,* 2003).

Though computational models have been used widely in diet optimisation, it has primarily been in linear programming where it is used to simulate different objective scenarios. However, most linear programming models applied in solving diet optimisation problems have focused on the minimum cost that mainly met nutritional constraints (Pirički *et al.*, 2008; Dibari *et al.,* 2012; Ryan *et al.,* 2014; Parlesak *et al.,* 2016; Deptford *et al.,* 2017; Brixi, 2018; Nykänen *et al.,* 2018; Alaini *et al.*, 2019; Lauk *et al.,* 2020). There is, therefore, the need to explore the full extent of computational modelling as applied to diet optimisation to ensure that all the aspects of a sustainable diet are fulfilled.

This study aimed to design mathematical models to facilitate the development of diet combinations from local foods at the least cost to increase affordability and ensure that they have a minimum environmental impact, meet nutritional requirements, and are culturally acceptable.

1.3 Study Questions

- Will it be possible to formulate sustainable diets from locally available foods, and will they be affordable?
- Can linear programming meet all the constraints to design a diet sustainable diet that is nutritious, and affordable?
- What algorithm can be used to solve multi-objective optimisation dietary problems?
- What trade-offs must be made in solving this multi-objective optimisation problem?

1.4 Overall objective

The main goal of this work is to:

Use mathematical diet optimisation to formulate products from locally available food ingredients that satisfy the constraints of nutritional, economic, cultural, and environmental adequacies.

1.4.1 Specific objectives

More specifically, the work aimed to:

1. Develop a least-cost model that satisfies nutrient and acceptability requirements.
2. Develop a least carbon footprint (greenhouse gas emission, GHGE) model that satisfies nutrient and acceptability requirements.

3. Develop a bi-objective optimisation model that balances cost and GHGE, subject to nutrient and acceptability requirements.

4. Develop an interactive graphical user interface to facilitate product formulation.

5. Assess the interface developed by using it to formulate a product based on defined nutrient recommendations for adolescents 10 to 18 years.

This thesis is structured into eight (8) chapters, followed by a bibliography and appendices. Chapter one (1) contains a brief background of the research and the identified problem area. The chapter also provides a summary of the objectives intended to be achieved in the space of the research study.

The second chapter (Chapter 2) dives into the literature review of the study area. It explores optimisation and mathematical modelling and their application in addressing diet-related issues. The traditional linear and classical multi-objective methods have been discussed to provide further insight. The approach adopted by other researchers to address the identified problems for resolution has also been elaborated. Based on the literature review, current gaps in mathematical approaches used in addressing dietary issues have been identified, serving as the motivation for this study. Chapters three to seven present a framework approach to the optimisation problem.

This is finally followed by the last chapter, which, is the conclusion and recommendations for future directions for diet optimisation in general, based on the research findings. A bibliography of literature cited in this write-up is then presented with some appendices. A summary of the thesis structure is shown in Figure 1.1 below.

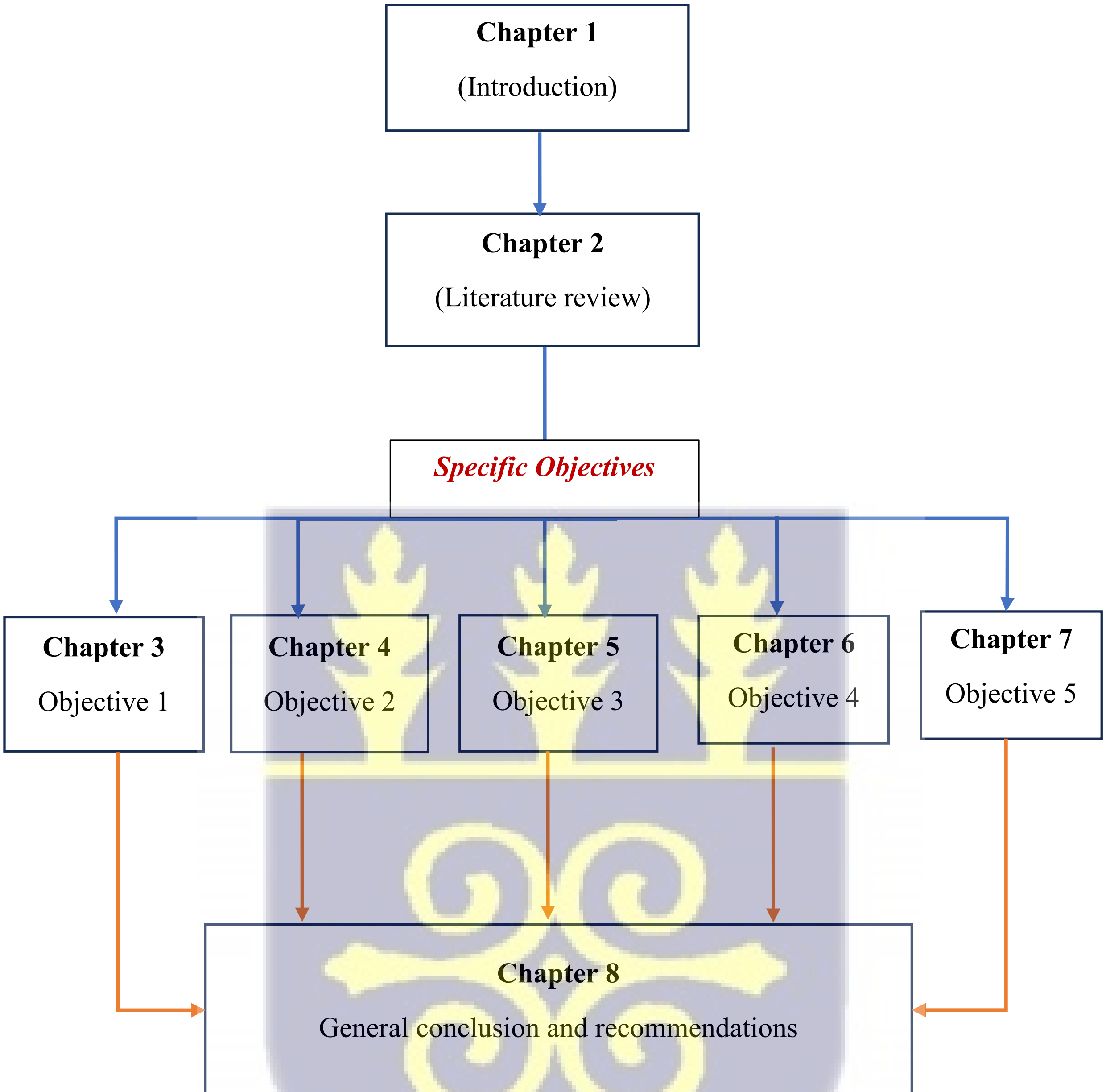

Figure 1.1: Representation of thesis structure

CHAPTER TWO

2.1 LITERATURE REVIEW

Global food systems are challenged with the issue of sustainability. With the gradual increase in population across the globe, production and consumption of food are likely to shoot up. According to Maybeck and Gitz (2017), there is an established relationship between dietary consumption patterns, increasing non-communicable diseases (NCDs), and environmental burden. The population's diets drive the food system, and some significant causes of these shifting dietary patterns include health, environment, and social and cultural dimensions (Meybeck & Gitz, 2017). For dietary habits to be considered healthy and sustainable, there is a need for these dimensions to be combined to make it a possibility (Meybeck & Gitz, 2017). With no internationally agreed definition for sustainable diets, the FAO defined them as "those diets with low environmental impacts which contribute to food and nutrition security and healthy life for present and future generations. Sustainable diets are protective and respectful of biodiversity and ecosystems; culturally acceptable, accessible, economically fair, and affordable; nutritionally adequate, safe, and healthy while optimizing natural and human resources" (FAO, 2010). Global trends require that our current demand be shifted from our growing dietary patterns to more sustainable food systems, which is perceived as a complex problem (Riley & Buttriss, 2011; Steenson & Buttriss, 2020). Its dimensions must be fulfilled to make our food systems more sustainable. Lawrence *et al.* (2019) stated that to make this dietary pattern shift possible, the distinctive characteristics of a sustainable diet should be defined. For this research, the dimensions of a sustainable diet are restricted to nutrition, affordability, environment, and cultural acceptability, as shown in Figure 2.1.

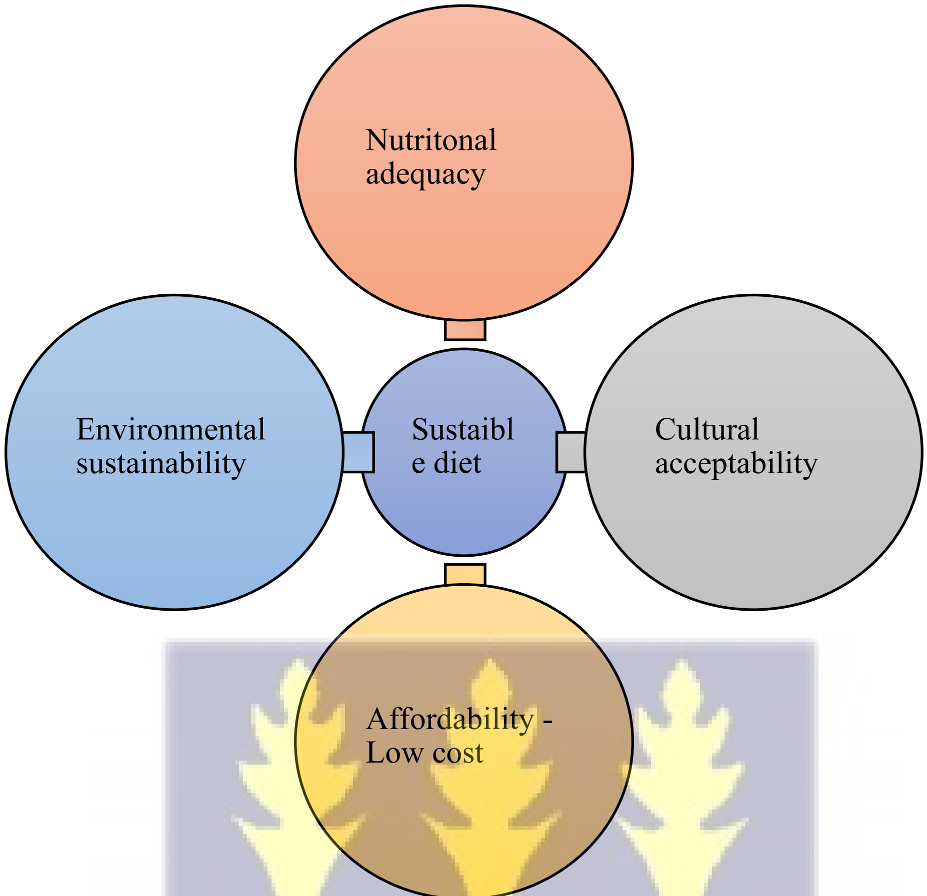

Figure 2.1: The dimensions of a sustainable diet

With the complexity of a sustainable diet, the question on the minds of many would be how to achieve these diets even after defining the necessary dimensions. Considering the current dietary trends' impact, which negatively impacts health and increases NCDs, Aikins *et al.* (2013) proposed a multidisciplinary approach to effectively address these dietary problems. The complexity of dietary trends exists when combinations of different foods must meet the defined dimensions of a sustainable diet (Figure 2.1). They are multi-objective and multi-constrained optimisation problems usually solved using computational models due to their complexities. Linear programming has traditionally been a popular computational approach for addressing dietary problems (Dube *et al.*, 2020). When the focus of a dietary problem is low cost, the question can be raised regarding the other dimensions of a sustainable diet (environment, cultural acceptability, health). Beyond linear programming, are there other ways of addressing complex diet optimisation problems?

Thus, the literature review expounds on knowledge of the dimensions of a sustainable diet and approaches to address its complexity, focusing on multi-objective optimisation methods.

2.1.1 The four dimensions of a sustainable diet

2.1.1.1 Affordability (cost)

The Food and Agriculture Organisations (FAO) of the United Nations embed economic factors as some of the pillars of food security (Kalkuhl *et al.,* 2016). At a world food summit in Rome in 1996, the FAO defined food security as "Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (FAO, Handbook for defining and setting up a Food Security Information and Early Warning Systems (FSIEWS), 2000). The economic aspect of ensuring food security can be measured as affordability. Price and affordability are significant constraints to accessing nutritious foods (Herforth *et al.*, 2020), with affordability as the cost of diet relative to one's income (Battle-Bayer *et al.*, 2020). Herforth *et al.* (2020) further defined affordability as "having enough income or other entitlement to obtain sufficient food at each time and place. Another definition for the affordability of food was provided by the USDA (2009) as "the price of a particular food and the relative price of alternative or substitute foods." When urban areas in Sub-Sahara West Africa are considered, for example, affordability of food poses significant problems due to the large number of poor people there, with food representing an average of 55% of a household's total expenditure (Allen, 2017) and a primary sustainable diet pillar (Battle-Bayer *et al.*, 2020). In a study conducted by Muzigaba and Puoane (2013) in South

Africa, it was observed that low income was a significant factor that influenced the healthy food-purchasing behaviour of participants.

Many factors drive or guide consumers' decisions in making food purchases, and one of these significant deciding factors is cost or price. Cost is a constraint to access available food and can be said to be the first factor among the many factors that drive consumer food choices (Deptford *et al.*, 2017; Drewnowski, 2004; Maybeck & Gitz, 2017; Lee *et al.*, 2011; Allen, 2017). Bachewe *et al.* (2017) hinted that economically challenged households may still be unable to purchase nutrient-rich foods even though there is enough market access and knowledge of their various benefits. Consumers face the challenge of comparing prices for foods that meet their needs but with other requirements like clothing, housing, etc. (USDA, 2009; Cohen & Garrett, 2010). A study by Zepeda & Li (2006) inferred that consumers might have an unchallengeable attitude towards purchasing local foods because they value other essential things and may view food as a commodity characterized by price and quantity. As a result, energy-dense food with low prices tends to influence the purchasing decisions of some consumers. Consumers want the lowest cost, with most households purchasing energy-dense foods in the US (Drewnowski, 2004). Master *et al.* (2018) also stated that low income could limit nutritious diets. Drewnowski (2004) further linked diet quality to income, socioeconomic status, and education in the United States. According to Allen (2007), at equivalent per capita income levels, food prices in Sub-Saharan Africa are about 30-40% higher than the rest of the world.

Although some schools of thought (Parlesak *et al.,* 2016; Pechey & Monsivais, 2016) suggest that healthy diets (thus food containing more micronutrients) are not always less expensive, Maillot *et al.* (2008) stated that it is possible to optimise nutritious diets as minimum cost. Parlesak *et al.* (2016) further stated that even in high-income countries, economic limitations cause people to eat diets that have a low micronutrient-energy ratio. Masters *et al.* (2018) stated the need for implementing policies or programs that aim to lower the cost of nutritious diets to make them more accessible to low-income earners, mainly because the cost can be used as a measure for healthy diets. However, what is the purpose of a low-cost diet if people do not accept it, or it does not consider the environment, or worse, it increases the burden of malnutrition? While providing low-cost nutrition is still relevant, there is an additional question of how to produce food with low environmental costs (Gephart *et al.,* 2016).

2.1.1.2 Environmental constraint

There is growing scientific consensus that alternative food systems must be considered sustainable solutions to the environmental and public harm caused by food insecurity. As concern for food prices grows among consumers, integrating environmental considerations into people's food choices is increasingly documented as an essential element of a policy response concerned with health, food security, and environmental sustainability (Barosh *et al.*, 2014). Food systems show an interconnection between the environment, nutrition, health, acceptability, and economics of a sustainable diet (Figure 2.2, adopted from Meybeck & Gitz, 2017).

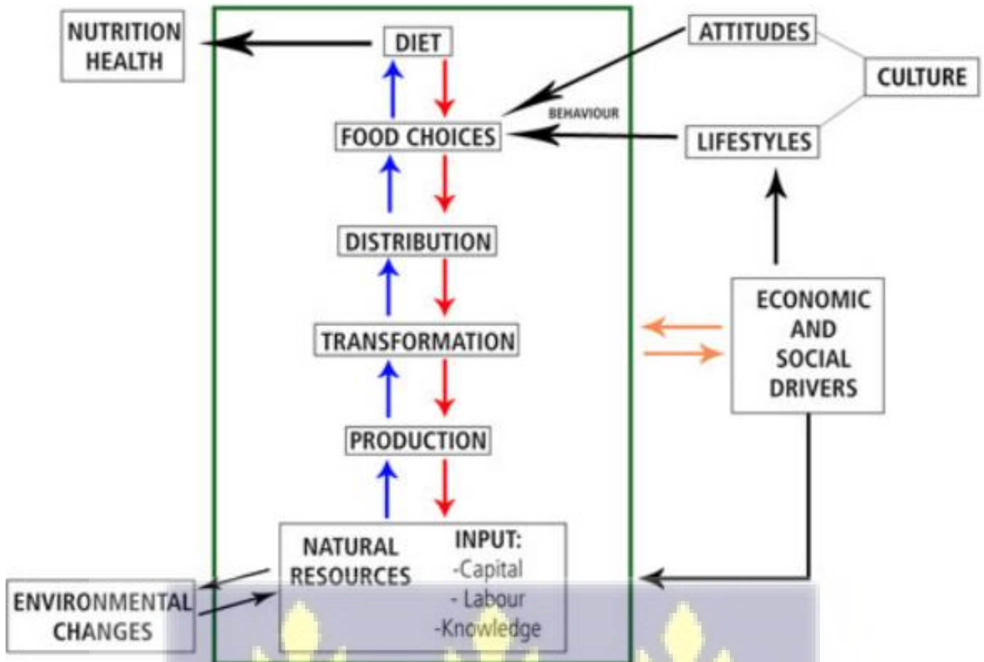

Figure 2.2: Food systems showing diet-related externalities

Current food systems pose problems, including climate change, a significant environmental threat. The environmental consequences of the food system are becoming a major issue for policymakers, especially in developed countries, considering less focus was given to the impact of food systems on the environment compared to the attention given to the impact of energy on the environment (Vieux *et al.,* 2012; van Dooren *et al.,* 2014). Climate change has emerged as one of the most debatable topics on the global environmental agenda (Carlsson-Kanyama, 1998). According to MacDiarmid (2013), the outcome of these greenhouse gas emissions into the atmosphere resulting in global warming is climate change. Greenhouse gas emissions from anthropogenic (human-induced) activities have been established as significant drivers of climate change (Colombo *et al.*, 2019). Emissions that are noted as significant greenhouse gases are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and hydrofluorocarbons (HCFCs), and they are closely associated with food production and consumption. During the life cycle of food, numerous human-induced activities cause emissions of these gases. For example, using fossil fuels in agriculture causes net emissions of CO_2, as the cultivation of organic soils often does. The fabrication and application of N-fertilisers cause emissions of N_2O. From the digestive tracts of cows, sheep, and pigs, CH_4 is released. Refrigerants in cold storage facilities often have a Global Warming Potential (GWP). They contribute to climate change when leaked, as shown in Figure 2.3 (adopted from Hyland *et al.*, 2017). (Carlsson-Kanyama, 1998).

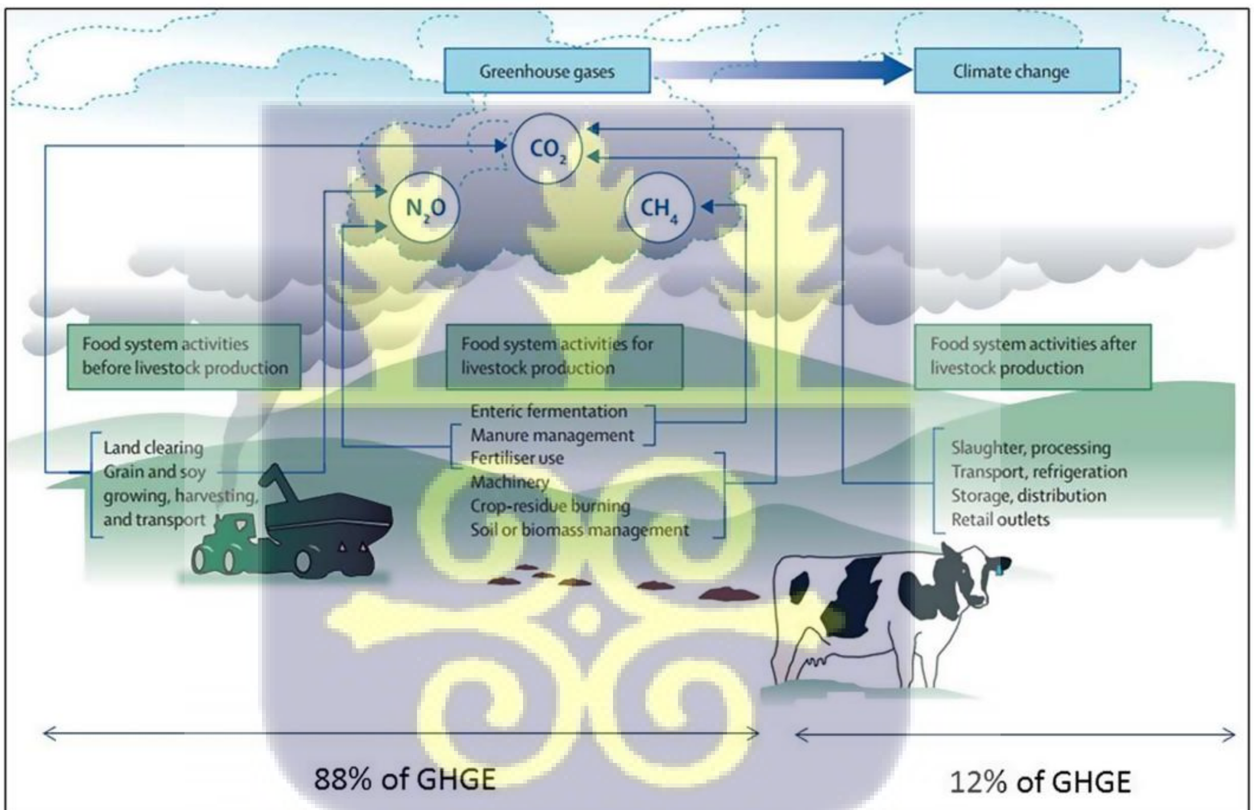

Figure 2.3: Activities in the food and agriculture system that contribute to GHGE, with more focus on meat

To compare and report on these GHGEs, they are categorized in terms of their carbon dioxide equivalent, represented at COeq (Hyland *et al.*, 2017). The current food production systems contribute about 25% of the world's anthropogenic (GHGEs), according to Colombo *et al.* (2019). Wilson *et al.* (2019) also stated between 19% and 29% contribution of food systems to global GHGEs, and Song *et al.* (2017) stated a range of 19 - 35% for the contribution of anthropogenic emission of GHG. Climate change and obesity were singled out as the two biggest challenges by society, and sustainable diets can be used to address them, according to a report by the UK government in 2011 (MacDiarmid, 2013).

The need to reduce the volume of GHGE caused by the food sector has consequently led several authors to consider the opportunities and potential effects of diet changes on GHGE variations. Moreover, environmental impacts resulting from the food system cannot be assessed in seclusion from their nutritional value (Gephart *et al.,* 2016). Though future food consumption patterns will continue to reflect our overall lifestyles, income levels, and values, they should also reflect a growing consideration for the state of the environment (Carlsson-Kanyama, 1998). Linking diet with human health and climate change has attracted considerable interest. The optimal objective of a low-carbon diet is to minimise the carbon footprint by combining different foods while meeting the nutritional requirements recommended for public health (Song *et al.,* 2017). The authors (Song *et al.,* 2017) conducted a study in China on how dietary changes can mitigate climate change. They found trade-offs between poultry and other meat products, and rice contributed the most to carbon footprint reduction. One limitation was that factors such as cost, and acceptability were not included.

A study assessed whether a low GHGE diet could be nutritious compared to the Nordic Nutrition Recommendations (diets composed of foods from from Nordic countries). GHGE data included agricultural inputs, food processing, distribution, and retail emissions. The diet with the lowest

CO_2eq provided an adequate intake of most nutrients. Though the lowest GHGE diet was obtained, this study did not consider the cost or the affordability factor (Bälter *et al.,* 2017).

Another study by Kramer *et al.* (2017) sought to find diets optimised for nutrition and environmental impact close to the current Dutch diet. Nutritional and environmental factors were set as constraints, and the meat was reduced in the optimised diet with a reduced environmental impact. However, one limitation of this study was that affordability was not considered.

Wrieden *et al.* (2019) also used the Life cycle assessment (LCA) to assess the environmental impacts of foods purchased by households in the UK. The study focused on assessing the environmental impact of these foods purchased by households, using a diet quality index to measure the quality of these foods. Results showed that the average UK diet did not meet the dietary requirements; their assessment proved that purchasing a healthy and sustainable diet at a low cost is possible. However, they eliminated households that could not purchase foods that could supply the needed energy, and they did not set to optimise diets.

2.1.1.3 Nutrition

Food is considered an integral part of human existence because it is vital for life and needed for health, growth, and reproduction (Lean, 2006; Mason & Lang, 2017). According to Lawrence *et al.* (2019), there is an existing relationship between diets and public health, where diets serve as an underlying factor of public health through their direct impact on nutrition. In that, any dietary inadequacies will contribute to the global burden of diseases. Elmadfa and Freisling (2005) highlighted that some major influencing factors of mortality and morbidity are nutrition, dietary, and lifestyle changes, which are, eventually, linked to chronic NCDs. Some NCDs include cardiovascular diseases (CVDs), cancer, diabetes, and chronic respiratory diseases, which are the leading triggers of deaths and disabilities across the globe (WHO, 2016; Cena & Calder, 2020).

These NCDs constituted 60% of deaths reported worldwide and 46% of the global burden of disease in the early 2000s (Elmadfa & Freisling, 2005). A survey report by the WHO (2016) showed an increased rate of 70% of global deaths resulting from NCDs, with a more significant part happening in low-income and middle-income countries. In Ghana, chronic NCDs were said to be significant causes of death, making it a public health problem that negatively impacted the country's development (Aikins *et al.*, 2013). Amponsem-Boateng (2017) also emphasised that malnutrition contributes to global disability-adjusted life years (DALY), is widespread in developing nations, and affects children the most. As stated by UNICEF (2016), malnutrition is a crucial hindrance to socioeconomic development even at individual and national levels; as such, there must be more attention given to people's nutrition. With nutrition and dietary changes being contributors to NCDs, consuming healthy foods can be an excellent way to reduce its impact.

Whereas a healthy diet is mainly about the appropriate amount of nutrient intake, which can be realized from many different combinations of foods, there have been drastic dietary changes over the past few decades. These dietary and nutrition changes can be captured broadly as over-nutrition (high energy dense, saturated fatty, cholesterol foods with low proportions of plant-based foods) and under-nutrition (low energy and low specific nutrients like riboflavin, vitamins, calcium, zinc, niacin, and magnesium) (Aikins *et al.*, 2013; MacDiarmid, 2013). Globally, more than two (2) billion individuals are suffering from one or more micronutrient deficiencies, with micronutrient deficiencies of vitamin A, zinc, iron, folate, and iodine being of great concern (Alsaffar, 2016). Ghana is faced with a nutrition challenge that has persisted for a while. A 2016 report by UNICEF Ghana indicated great concern for micronutrient deficiencies, including vitamin A, iodine, and iron, among all age groups, with severe, disturbing cases of anaemia in the northern parts of the country (USAID, 2014; UNICEF, 2016). A varied diet is necessary to protect people from malnutrition (under and over-nutrition) and other NCDs related to poor dietary patterns (Alsaffar, 2016; Lawrence *et al.*, 2019). In the global fight against malnutrition, a quality or balanced diet has been said to play a role (Frempong & Annim, 2017). A step toward improved nutrition will be increased consumption of foods with high micronutrients and less energy-dense (Parlesak *et al.*, 2016).

Balanced diets contain adequate amounts of the various food groups: cereals, starches/sugars, milk products, fats and oils, pulses and meat, fruits, and vegetables. The nutrients obtained from foods can be classified as proteins, carbohydrates, fats, vitamins, minerals, water, and fiber (Goyal & Gupta, 2012). Energy, measured in kilocalories, is not a nutrient but is derived from the breakdown of macronutrients (carbohydrate, protein, fat), which is necessary when assessing nutrient supply from diets (Anderson *et al.*, 2014). There is a need for diets that meet recommended requirements or can be controlled to serve specific purposes, such as treating some level of malnutrition and sustaining certain specific diets like the Mediterranean, Nordic, or vegetarian.

In a nutritious porridge mix developed in rural Mozambique for children aged 1-2 years, energy, macronutrients (fat, protein, carbohydrate), and micronutrients (calcium, iron, zinc, vitamin A) requirements were met from food groups like starchy flours, vegetable oil, nuts, fruits, vegetables, legumes, and rice (De Carvalho *et al.,* 2015). Twelve (12) micro-nutrients were the focus of Ferguson *et al.* (2015), who attempted to ensure adequate nutrient intake for complementary feeding for children 6-23 months old. These nutrients were calcium, iron, zinc, thiamine, folate, niacin, riboflavin, and vitamins A, B_6, B_{12}, and C.

Johnson-Down *et al.* (2019) ensured that dietary reference intakes (DRIs) were met for an indigenous selected Canadian population. They aimed at meeting the acceptable level of macronutrients (protein, carbohydrate, fat) and micronutrients, including calcium, zinc, dietary folate, fibre, iron, linoleic acid, linolenic acid, riboflavin, sodium, thiamine, and vitamins A, B_6, B_{12}, C, and D.

2.1.1.4 Acceptability

Food consumption patterns are not only a reflection of nutritional needs but also of preferences for taste, odour, and texture, as well as culture and ethics (Carlsson-Kanyama, 1998). Consumers are considered very important when GHGE-related food products are considered because they hold the ultimate preference choices for food (Verly-Jr *et al.*, 2021). According to Fletcher *et al.* (1994), although linear programming has been used to design a diet for humans and animals, some researchers focused on its application from a more mathematical viewpoint with less focus on its palatability. With changing lifestyles and increasing urbanisation, consumer dietary patterns have changed considerably over the past four to five decades (Johnston *et al.*, 2014). According to Meybeck & Gitz (2014), the FAO reported that increasing population growth coupled with changing consumption trends will most likely increase global demand by sixty percent (60%) by 2050, as projected from 2007. In a least-cost diet optimisation (Deptford *et al.*, 2017), they considered foods that were mostly consumed and the portion sizes to ensure a realistic amount of foods in the optimised diet (portion sizes and diet habits). One challenge likely to be encountered in designing a diet for a group of people will be whether it will be acceptable to them or not. Kanellopoulos *et al.* (2020) implied that defining acceptability when planning diets might be challenging.

However, it can be considered in terms of the lower and upper limits of specific food items consumed by a group of people, as well as deviations in energy intake of an optimised diet from ones already consumed by the people (Maillot *et al.,* 2010; Colombo *et al.,* 2019). Another way of addressing the acceptability of a sustainable diet is to ensure that the proposed dietary patterns compare closely to the observed patterns of the population (Faksová *et al.*, 2019; Sugimoto *et al.,* 2022).

Though the different dimensions of a sustainable diet focused on in this research are very important, they are not always compatible or synergistic, and often trade-offs must be made between the different demands such as nutritional adequacy, environmental impact, and affordability (Colombo *et al.*, 2019). Parlesak *et al.* (2016) hinted at the need for mathematical models that calculate foods to supply ideal nutrient recommendations at minimum cost, especially for low-income households, incorporating other environmental and acceptability considerations. In recent years, mathematical programming techniques have been applied in diet optimisation to design sustainable dietary choices (Sugimoto *et al.,* 2022).

2.1.2 Mathematical optimisation techniques in dietary problems

Mathematical optimisation programming is a commonly used method for solving problems in operations research (Liu, 2009). According to Westrich *et al.* (1994), mathematical optimisation techniques can better solve dietary problems than rigorous trial-and-error methods. Though optimisation can be interpreted differently depending on what problem is being solved, its applicability is widespread and cuts across many disciplines (Yang, 2018). Optimisation is the process that delivers an optimal or most efficient solution to a problem (Sharma *et al.,* 2021). It is considered the central pillar of systems that require decision-making and optimal approaches (Nayak, 2020). According to Guenin *et al.* (2014), scientific and mathematical approaches can offer better solutions during optimisation. Nayak (2020) further stated that optimisation is critical in mathematics, computer science, and operations research.

When linear models with defined inequality constraints are considered, mathematical programming techniques are needed to solve them (Rustagi, 1994). When an optimisation problem is encountered, the approach to obtain an optimal solution is to transform that real-life or physical problem into a mathematical form (mathematical modelling) and then solve it using optimisation techniques (Nayak, 2020). This is represented in Figure 2.4 below.

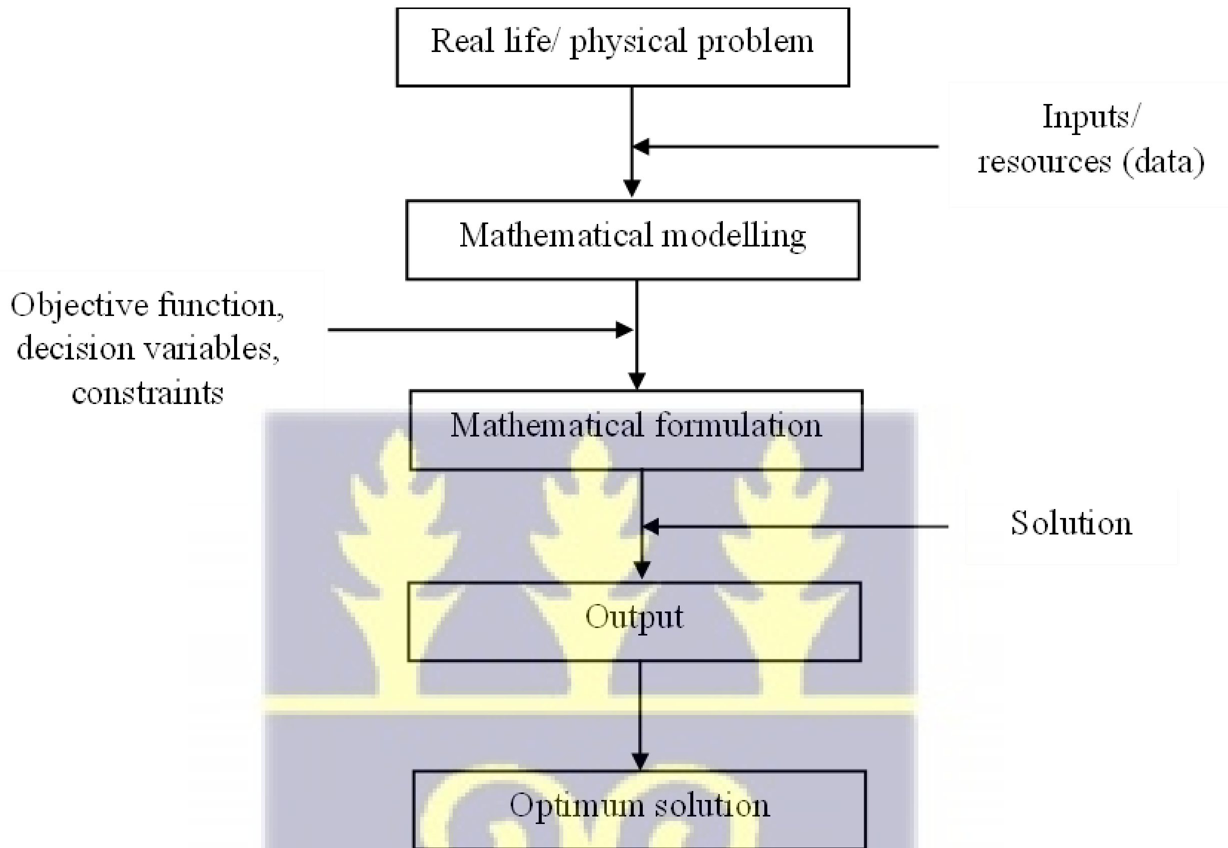

Figure 2.4: A schematic representation of obtaining an optimum solution from a real-life situation

However, the success of obtaining an optimum solution is formulating the physical problem into a mathematical representation and finding the best algorithm to use. A well-formulated problem contains the basic parameters of optimisation: which include: the objective function, decision variables, and constraints (Boyles, 2015; Gazan *et al.,* 2018; Sharma *et al.*, 2021). The data from a problem to be formulated must be understood in terms of the parameters and constraints of the decision variables (Nayak, 2020).

2.1.3 Parameters for Optimisation

2.1.3.1 Decision variables

Decision variables in mathematical diet optimisation are essential because they are the factors that can be controlled by a decision-maker who is in search of an optimal solution (Briend *et al.,* 2003; Jones & Tamiz, 2010). Nayak (2020) stated that the optimisation process is influenced by the decision variable(s), and the user or decision maker holds the power to decide which parameters are important. They are physical measures that are usually denoted by mathematical symbols like x with some examples as concentration or temperature (Sharma *et al.*, 2021) that can be represented as continuous (actual number), integer numbers (integer or discrete), and permutations on a set of numbers of finite size (Collete & Siarry, 2003).

2.1.3.2 Constraints

These represent any physical, economic, technological, legal, ethical, or other restrictions on the decision variables. These are the linear equations and inequalities in the linear program (Matoušek & Gärtner, 2007) that are expressed as equality (=) and inequality (≥ or ≤) (Arora, 1993). The constraints define the region of feasibility, which is the value sets that satisfy all constants (Sallan *et al.,* 2015). Constraints are necessary to define an optimisation problem (Collete & Siarry, 2003) and are unavoidable in multi-objective optimisation problems (MOOPs) (Deb, 2001). When these problems are solved, the value of the decision variables obtained should meet the constraints to obtain an acceptable or feasible solution (Nayak, 2020). In other words, the dependencies experienced among the decision variables are described by the constraints imposed (Coello *et al.*, 2007). Some of these are called hard constraints, which must be satisfied and not violated;

otherwise, the solution becomes infeasible. Soft constraints, on the other hand, are those that a decision maker (DM) would like to satisfy but that which is not entirely obligatory (Burke & Kendall, 2014).

2.1.3.3 Objective function

In linear programming, this indicates the variable (value of the function) to be optimised (minimised or maximised) (Matousek & Gärtner, 2007; Barzaraa *et al.*, 2011). It describes the criteria for selecting the best solution from all other solutions (Briend *et al.,* 2003). The objective function in optimisation problems is represented by f or z and can result in either minimization or maximization (Nayak, 2020; Boyles, 2015). For example, if one aims to get more revenue at the end of the month, then the objective function would be to maximise revenue. If one is looking at reducing the time spent in carrying out an activity, that presents a minimization objective. Objective values often obtained during optimisation are represented as a numerical solution.

2.1.4 Multi-objective optimisation (MOO)

Considered an extension of LP problems (Liu, 2009), they are continuous problems (Branke *et al.,* 2008) that cut across areas of engineering, mathematics, economics, etc., and have more than one objective function to be addressed. These types of optimisation problems are generally expressed as minimise/maximise $[f_1(x), f_2(x) \ldots \ldots . f_n(x)]$ for p defined objective functions and $f_i: R^n \rightarrow R$ subject to several equality and inequality constraints (Abraham & Jain, 2005). When multiple objectives conflict, multi-objective decision-making is employed (Smieee *et al.*, 2016). To solve a MOOP, there is the need for both optimisation and decision-making methods because the final solution will be an optimal set of solutions that reflect the interest of the decision maker (DM) because he or she is perceived to know the problem best (Parreiras *et al.*, 2006). The DM is an individual or group with better insight into the problem being solved and can better express the preferences concerning the different objective functions (Miettinen, 1998a). As such, a multi-objective model is a practical tool that can assess trade-offs among a selected number of objectives to make a deliberate decision (Ghaithan *et al.,* 2017) and is increasingly being applied to solve more complex real-time problems (Pei & Liu, 2009), following the algorithm represented in Figure 2.5. The first phase (step 1) is used to obtain a solution set from the multiple trade-offs of the objective functions, and the second phase (Step 2) selects a solution from the solution set based on higher-level information (Deb, 2001).

Considering a given MOOP function F(P) with a Pareto optimal set denoted by Ω, the Pareto front PF* will be defined as PF*=$\{F(P) = f_1(P), f_2(P), \ldots\ldots f_n(P) | P \in \Omega\}$. The Pareto front will be an (n-1) dimension surface in the n-objective optimisation problem (Tan *et al.,* 2005). Multi-objective optimisation allows a degree of freedom, making it more flexible but not without consequences. This approach does not give a single unique solution like in the case of single-objective problems. However, it yields a set of solutions, making it challenging to select one solution (Collete & Siarry, 2003) which is referred to as the Pareto solution (Wang & Sun, 2009).

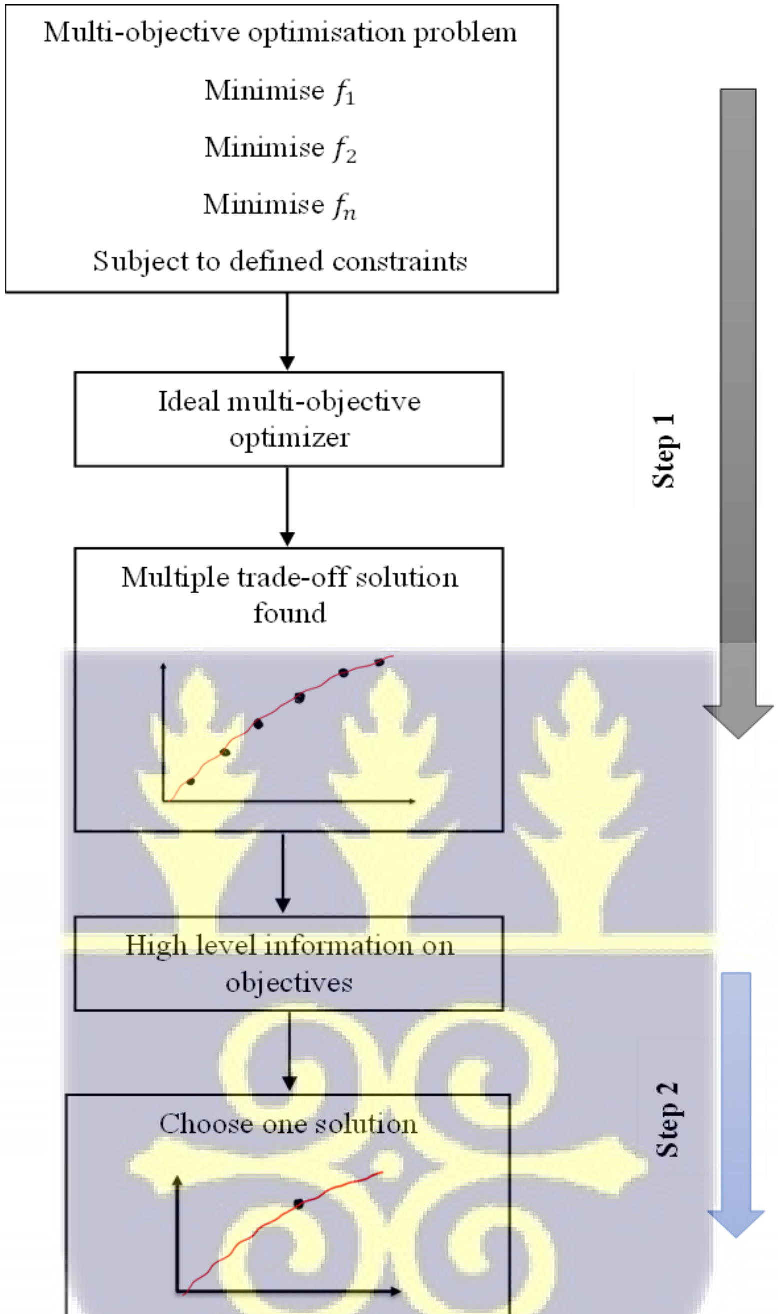

Figure 2.5: Schematic representation of an ideal multi-objective optimisation process

2.1.4.1 Pareto optimal solution and front

One distinct characteristic of MOOP is the non-existence of a unique solution but the set of mathematically equally good solutions that are nondominated, efficient, non-inferior, or Pareto optimal (Miettinen, 2008b). One major problem of MOO is deciding to carry out a tradeoff among the different objectives (Gunantara, 2018). Due to the trade-offs made, solutions obtained might be favourable to one objective function over the other with no single superior or best solution. The Pareto optimal solution set is, therefore, the set of solutions that satisfies at least one objective function (Pei & Liu, 2009; Wang & Sun, 2009). Collette and Siarry (2003) refer to these solutions as the tradeoff surface. The tradeoffs, according to Tan *et al.* (2005), can be conflicting, partially conflicting, or may not conflict. An ideal tradeoff surface (Pareto-optimal front) will have non-dominating solutions that are evenly spaced (Bonilla-Petriciolet & Rangaiah, 2013) (Figure 2.6), take a convex or concave form, or consist of both as shown in Figure 2.7.

In multi-objective optimisation, a Pareto front must be generated because it allows the DM to make an informed decision from the wide range of options available (Ngatchou, Zarei, & El-Sharkawi, 2005). To better explain the Pareto optimal solution, let us consider a processing plant that wants to save energy usage and reduce its cost of production to ensure its customers can afford their product to increase revenue. Considering this as a multi-objective optimisation problem, one solution obtained might achieve a minimum cost of production but less reduced energy consumption. Another solution might be minimum energy consumption achieved but at a slightly higher production cost. All the obtained solution sets are referred to as a Pareto optimal solution. Researchers have proposed different algorithms to obtain the Pareto optimal solution set (Nagatchou *et al.,* 2005; Mavrotas, 2009; Zhang & Rangaiah, 2013; Chiandussi *et al.,* 2012).

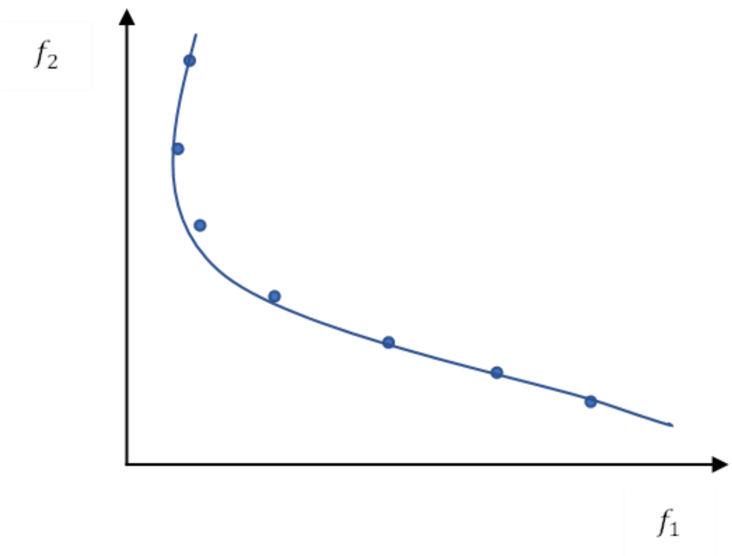

Figure 2.6: Diagram of an evenly distributed trade-off surface for two multi-objective optimisation problems (minimise f1and f2) (Source: (Collete & Siarry, 2003).

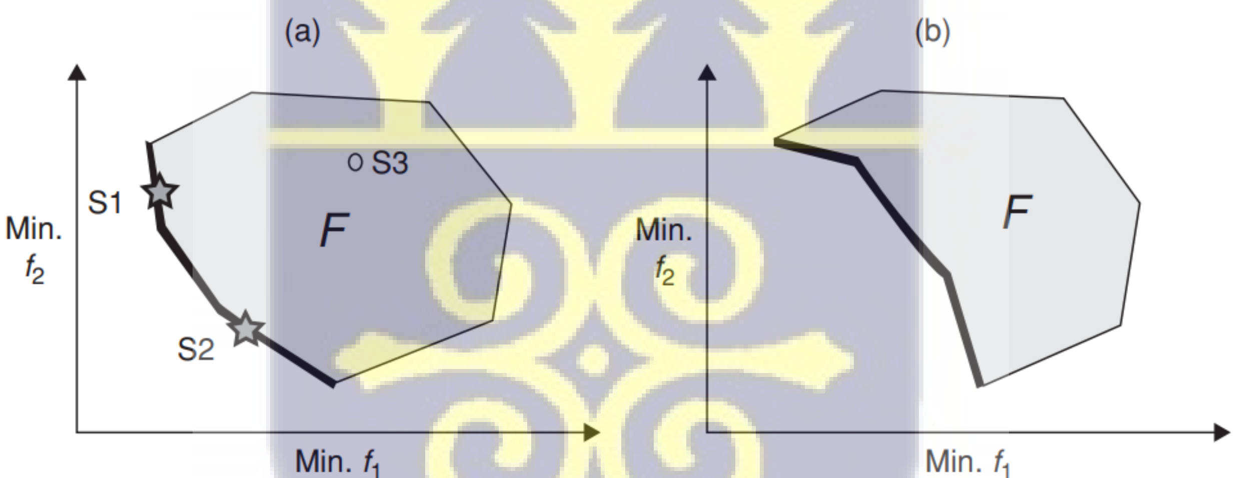

Figure 2.7: Possible Pareto-optimal front for multi-objective optimisation with two objective functions (a) convex and (b) concave (Bonilla-Petriciolet & Rangaiah, 2013).

2.1.5 Classification of optimisation approaches

Optimisation processes can be classified differently based on the solved problem and the factors/ parameters available. One of the significant ways is by considering them in terms of the method used to solve them. A summary of the methods of optimisation is represented in Table 2.1.

Table 2.1: Table describing the different classifications of optimisation methods by different sources.

No.	Classification	Source
1	• Calculus method • Nonlinear programming • Geometric programming • Quadratic programming • Linear programming • Integer programming • Stochastic programming • Multi-objective programming • Neural networks	(Rao, 1996)
2	▪ Linear programming ▪ Allocation models (transportation and assignment models) ▪ Network models ▪ Scheduling and sequencing ▪ Replacement model	Sharma *et al.* (2021)

	▪ Game theory ▪ Dynamic programming ▪ Integer programming ▪ Goal programming ▪ Decision making	
3	▪ Calculus methods ▪ Calculus of variations ▪ Geometric programming ▪ Game theory ▪ Linear programming ▪ Nonlinear programming ▪ Quadratic programming ▪ Stochastic programming ▪ Multi-objective programming	(Nayak, 2020)

From the classification methods offered by Rao (1996), Nayak (2020), and Sharma *et al.* (2021) in Table 2.1, the focus of this literature review will be linear programming, integer programming, and multi-objective programming.

2.1.5.1 Linear programming

The origins of linear programming can be traced to the transportation and diet problems solved by the economists Professor Leontief and Stigler in the 1940s and 1945, respectively. This was closely followed by the development of the simplex method to solve linear programming by Professor George Dantzig (Dorfman *et al.*, 1986; Shenoy, 1998). However, some accounts of the beginning of linear programming associate the first application with Professor Leontief (Shenoy, 1998), Professor Dantzig is usually credited with the optimisation term when he used it to develop a planning tool for the United States Airforce (Bazaraa *et al.,* 2011). According to Matousek & Gärtner (2007), linear programming was not directly related to computer programming because computers were scarce around the 1950s when the term was introduced. However, computer advances have allowed complex problems with large amounts of data to be solved quickly (Shenoy, 1998).

It is considered the first most applied and extensively used optimisation tool (Sallan *et al.*, 2015; Kim, 2020) and a particular case of the constrained optimisation problem (Chong & Żak, 2013). This technique is a mathematical approach that makes it possible to obtain ideal solutions that satisfy several constraints at once (van Dooren, 2018). Karloff (2009) also defined linear programming as minimising or maximising a linear objective function with a finite number of linear equality and inequality constraints imposed on it. van Dooren (2018) stated that linear programming is a good tool that makes it possible to convert precise imposed nutrient constraints to obtain food combinations.

Mathematically, a linear programming model is represented by Equation 2.1.

$$c_1x_1 + c_2x_2 + \cdots\cdots\cdots c_nx_n = z \qquad \text{Eqn 2. 1}$$

subject to

$$\begin{matrix} a_{11}x_1 + & a_{12}x_2 + & a_{1n}x_n \langle \leq \mid = \mid \geq \rangle b_1 \\ a_{21}x_1 + & a_{12}x_2 + & a_{2n}x_n \langle \leq \mid = \mid \geq \rangle b_2 \\ \vdots & \vdots & \vdots \end{matrix} \qquad \text{Eqn 2. 2}$$

$$a_{m1}x_1 + a_{m2}x_2 + a_{mn}x_n \langle \leq \mid = \mid \geq \rangle b_m \qquad \text{Eqn 2. 3}$$

Where $z -$ the objective function to be minimised or maximised

$x_1, x_2, \dots \dots . x_n -$ the decision variables that can be controlled and are subject to m + 1 constraints

$x_1, x_2, \dots . . . x_n \neq 0$ (Lewis, 2008).

The first mention and application of diet problem was by George Stigler when he tried to define the minimum cost of feeding an adult for a year (Amin *et al.*, 2020), and this was solved by Dantzig, who used the simplex algorithm (Bas, 2014), following the traditionally accepted linear programming technique. Though linear programming has been highly applied since its conception, introducing integer and mixed integer linear programming has improved its applicability. Guenin *et al.* (2014) also hinted that optimisation problems do not always end as linear problems, supporting the validity of integer programming. While linear programming is effective at solving problems that can be expressed in a linear form, its' applicability becomes limited when dealing with more complex situations (Collete & Siarry, 2003).

2.1.5.2 (Mixed) Integer programming

Integer and mixed integer linear programming have all or some of the decision variables represented as integers, respectively (Sallan *et al.*, 2015). Assuming that all the variables are defined to take up integer values or when they do not only take up integer values but also have some continuous variables (Liu, 2009). These variables (integer or continuous) are, however, still linked by linear constraints (Milano & Trick, 2004). Bosch & Trick (2014) added that these types of problems start with linear programming with an extra constraint of some or all of the variables taking on integer values, with the most used type being the binary. The binary variable sets integer values to take strictly 0 or 1. Consider a minimization problem represented mathematically as:

$$\textbf{minimise cx} \qquad \text{Eqn 2.4}$$

Subject to

$Ax \leq b$ Eqn 2.5

$x \geq 0$ and integer Eqn 2.6

The x constraint equation makes the problem an integer because it states that the x values should be integers. However, should the x constraint equation be defined as $x \in \{0, 1\}^n$, then this makes the problem a binary integer program (Wolsey, 1998). Many real-world problems encountered are in mixed integer programming because the decision variables are constrained to be a mixture of continuous and integer values (Chen *et al.*, 2010).

2.1.6 Multi-objective optimisation approach to Pareto optimal solution

Over the years, researchers have proposed two methods to solve MOOPs, and they are:

- Generating methods and
- Preference-based methods

The generating method includes subgroups such as:

- No-preference method
- Posteriori method that uses a multi-objective approach
- Posteriori method that uses a scalarisation transformation (Deb, 2001; Keller, 2017).

Scalarization methods have been proposed as one of the most efficient and commonly used classical approaches to solving MOOPs (Miettinen, 2008b). These classical methods are hard to implement, but with the aid of optimisation solvers, they give guaranteed results (Gholizadeh-Roshanagh, Zare, & Marzband, 2016). According to Cui *et al.* (2017), these classical optimisation methods are efficient with fast convergence speed because they start iteration from an initial point and continue from there. By scalarization, the objective functions are converted into a single objective using a relative preference vector and solved using a suitable optimiser (Deb, 2001; Miettinen, 2008b) such that each solution obtained for a single objective function problem corresponds to one Pareto-optimal solution (Zhang & Rangaiah, 2013). Keller (2017) and Mavrotas (2009) stated that the ε-constraint and weighted methods are examples of widely applied scalarization methods. Solutions obtained for MOOPs can be classified as scalarization and Pareto methods (Gunantara, 2018).

2.1.6.1 Weighted sum approach

The weighted sum approach to multi-objective optimisation has one major problem, which has to do with assigning a weight to the objectives depending on the importance of the objectives to the decision maker, hence, the tendency to obtain a bias in the trade-off solution (Gunantara, 2018). By taking this approach, weights are assigned to each objective function and then combined to develop a single weighted objective function (Collete & Siarry, 2003). Deb (2001) stated that solving the composite objective function obtained results in optimizing the individual objectives functions that were weighted. Furthermore, to obtain multiple solutions using this approach, different weights can be applied to do so (Konak *et al.*, 2006). According to Marley (2005), the weights assigned to the different objective functions denote their importance before the problem is solved. One advantage of this method is its efficiency and ease of implementation (Chiandussi *et al.*, 2012). However, selecting the weights to reflect the DM's preference can be challenging since it impacts the result (Konak *et al.*, 2006). The selection of the weights does not necessarily mean the final solution obtained will be a good reflection of the intended preferences for which the weights were included (Marler & Arora, 2009).

2.1.6.2 ε-constraint method

Aside from the weighted approach, the ε-constraint method is probably the best-known technique to solve MOOPs (Ehrgott, 2005), which minimises one objective among all the objectives and sets the others as constraints (Amin *et al.*, 2020). Applying the ε-constraint method, one objective function is optimised while the other(s) is/are kept as constraints (Gholizadeh-Roshanagh *et al.*, 2016; Gunantara, 2018). Consider two objective functions $f_1(x)$ and $f_2(x)$ with the decision variable set and bounded by $g(x)$ and $h(x)$ inequality constraints. This can be represented mathematically as

$$\text{minimise } f_1(x) \qquad \text{Eqn 2.7}$$

$$\text{minimise } f_2(x) \qquad \text{Eqn 2.8}$$

Subject to

$$g(x) \leq 0 \qquad \text{Eqn 2.9}$$

$$h(x) \geq 0 \qquad \text{Eqn 2.10}$$

To solve the above mathematical problem using the ε-constraint, let us assume $f_1(x)$ as a constraint while optimizing $f_2(x)$. The problem now becomes

$$\text{minimise } f_2(x) \qquad \text{Eqn 2.11}$$

Subject to

$$g(x) \leq 0 \qquad \text{Eqn 2.12}$$

$$h(x) \geq 0 \qquad \text{Eqn 2.13}$$

$$f_1(x) \leq \varepsilon \qquad \text{Eqn 2.14}$$

The ε introduced is a suitable value that makes the objective function f_1 small enough and can be varied to a large number to obtain a solution set (Zhang & Rangaiah, 2013).

Due to the additional constraint introduced when using this method, the problem might be challenging and not give a good Pareto distribution. Nonetheless, it is a well-applied method for solving MOOPs with two objective functions (Zhang & Rangaiah, 2013). This method provides some advantages over the weighted sum method. Whereas the weighted sum method yields extreme (corner) solutions, the ε-constraint method can alter the original solution and yield non-extreme solutions that are efficient. The ε-constraint method can produce a different efficiency with each run, yielding a good representation of the optimal solution set. This is not the same for the weighted method. Also, whereas the weighted sum method cannot produce unsupported efficient solutions in multi-objective integer and mixed integer problems, it is not the same for the ε-constraint method. To make up for the pitfalls of the ε-constraint method, Mavrotas (2009) proposed the augmented method. Though implementing the ε-constraint method comes with some ease (Coello *et al.*, 2007), extensive computational effort is needed to generate the Pareto front (Ngatchou *et al.*, 2005; Coello Coello *et al.*, 2007). Also, the computation method can be costly, and encoding can be difficult (Chiandussi *et al.*, 2012).

2.1.7 Modelling language for optimisation

There are computational methods that have been utilized to solve MOOPs and have been implemented in software like Microsoft Excel Solver, optimisation toolbox in Matlab, GAMS, etc. (Bonilla-Petriciolet & Rangaiah, 2013). To effectively use these algorithms to solve MOOPs, it is essential to provide appropriate codes for the widely applied solvers (Mavrotas, 2009). Blank and Deb (2020) stated that executing an optimisation algorithm effectively can be challenging, time-consuming, and will require a suitable programming language.

Python has increasingly become a favorite programming language for researchers in different areas (Blank & Deb, 2020) and is even more popular in the scientific and industry communities (Podržaj, 2019; Simonne *et al.*, 2022). Python is an interactive, interpreted, object-oriented programming language that gives high-level data structuring (Sanner, 1999) close to simple maths thinking and reasoning (Bogdanchikov *et al.*, 2013). Object-oriented programming is when objects are a collection of both data and methods that are used to work on the data (Hart *et al.*, 2017). Though it has a simple syntax, it is a robust and general-purpose programming language (Sanner, 1999). Garrido (2016) defines syntax as grammar rules and vocabulary. This programming language offers code reliability and has copious libraries that make data analysis and scientific computing easy and easier to read compared to other languages like C++ and Java (Srinath, 2017). Libraries with Python are open source, with some standard ones like SciPy, Matplotlib, pandas, and NumPy, which are used for scientific computing exercises (Hill, 2020). Stewart (2016) tipped Python as one of users' best programming language options. Hart *et al.* (2017) also indicated that Python supports formulating and analysing mathematical models intended for complex optimisation applications, which are commonly associated with some commercial algebraic modelling languages (AML) like GAMS. Open-source packages that can be used in Python include Pyomo and PuLP (Hart *et al.,* 2011). Pyomo allows these algebraic capabilities to be implemented in Python (Hart *et al.*, 2017). Whereas Pyomo creates concrete and abstract models, PuLP only expresses concrete model instances (Hart *et al.*, 2011).

2.1.8 Applications of linear programming in diet optimisation

Linear programming was used to formulate and optimise macronutrient ratios of cereal-legume combinations to obtain a complementary feed, focusing on six (6) locally available cereals and legumes (maize, millet, sorghum, peanut, soybean, and cowpea) in Ghana, in comparison with

'*Koko,*' a traditional baby porridge that is made from fermented maize dough with added sugar. The second objective was also to use the linear programming tool to optimise the cereal-legume combinations with other ingredients to enhance the energy balance and ensure adequate macronutrient ratio and improved protein quality. With predefined macro and micro-nutrient requirements from recommendations, the Solver function in Excel was used for the optimisation process. Results obtained showed that *koko* did not meet the WHO/FAO protein and amino acid requirements, and the traditional cereal legume did not also meet the macronutrient requirements on its own. However, if lysine was added to the cereal-legume combinations, protein utilization was improved by 1 to 10% in the soybean mix, 35 to 40% in the peanut mix, and 14 to 24% in the cowpea mix (Suri *et al.*, 2014).

Alaini *et al.* (2019) aimed to develop LP models that provided a healthy balanced menu that may well help prevent cancer at minimum cost following guidelines provided by WCRF/AICR (World Cancer Research Fund/ American Institute for Cancer Research), MDG (Malaysian Dietary Guidelines) and RNI 2017. The study in Kuala Lumpur, Malaysia, selected one hundred (100) people from a university, collected their dietary intakes, and *analyse*d them using Nutritional Pro and SPSS software. Afterward, LP was formulated with an objective function to minimise cost subject to the constraints defined by the WCRF/AICR, MGD, and RNI 2017 and solved using the solver function in Microsoft Excel. The results obtained following the optimisation showed that the defined nutrient recommendations were met even though they found that the selected population could not have been a good representation of the whole population.

A comprehensive linear programming model was developed to create novel Ready-to-Use Therapeutic Food (RUTF) formulations for Ethiopia. The objective function was to minimise the cost of ingredients while controlling the ingredient weights and the nutritional and product-related quality. Finally, four formulations were selected out of 32 predicted feasible formulations obtained. The model developed took into consideration more ingredients, combining the objectives of obtaining combinations that had minimised costs and therapeutic (Ryan *et al.,* 2014).

Mamat *et al.* (2011) used fuzzy LP to design a diet low in fat and carbohydrate, with minimum cost. By using the probabilistic and linear membership approaches, diets that satisfy the nutrient requirements for humans were achieved at low cost.

Linear programming was used to design a predefined food group, the ideal quantity and size of servings of frequently consumed foods in Benin (Levesque *et al.,* 2021). Though this was a dietary problem, it looked at only one dimension of a sustainable diet.

Nyakänen *et al.* minimised the cost of a food basket for a family of four: mother, father, and two children in Ghana (2018). Even though the study achieved an optimised food basket for the family, acceptability was not considered.

Faksová *et al.* (2019) also sought to model the minimised cost of food baskets for a family in the Czech. Brixi (2018) also set an objective to find the minimum cost of ready-to-use foods (RUFs) to make them more available and reasonably priced to the malnourished population. Also, Dibari *et al.* (2012) minimised the cost of a diet that can treat wasting among Eastern African children, a condition often referred to as acute malnutrition.

Masset *et al.* (2008) sought to identify food plans that were as close as possible to the consumption patterns for a specific gender of a selected population. Dietary intake data collected from the population served as observed data. They then modelled a diet that meets the nutritional requirements of the World Cancer Research Fund/American Institute of Cancer Research (WCRF/AICR) dietary guidelines. Constraints were defined based on the recommended requirements of the WCRF/AICR, aiming to minimise the deviation between the observed dietary patterns and the modelled diet. The optimised diet models achieved cancer prevention goals that need little change to the observed patterns, with minimal impact on quality and cost.

One study (Raymond *et al.,* 2017) assessed the consumption patterns of 400 children (6 – 23 months) in central Tanzania and modelled a diet that meets the nutritional requirement for these age groups with an objective function to minimise possible deviations between the observed patterns and modelled diet(s). Though there were differences between the optimised food intake patterns, they ranged within the 10th and 90th percentile limits of the food groups, which was a good indication of the cultural eating patterns of the people used for this study.

Furthermore, with growing concerns for the environment regarding food consumption and growing consumption patterns, some studies (Ferrari *et al.,* 2020; Larrea-Gallegos & Vázquez-Rowe, 2020; Patterson *et al.,* 2021) set objectives functions to minimise the GHGE for diets that meet nutritional requirements.

Though traditionally mathematical programming techniques have been used to plan human diets, there used to be difficulties like no feasible solution, a better solution outside a constraint, etc, associated with their application (Mitani & Nakayama, 1997). In practicality, many problems have conflicting objectives, making the traditional linear programming methods inefficient in tackling them (Nakayama, 1993). Hence, techniques that use multi-objective programming have been proposed to tackle the challenge mentioned above (Mitani & Nakayama, 1997).

A multi-objective genetic algorithm was used to solve the hypertension nutritional diet problem in China. The focus of the multi-objective optimisation was to ensure the diet had limited amounts of energy and sodium and the appropriate amount of protein. Though the target was achieved, this multi-objective problem was focused mainly on these three nutrients (Wang & Sun, 2009).

Though linear programming and multi-objective optimisation tools have been applied to address different diet optimisation problems, their application to include all the dimensions of a sustainable diet is limited. Also, multi-objective optimisation is less explored in solving dietary problems. Furthermore, the generation of a Pareto-optimal front to help DMs know the extent of trade-offs among the objective functions has also not been done in addressing dietary problems from the literature search conducted. This, thus, forms the basis for this research.

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CHAPTER THREE

OPTIMISING A NUTRITIOUS, AFFORDABLE, AND CULTURALLY ACCEPTABLE DIET FOR GHANAIAN ADOLESCENTS USING LINEAR PROGRAMMING

ABSTRACT

Introduction: Adolescent nutrition is crucial because it directly influences their health and long-term well-being. As this demographic undergoes rapid growth and development, the significance of proper nutrition is paramount. However, ensuring adequate adolescent nutrition is complex due to economic constraints in the developing world. Recognising the socioeconomic challenges that often hinder access to quality diet, the present study aimed to design affordable and culturally acceptable food baskets for adolescents in Ghana that fulfil nutritional and socio-cultural constraints using locally available ingredients at a minimum cost.

Method: A linear programming approach was used to identify the set of ingredients where the total cost of the food basket was considered as the objective function to be minimised. Locally available food items with their prices and nutrient composition were used to obtain the optimised food baskets for the defined target groups at minimum cost.

Results: The optimised food baskets met FAO & WHO and the Institute of Medicine's nutrient requirements for adolescent males and females within specified limits. The proposed ingredient lists were estimated at minimum costs of GHS 15.70 and 15.57 per food basket, respectively for adolescent males and females. A total of 15 food items each were included in the food baskets for adolescent males and females, and nutrient requirements stayed within the lower and upper levels defined.

Keywords: diet optimisation, healthy diets, nutrients, cultural acceptability, adolescent nutrition.

3.1 INTRODUCTION

Dietary choices during teenage years are crucial for determining overall long-term health. Healthy diets ensure that individuals are well nourished and maintain good well-being by providing the nutrients needed for physical and cognitive development (Singh, 2004; WHO, 2020). These diets also serve as a critical measure of the health-promoting aspects of food systems (Schneider, 2021). Rapid growth and maturation are experienced during adolescence, from childhood to adulthood (Azupogo *et al.*, 2020), and good nutrition is required to achieve this. Wiafe *et al.* (2023) highlighted the need for improved nourishment to support adolescents' biological and physiological growth. Currently, there is an increasing trend of diet-related-non communicable diseases (Nykänen *et al.,* 2018), with a prevalence of overweight of approximately 3.2% and 10.4% among adolescent males and females in Ghana, respectively (Alicke *et al.*, 2017). Azupogo *et al.* (2020) further indicated the prevalence of stunting, underweight, and overweight among adolescents aged 15 – 17 due to poor nutrition. Furthermore, a study (Gyimah *et al.,* 2021) on the correlation of dietary diversification among pregnant adolescent girls in Ghana showed that inadequate dietary diversification is associated with rural living, food insecurity, and poverty. A study conducted by Abubakar *et al.* (2023) in the Tamale metropolis of Ghana showed that some adolescents were underweight, and the leading causes were unhealthy dietary habits and socioeconomic status. However, maintaining a healthy and nutritious diet can be expensive because of the rising cost of nutritious foods (Dizon & Herforth, 2018). Liese *et al.* (2015) indicated a positive correlation between quality diet and reduced risk of mortality from non-communicable diseases. Thus, nutritious diets can reduce the prevalence of non-communicable diseases.

Some studies (Nykänen *et al.,* 2018; Gurmu *et al.*, 2019) have examined the cost and affordability of meeting the recommended nutrient intakes from locally available foods. These studies indicated the possibility of designing nutritious diets at minimum costs. Temple and Steyn (2011) highlighted the need for healthy diets for low-income households in South Africa.

Cost can be a significant barrier to accessing healthy diets because consumers must consider other competing needs, such as clothing and accommodation. Darmon and Drewnowski (2015) emphasised the significant role of economic factors, particularly food prices, in influencing consumers' food choices and dietary quality. The study highlighted that the cost of healthy foods can be a barrier for financially under resourced people, forcing on them inexpensive and less nutritious options. The findings of this review are consistent with the current trend of increasing prices for nutritious foods (Dizon & Herforth, 2018). This trend could exacerbate disparities in health outcomes among different socioeconomic groups, as people with limited financial resources may have limited access to healthy dietary options.

Economic deprivation comes with the burden of malnutrition (undernutrition), with many low-income sub-Saharan countries, including Ghana, showing increasing rates of undernourished children (UNICEF, 2021). Low-income consumers are more affected by poor-quality diets than wealthier consumers due to high food prices (Schneider, 2022). Thus, it is critical to consider the affordability of a nutrient-adequate diet when attempting to solve dietary problems to promote health equity and reduce health disparities (Herforth *et al.*, 2020).

Linear programming (LP) is an excellent approach for formulating diets to solve nutritional problems (Parlesak *et al.*, 2016; Chungchunlam *et al.*, 2021) and can also be used to propose foods that meet dietary guidelines. Even though LP has been a practical approach to obtaining nutrient-dense foods at a minimum cost, consideration should not be on meeting only nutrient requirements but also on consumer acceptability (Gurmu *et al.,* 2019). This is because consumers can reject very nutritious diets that do not appeal to them. A low-cost, nutritionally adequate diet with a low climate impact was achieved using linear programming, although cultural acceptability was not considered (van Dooren *et al.,* 2015). Similarly, Brimblecombe *et al.* (2013) used linear programming to design a least-cost diet that was nutrient-dense and adequate but did not consider consumer acceptability.

This study aimed to design minimum-cost food baskets that are nutritionally adequate and culturally acceptable for adolescent males and females aged 14 to 18 using locally available food items in Ghana.

3.2 METHODOLOGY

3.2.1 Operational Definitions

In this study, the following classifications were provided for key terms that will be used (Table 3.1) to ensure consistency and aid in results discussion.

Table 3.1: Locally available food items in Ghana (n=98) included in the linear programming analysis

Food groups	Subgroups	Number of food items
Staples	Cereals, grains, starchy foods	27
Legumes, seeds, and nuts	Beans, seeds, nuts (for example, peanut), pulses	10
Fruits and vegetables	Fruits, leafy, and wild vegetables	32
Animal-sourced foods	Beef, mutton, pork, poultry, seafood	14
Fats and oils	Animal and plant-based fats and oils	6
Miscellaneous	Spices, salt, *milk powder, *yoghurt, and mushroom	7
	Total	**98**

*Yoghurt and milk powder were included in the miscellaneous because of their low consumption rate in Ghana.

3.2.2 Dietary data and food groups

The prices of food items were obtained from a study that collected data from 11 urban marketplaces and supermarkets in the Ashanti, Central, and Greater Accra regions, as well as eight rural marketplaces in the Ashanti and Volta regions of Ghana between February and April 2016 (Nykänen *et al.*, 2018). Additional data on the cost of locally available foods from the major markets across the country from 2021 to 2022 was obtained from the Ministry of Food and Agriculture (MoFA), Ghana. In cases where the nutrient composition of the food items was incomplete, data was complemented with information from the FAO food composition table for West Africa (FAO, 2019; Stadlmayr *et al.*, 2012). To ensure that the most current prices were reflected, the prices were adjusted for inflation using the Consumer Price Index (CPI) from February 2017 to February 2023 (Ghana Statistical Services, 2023). Sugar was excluded from the food list to prevent the inclusion of empty calories.

3.2.3 Nutrient requirements

This study considered macronutrients, including fat, protein, and carbohydrates, and focused on micronutrients (iron, zinc, and Vitamin A) of Ghana's public health concerns. The minimum level for the nutrients was defined as the Recommended Dietary Allowance (RDA), which is needed to satisfy nearly all healthy individuals in a population's group (97 to 98%) (Table 3.3) (Institute of Medicine, 2000; 2001; 2011; National Academies of Sciences, Engineering, and Medicine, 2019; 2023), with slight modification to the inequality equations for mathematical suitability (Eqns 3.2 and 3.3). For example, the requirement for thiamine was defined as 1.2 mg with no adverse effect for higher amounts in the recommendation for adolescent males, and it was defined as ≥ 1.2 mathematically. Recommendations that were not modified are indicated with an asterisk in Table 3.3. Maximum intake levels of each were based on the upper-level intake for the nutrients defined.

3.2.4 Defining Parameters and Variables

The total cost of the food basket was defined as the objective function in the LP formulation. The goal was to obtain a list of ingredients that met specific requirements for nutrients and acceptability at a minimum cost. The decision variables were the quantity of ingredients needed in the formulation. Constraints were set for the minimum and maximum limits of each nutrient.

3.2.5 Mathematical modelling

A linear programming model was adopted using the equations below to select ingredients that meet all the requirements at minimum cost.

$$Z = \sum_{j=1}^{n} c_j x_j \qquad \text{Eqn 3.1}$$

Subject to

$$\sum_{j=1}^{n} a_{ij} x_j \geq l_i \qquad i = 1,2,3, \ldots \ldots \ldots m \qquad \text{Eqn 3.2}$$

$$\sum_{j=1}^{n} a_{ij} x_j \leq u_i \qquad i = 1,2,3, \ldots \ldots \ldots m \qquad \text{Eqn 3.3}$$

$$x_j \geq 0 \text{ (x is a continuous variable)} \qquad \text{Eqn 3.4}$$

$$FG_1 = p_1 * T \qquad \text{Eqn 3.5}$$

$$FG_2 = p_2 * T \qquad \text{Eqn 3.6}$$

$$FG_3 = p_3 * T \qquad \text{Eqn 3.7}$$

$$FG_4 = p_4 * T \qquad \text{Eqn 3.8}$$

$$FG_5 \leq p_5 * T \qquad \text{Eqn 3.9}$$

$$FG_6 = p_6 * T \qquad \text{Eqn 3.10}$$

$$\text{Tomatoes} \geq 164\text{g} \qquad \text{Eqn 3.11}$$

$$\text{Onions} \geq 76\text{g} \qquad \text{Eqn 3.12}$$

$$\text{Pepper} \leq 50\text{g} \qquad \text{Eqn 3.13}$$

Where:

Z – total cost to be minimised (objective function) n – total number of food items in the LP analysis

x_j – portions of food item j in g

c_j – the cost of food item j per 100 g

a_{ij} – amount of nutrient i in food item j

l_i – the lower bound for nutrient i (g or mg or kcal)

u_i – the upper bound for nutrient i (g or mg or kcal)

m – represents the number of inequalities

FG_i = the respective food groups (FOs, FVs, LSNs, ASFs, S, and M, respectively)

FOs – fats and oils

FVs – fruits and vegetables

LSNs – Legumes, seeds and nuts

ASFs – Animal sourced foods

S – Staples

M – miscellaneous

p_i – the recommended percentage of the selcted food items for FG_i

(the respective percentages specific for the Ghanaian setting in the study scope are 0.4%, 35%, 13.07%, 9.5%, 44% and 2.77%, respectively for FOs, FVs, LSNs, ASFs, S, and M.).

T – the summation of food items x_j

The weight contribution of the various foods is based on recommendations from the food-based dietary guidelines (FBDG). for Ghana (MoFA & GSPH, 2023) and modified as required for feasibility using Eqns 3.5 to 3.10. Further constraints (Eqns 3.11 to 3.13) were included to select three ingredients (onions, pepper, and tomatoes) common in the local Ghanaian diet based on the daily minimum requirements recommended by the FBDG for Ghana. These constraints were defined to account for cultural acceptability. The constraint on pepper was set not to exceed a maximum quantity because it is usually consumed in small amounts. Constraints on the food baskets were imposed to achieve dietary diversification and ensure familiar patterns based on the FBDG.

The constraints were included in a stepwise manner. The first step was to solve the problem with only nutrient constraints by implementing Eqns 3.1 – 3.4. This was followed by constraining the food groups, including tomatoes, onions, and pepper (should they not be previously selected).

3.2.6 Software

To efficiently solve the cost optimisation problem defined above, the Gurobi solver (version 10.0.2) was used. The solver was integrated with the Pyomo package in the Python programming language. The hardware configuration provided sufficient computational resources for the optimisation process.

3.3 RESULTS AND DISCUSSION

3.3.1 RESULTS

The optimisation process involved a stepwise approach, starting with nutrient constraints (Eqns 3.1 – 3.4) and gradually adding the requirements defined for the food groups and specific ingredients (Eqns 3.5 – 3.13). The stepwise optimisation process was necessary because the first optimisation process, with only nutrient constraints, selected only seven food items with large unrealistic amounts and unsuitable combinations to be included in a diet. Selection increased to fifteen food items as requirements on food groups were included. Restrictions on fruits and vegetables had to be relaxed by adjusting them upward by 5% to allow for the inclusion of specific ingredients. This adjustment represented the minimum necessary increment to achieve a feasible solution.

Furthermore, the nutrient values obtained after the linear optimisation stayed within the established lower and upper limits. However, the lower requirements for n-6 PUFAs, calcium, vitamin A-RAE, and vitamin E were binding in the model for adolescent males. Similarly, n-6 PUFAs and vitamin E were the binding constraints in the model for adolescent females. The upper requirements for cholesterol, sodium, and niacin were also binding constraints in the results for male and female adolescents.

Although the recommended dietary allowance of nutrients is considered an essential factor in a least-cost diet optimisation problem, the consumer acceptability of food items is also crucial to ensure long-term compliance with the proposed food baskets.

The results focused on the cost of the food baskets, their total weights, ingredients, and their contribution to the nutrient values obtained within the defined lower and upper bounds. The results show that least-cost diet optimisation for the defined target group is feasible because the linear programming algorithm could select affordable combinations that satisfied the defined requirements (Figure 3.1). Also, dietary recommendations can be transformed into practical dietary advice for Ghanaian consumers.

The step-by-step inclusion of the nutrient constraint increased the cost of the food basket until all the nutrient constraints were satisfied. The minimum cost of the food baskets for adolescent males and females was **GHS 15.70** and **GHS 15.57** per food basket (1 GHS = 0.1 USD, 30th November 2023, source: www.bog.gov.gh), respectively (Figure 3.1).

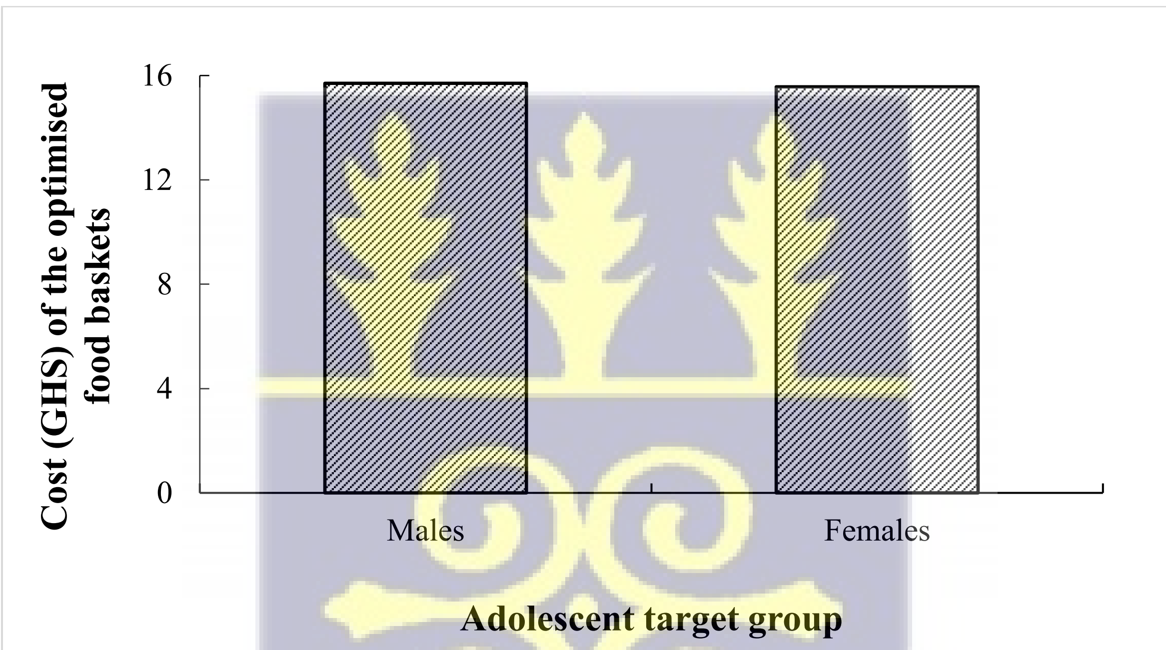

Figure 3.1: Cost of the optimised food basket for adolescent males and females aged 14 to 18. GHS – Ghana Cedis

The contribution of the ingredients in terms of food groups to the total cost is represented in Figure 3.2. For both food baskets, fruits and vegetables contributed the most to the cost, followed by animal-sourced foods, staples, legumes, seeds, and nuts, miscellaneous, and fats and oils.

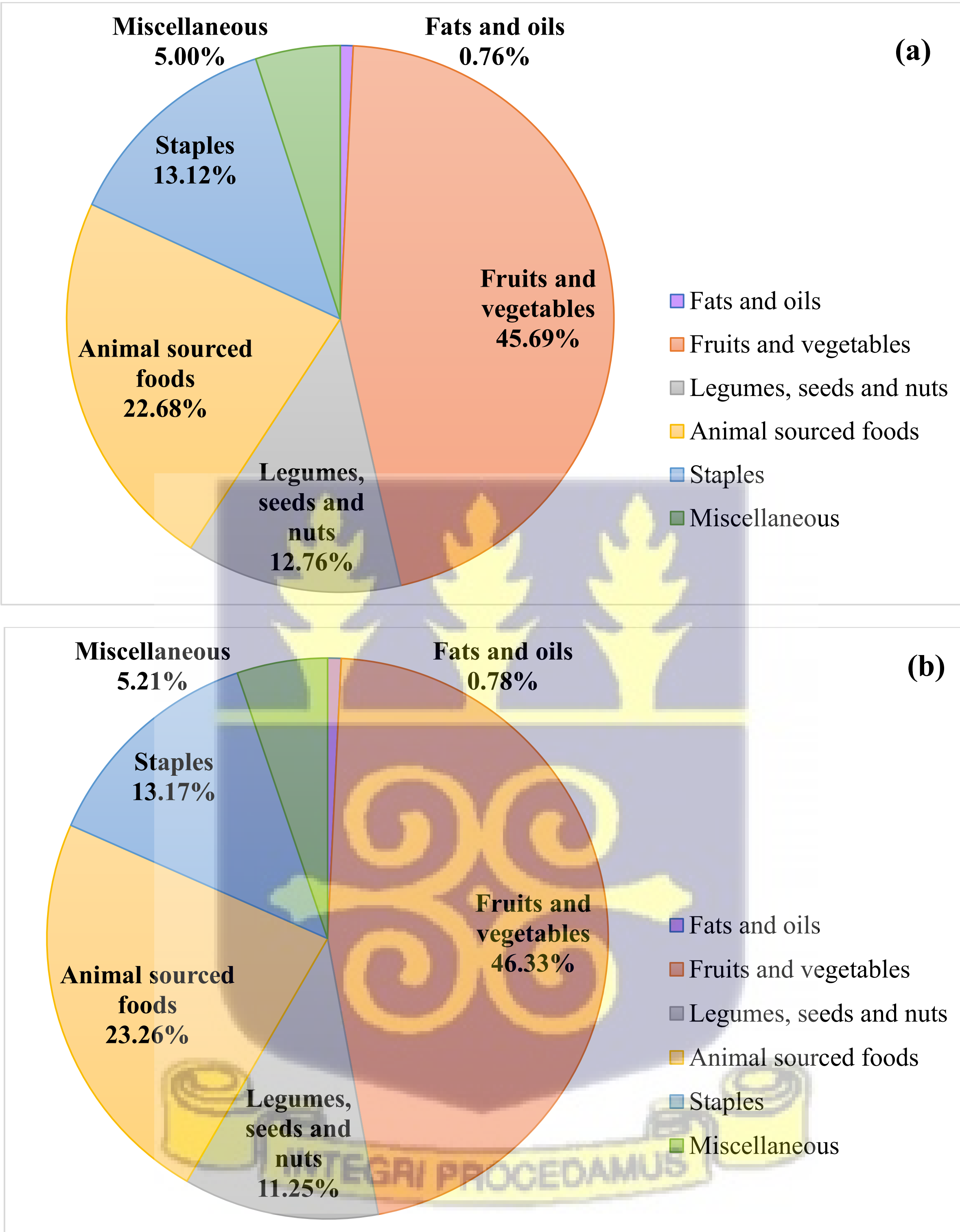

Figure 3.2: Contribution of the different food groups to the overall cost achieved for adolescent males (a) and females (b) aged 14 to 18 years.

Table 3.2 displays food items for adolescent males and females with corresponding amounts and costs to meet their nutritional needs. The male and female food baskets were similar in weight.

Table 3.2: Optimised food baskets (ingredients and cost) for the daily nutritional requirements for adolescent males and females aged 14 to 18 years

	Males			Female		
Food Groups	**Food items**	**Amount (g)**	**Cost (GHS)**	**Food item**	**Amount (g)**	**Cost (GHS)**
Fats and oils	Vegetable oil	6.23	0.12	Vegetable oil	6.33	0.12
		6.23	**0.12**		**6.33**	**0.12**
Fruits and vegetables	Avocado	233.62	1.33	Oranges	77.38	0.30
	Dried pepper	3.37	0.12	Avocado	159.94	0.91
	Tomato	164.00	1.87	Dried Pepper	12.13	0.43
	Dried okro	68.12	2.75	Tomato	164.00	1.87
	Onion	76.00	1.10	Dried okro	64.29	2.60
				Onion	76.00	1.10
		545.11	**7.18**		**553.74**	**7.21**
Legumes, seeds, and nuts	Unshelled Groundnut	8.46	0.17	Soya Bean	99.62	0.94
	Soya Bean	195.10	1.83	Oil palm nut	107.16	0.81
		203.56	**2.00**		**206.78**	**1.75**

Animal sourced foods	Egg	55.88	1.39	Egg	55.62	1.38
	Fresh kpanla (Barracuda)	55.86	1.46	Fresh kpanla (Barracuda)	58.29	1.52
	Smoked tuna	36.22	0.71	Smoked tuna	36.39	0.72
		147.96	**3.56**		**150.30**	**3.62**
Staples	White maize	14.89	0.09	Cassava	621.14	2.05
	Cassava	596.57	1.97			
		611.46	**2.06**		**621.14**	**2.05**
Miscellaneous	Cow milk (Pasteurized)	40.36	0.77	Cow milk (Pasteurized)	42.12	0.80
	Iodised salt	2.78	0.02	Iodised salt	1.71	0.01
		43.14	**0.79**		**43.82**	**0.81**
Total		***1557.46***	***15.70***		***1582.13***	***15.57***

There were no constraints imposed on individual portion sizes. GHS – Ghana Cedi

Staples, fruits, and vegetables were the most significant contributors to the weight of food baskets, followed by legumes, seeds and nuts, animal-sourced foods, miscellaneous, and fats and oils (Figure 3.3). Furthermore, the results show a good representation of food items from the different groups, providing variety in the optimised food basket.

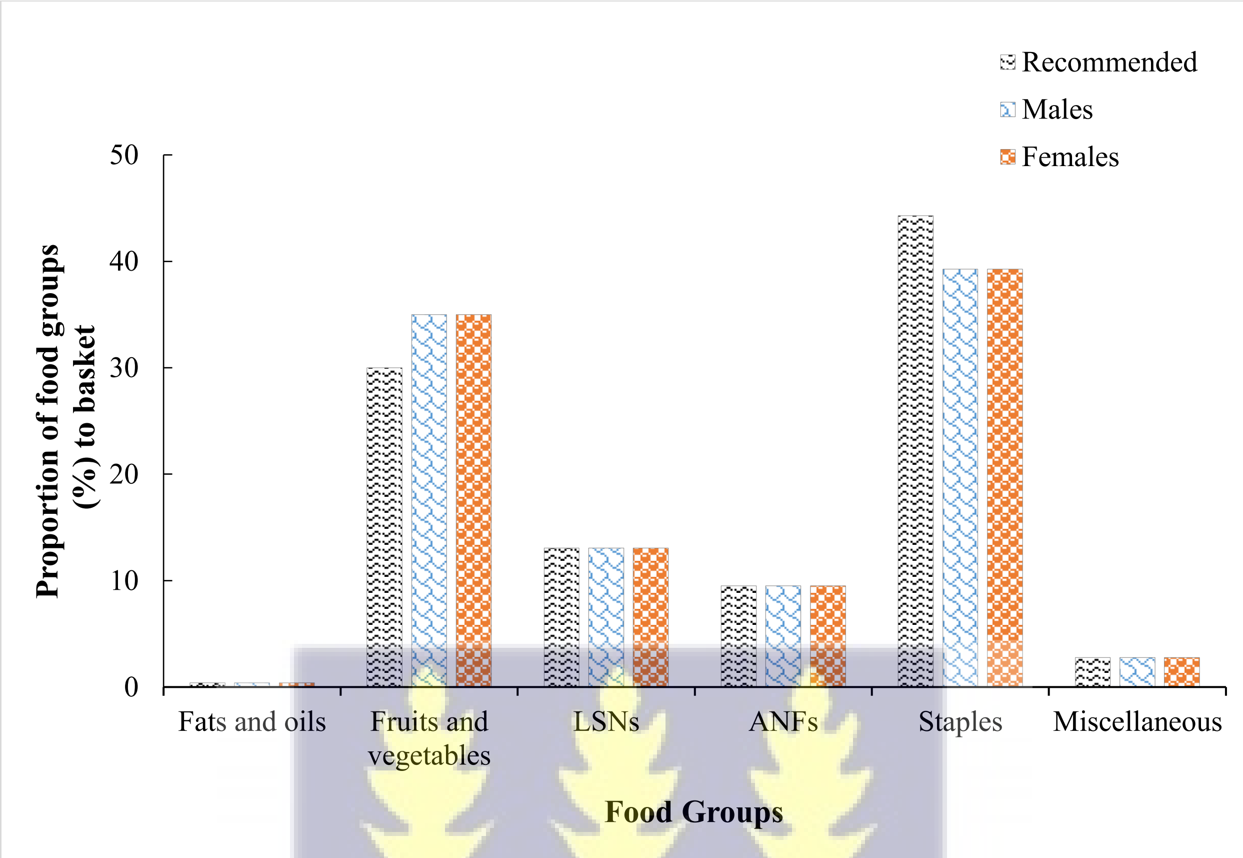

Figure 3.3: Optimised proportion of food groups and their contribution to the optimised food baskets against the recommended proportions in the FBDG for Ghana (MoFA & GSPH, 2023) for adolescents 14 to 18. LSNs – legumes, seeds and nuts, ANFs – animal sourced foods

Table 3.3 summarises the estimated nutritional values of 27 nutrients in the optimised food baskets for adolescent males and females. The optimised food baskets met all the micronutrient requirements (lower and upper limits).

Figure 3.4 further shows the contribution of the different food groups to energy and macronutrient values obtained from the optimised food baskets for adolescent males and females. In general, similar trends were observed for the contribution of the different food groups to the nutrient values obtained after optimizing the food baskets. Staples contributed the most to energy and carbohydrates, accounting for 43.85% of energy and 83.87% of carbohydrates for the food basket for males. For the female food basket, staples contributed 36.75% to energy and 75.51% to carbohydrates. Animal-sourced foods contributed the most to the proteins. It contributed 38.01% for the food basket for males and 43.26% for the food basket for females. Fruits and vegetables contributed 53.14% to the optimised fat value for the food basket of males, whereas legumes, seeds, and nuts contributed 55.89% to that of females.

Table 3.3: Recommended daily nutrient intake for adolescents and the estimated nutrient content of the proposed least-cost diet

Nutrients		Males		Females	
		Recommended values	Proposed least-cost diet	Recommended values	Proposed least-cost diet
Energy	Kcal	2000-3200	2050.18	1800-2400	2400.00
Protein	g	≥52	90.12	≥46	80.74
Fat	g	ND	72.12	ND	100.82
n-3 PUFAs	g	≥1.6	2.53	≥1.1	1.92
n-6 PUFAs	g	≥16	16.00	≥11	11.00
Cholesterol	mg	≤300	300.00	≤300	300.00
Carbohydrate	g	≥130	273.12	≥130	302.70
Fibre	g	≥38	79.00	≥26	72.56
Sodium	mg	≤1500	1500.00	≤1500	1500.00
Potassium	mg	≥3000	6880.18	≥2300	6603.74
Calcium	mg	1300-3000	1300.00	1300-3000	1300.00
Magnesium	mg	≥410	843.13	≥360	992.30
Iron	mg	11-45	19.23	15-45	25.46
Zinc	mg	11-34	12.88	9-34	14.38
Copper	mg	0.89-8	2.47	0.89-8	3.65
Selenium	µg	55-400	113.31	55-400	113.39
Phosphorus	µg	1250-4000	1676.13	1250-4000	1636.85

Iodine	µg	150-900	185.93	150-900	158.06
Vit A-RAE	µg	900-2800	900.00	700-2800	1139.17
Thiamine	mg	≥1.2	2.29	≥1.0	2.50
Riboflavin	mg	≥1.3	1.45	≥1.0	1.46
Vitamin B6	mg	1.3-80	3.10	1.2-80	3.12
Vitamin B12	µg	≥2.4	4.02	≥2.4	4.10
Vitamin C	mg	75-1800	297.97	65-1800	335.77
Vitamin E	mg	15-800	15.00	15-800	15.00
Folate	µg	400-800	772.98	400-800	712.91
Niacin	mg	16-30	30.00	14-30	30.00

The range in the third column reflects the nutrients' lower and upper intake limits. To indicate nutrients that have only lower or upper limits, ≤ or ≥ was respectively used. RAE – retinol activity equivalent, n-3PUFAs – alpha-linolenic acid, n-6 PUFAs – linoleic acid, ND – not defined. (Source: WHO & FAO, 2004; Institute of Medicine, 2000; 2001; 2011; National Academies of Sciences, Engineering, and Medicine, 2019; 2023).

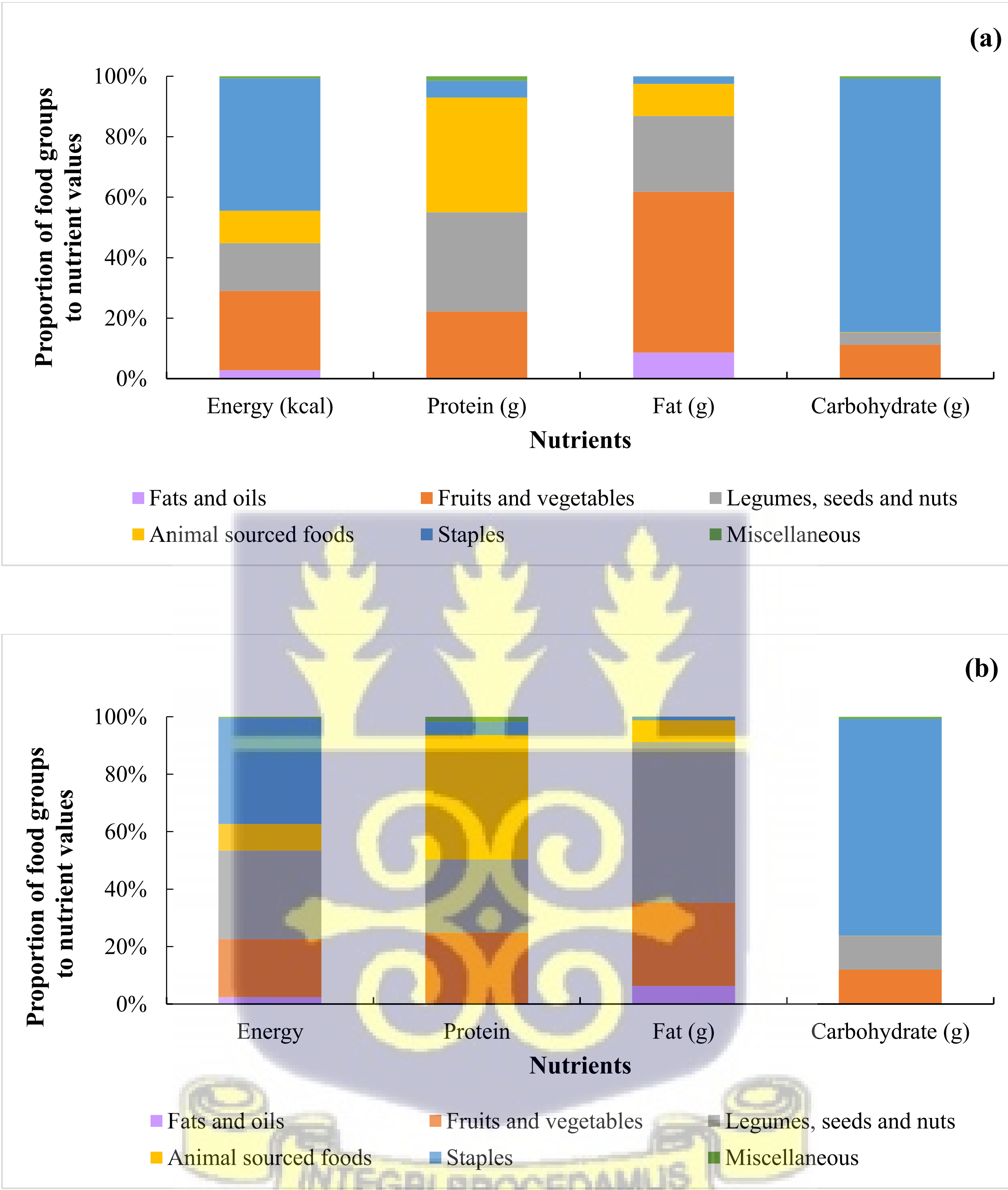

Figure 3.4: Proportion of food groups and their contribution to the energy and the primary macronutrient values obtained for adolescent males(a) and females aged 14 to 18 years.

3.3.2 DISCUSSION

The results showed that obtaining food baskets for adolescent males and females at a minimum cost using locally available food items was feasible. Increasing the number of constraints increased the cost of the food baskets. The positive correlation between the number of constraints and cost was supported by the studies conducted by Suri *et al.* (2014), De Carvalho *et al.* (2015), and Parlesak *et al.* (2016), who indicated that including more constraints in addition to nutrient recommendations increased the lowest cost of the diets they optimised. An increased number of constraints could have limited the solution space, making it difficult to find a solution at a low cost. This could have forced the algorithm to include more expensive food items, increasing cost. In addition, increased dietary diversity, ensuring specific percentages from the food groups, could have also contributed to the cost obtained for the food baskets.

The number of items in the food baskets for adolescent males and females was the same after the final inclusion of nutritional constraints and acceptability requirements. Fifteen food ingredients were obtained for both adolescent males and females from the 98 items used for the optimisation exercise. This implies that only a few ingredients (15.3%) were needed to meet the nutrient recommendations for adolescent males and females. Parlesak *et al.* (2016) reported similar trends, stating that very few foods were required to meet nutrient and dietary recommendations at the lowest possible cost. Wilson *et al.* (2013) also reported ten items in a food basket for a least-cost diet with a low environmental impact. A minimum food basket cost developed for rural and urban families in Ethiopia resulted in 16 and 19 food items, even though the authors indicated less dietary diversity with the results (Gurmu *et al.,* 2019). Furthermore, in a study by Lauk *et al.* (2020) to optimise food baskets for families in Estonia, the optimised food basket without considerations for cultural acceptability resulted in 9 food items. The results further indicate the need to consider common foods consumed by a population when developing LP diet recommendations. Also, the smaller number of food items for adolescent males and females could have been due to the tendency of the algorithm to select fewer food items that met the defined constraints because of the direction of the objective which was to minimise cost.

Food items under fruits and vegetables amounted to GHS 7.18, contributing 45.73% of the cost of the food basket for adolescent males. That of the food basket for adolescent females cost GHS 7.21, contributing 46.31% of the total cost. Animal-sourced foods amounted to GHS 3.56, contributing 22.68% of the cost of the food basket for adolescent males, and for food baskets for females, it was GHS 3.62 making up 23.25%. The high contribution of the cost of food items from this food group category is expected because the production of animal-based food products requires significant resources, making them expensive food sources (Pimentel *et al.,* 2008). This was followed by staples contributing 13.12% of the total cost for adolescent males and females. Even though the optimisation provided dietary diversification, the high-cost contribution of fruits and vegetables could be expensive for some low-income earners.

These trends highlight diets consisting of staples, legumes, fruits and vegetables, and animal-sourced foods, with minimum fats and oils for adolescent males and females. The optimised proportions of fruits and vegetables were slightly higher than the 30% recommended in the FBDG for Ghana. However, it aligns with many health organisations, like the Centre for Disease Control and Prevention, which recommends that people consume about four servings to maintain a healthy diet (CDC, 2021). The slight increase in the recommended intake compared to the amount suggested by the Ghanaian FBDGs can be considered good because it skews towards the recommendations by the EAT-Lancet (Willet *et al.,* 2019). The EAT-Lancet stated that an increase in plant-based foods in consideration for a sustainable diet is gaining increasing recognition. The slight decrease in staples can be considered a good outcome because it aligns with a recommendation from the World Health Organisation (WHO) that hints at a decrease in staple consumption to prevent excess calorie intake, which can cause overweight and obesity (WHO, 2018). The low inclusion of fats and oils at 0.4% of the total weight of the food basket was in line with the recommendation of 6g of oils by the FBDG for Ghana. Also, the low contribution from that food group means lower consumption, which can benefit overall health (Harvard School of Public Health, 2023). Although fruits and vegetables are generally low-fat foods, the high contribution of fruits and vegetables to the fat is due to the high amount of avocado (233.62 g) in the food basket for adolescent males. Additionally, although the fat contribution of fruit and vegetables was high, their percentage contribution to the total diet was 0.4%.

There was adequate representation of legumes and animal-sourced foods in the food baskets for males and females, in alignment with the recommendations of the Ghanaian FBDG (MoFA & UGSPH, 2023). These scenarios form a reasonable basis for interventions that promote healthier eating habits and reduce the risk of diet-related chronic diseases (WHO, 2018). The diversity of the food items included in the food baskets for adolescent males and females indicates healthy eating. Omari *et al.* (2017) hinted that dietary diversification and FBDG are some of the critical approaches that can be used to control and eliminate micronutrient malnutrition in Ghana. These results offer the possibility of addressing these unhealthy dietary habits among adolescents at a minimum cost.

Constraints are said to be binding when a change to them results in changing the optimal solution obtained (Boyd & Vandenberghe, 2004). For example, decreasing the minimum n-6 PUFA (an essential fat that is important for maintaining health) requirement for adolescent males and females will decrease the optimal cost value. Interestingly, even though iron deficiency (anaemia) is a problem among different populations in Ghana (Coomson & Aryeetey, 2022; Wiafe *et al.,* 2023), iron was not a binding constraint and therefore did not affect the cost of food baskets. The optimised food baskets, however, met iron constraints, which can be an excellent way to develop interventions for adolescent males and females in real-life applications.

The consumption of staples like starchy roots, cereals, and legumes is typical in Ghanaian diets as they provide enough energy and nutrients, mainly carbohydrates. According to Ogedengbe *et al.* (2017), legumes contain many nutrients and are vital for providing energy, carbohydrates, protein, and fibre. Hence, they are essential to the optimised food basket.

The optimised food baskets can be said to have ensured cultural acceptability since the combination of locally available foods is essential in ensuring acceptability, which can encourage long-term dietary improvements. This is mainly because locally available foods are familiar and accessible, making them more likely to align with traditional culinary practices and preferences.

Additionally, fruits and vegetables met most micronutrient needs, including iron, potassium, riboflavin, Vitamin C, folate, and niacin for both genders. Results obtained from the study show that LP could be a great approach to developing interventions to encourage healthy diets among adolescents. From the study, it is possible to use an optimisation algorithm to propose food baskets that have feasible combinations and can help identify foods that can be promoted by policymakers and dietary patterns that can even be adopted for school feeding programs.

This typical example of a food-based solution can be leveraged in the campaign against micronutrient deficiencies and other non-communicable diseases among adolescents in Ghana. Also, the current provision of the Ghanaian FBDG can be adapted and incorporated as a guide in linear optimisation, as done in this study.

It is worth noting that the study has certain limitations. Firstly, the seasonality of some or most foods was not considered. Secondly, the portion sizes of individual food items were not restricted, which could lead to the algorithm recommending either too little or too much of certain food items. Additionally, although the inclusion of constraints on food groups offered variety, the continued consumption of the proposed items could become monotonous as only fifteen items were selected. Although constraints were imposed on the different food groups, it did not consider the different ethnic groups.

3.4 CONCLUSION

The study aimed to propose food baskets from locally available ingredients that met nutrient requirements and acceptability constraints for adolescent males and females. It was possible to obtain these food baskets at a minimum cost of GHS 15.70 for males and GHS 15.57 for females, with 15 food items each. Selected food items represented all the food groups defined, indicating dietary diversification. The estimated nutrient contents stayed within the lower and upper requirements, even though nutrients like calcium, vitamin A, and E were limiting. Also, fruits and vegetables significantly met the micronutrient requirements, and staples and legumes contributed to energy and macronutrients.

The linear programming algorithm was used to solve the dietary problem defined in the objective. Including dietary diversification and consideration for essential ingredients can influence food selection patterns, which has implications for the nutritional quality and cost of food baskets.

The results from the study imply that it is possible to improve the accessibility of affordable diets for adolescents.

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CHAPTER FOUR

DESIGNING A NUTRITIONALLY ADEQUATE, ACCEPTABLE, AND LOW-CARBON DIET FOR PREGNANT AND LACTATING WOMEN IN GHANA: AN OPTIMISATION EXERCISE

ABSTRACT

Optimal nutrition is critical during pregnancy and lactation because it ensures the well-being of the child and mother. These stages require a balance between meeting their critical nutritional needs and sustainability because they require higher levels of specific nutrients such as protein, calcium and iron. Foods rich in essential nutrients for women who are at the stages of pregnancy and lactation include red meat and dairy, and these foods tend to have high carbon footprints. Hence, there is a need to encourage low GHGE, nutritionally adequate diets which align with efforts to address climate change while improving health outcomes among lactating and pregnant women.

The study adopted a linear programming approach to design and optimise nutritionally adequate and socio-culturally acceptable diets with low greenhouse gas emission (GHGE) values for pregnant and lactating women aged 19 to 50 years. The objective was set to minimise the total GHGE values of the food baskets subject to nutrient and acceptability requirements.

The food basket defined for pregnant women had a GHGE value of 1.06 kg CO_2eq./day, and that of lactating women had a value of 1.48 kg CO_2eq./day. Both groups had 19 and 21 food items in their respective food baskets, including three common ingredients in almost all Ghanaian diets. The optimisation process satisfied the nutrient constraints with no deviations. The general trend

observed was a shift towards more plant-based foods, legumes, seeds, and nuts, less contribution from staples, and complementary protein-sourced foods with no red meat.

Results obtained can be adopted for nutrition programs for pregnant and lactating women and possibly incorporated into the Ghana food-based dietary guidelines.

Keywords: greenhouse gas emissions, sustainability, adequate nutrition, linear programming, sustainability.

4.1 INTRODUCTION

There have been growing concerns about the environmental impact of food production and consumption in recent years. The current food consumption and production methods threaten the planet's health (Hirvonen *et al.,* 2019). According to some reports, global food systems produce about one-third of the global greenhouse gas emissions (Vermeulen *et al.*, 2012; IPCC, 2019). Steenson and Buttriss (2020) highlighted that, even though global figures for emissions from the food systems are one-third of total emissions, they could be over-reported for some countries because the environmental impact of food may vary significantly between different producers and regions. The authors further stated that in 2018, the emissions recorded from agriculture in the UK were 10% of their total emissions, compared to the global figure of about 29% from the food systems.

Nonetheless, there is a tendency that the impact of consumers on the environment will continue to worsen as the world population grows exponentially and dietary patterns shift towards higher meat and dairy consumption (Springmann *et al.,* 2018). This is because current dietary trends and the projected population growth of about ten billion by the year 2050 will exacerbate risks to the people and the planet (Willet *et al.,* 2019). As a result, there is a need to identify sustainable food choices with a low carbon footprint. Using locally available ingredients can be a good start for optimising diets with a low carbon footprint.

According to some researchers, diets that are primarily based on locally available ingredients tend to have a lower carbon footprint compared to those that rely heavily on imported and processed foods mainly due to the shorter supply chain, which reduces energy consumption and carbon emissions associated with transportation (Peters *et al.*, 2007; Garnett, 2011; González *et al.*, 2011; and Perigon *et al.*, 2016).

There are diverse food crops and livestock in Ghana, which offer a wide range of options for sustainable dietary choices. These locally available ingredients can be used to minimise the carbon footprint of food production and consumption while promoting healthy and nutritious diets among different populations.

Recently, diet formulations have focused on cost and extended to sustainability in terms of the environment (Mackenzie *et al.,* 2016). According to Vieux *et al.* (2013), the diet optimisation method can be practically used to achieve sustainable diets with low-carbon footprints. It involves selecting and combining different foods in different quantities to meet nutrient needs and other constraints while considering the environment. Macdiarmid *et al.* (2012) successfully used a diet optimisation technique to propose diets for males and females in the UK. Another study in Italy proposed nutritionally adequate patterns that minimised greenhouse gas emission (GHGE) values in the diet of adult males and females (Ferrari *et al.,* 2020). Masino *et al.* (2023) also used linear programming to plan a climate-friendly and healthy omnivorous diet for adults in Germany.

According to a report by the Lancet Commission, the lack of scientific targets for achieving healthy diets from sustainable food systems hinders progress (Willet *et al.,* 2019). In addition, a diet with less environmental impact may not be desirable to consumers if they are unfamiliar with the foods. Hence, developing dietary guidelines that promote minimum carbon footprint diets for specific populations will be necessary to achieve climate and health goals (Willet *et al.,* 2019).

There is no unique approach toward sustainable and healthy eating. Furthermore, optimal diets may vary depending on what foods are available in a particular locality, cultural preferences, and consumers' nutritional needs (Joy *et al.,* 2017; Hawkes *et al.,* 2020). Also, choosing foods that can be considered sustainable from many foods is not simple. Although it is not easy to propose combinations of these foods that can be classified as sustainable, it is possible. In Ghana, for instance, many foods are available, from fresh foods to processed ones. Additionally, there is no country-specific standardised environmental food database of GHGE value available in Ghana. In the context of this study, no diet has been optimised to minimise GHGE values for Ghana's population.

This study, therefore, contributes to ensuring sustainable food consumption, particularly considering locally available foods in Ghana for different population groups, but focused on pregnant and lactating women. Paying particular attention to the nutritional needs of these groups of individuals with unique circumstances is essential. Proper nutrition during these stages is essential for optimal health, foetal development during and after pregnancy, and lactation (Brink *et al.,* 2022). It is also critical in determining an individual's lifetime risk of certain diseases (Marshall *et al.,* 2022). According to Thomas (2022), it is crucial to streamline healthcare and nutrition programs to address the well-being of women and children during the first one thousand days, from pregnancy to a child's second birthday. Unfortunately, many countries neglect to invest in this critical period.

The study explored the possibility of optimising diets with minimal carbon footprint using locally available ingredients in Ghana for lactating and pregnant women aged 19 to 50 years old.

4.2 METHODOLOGY

4.2.1 Operational Definitions

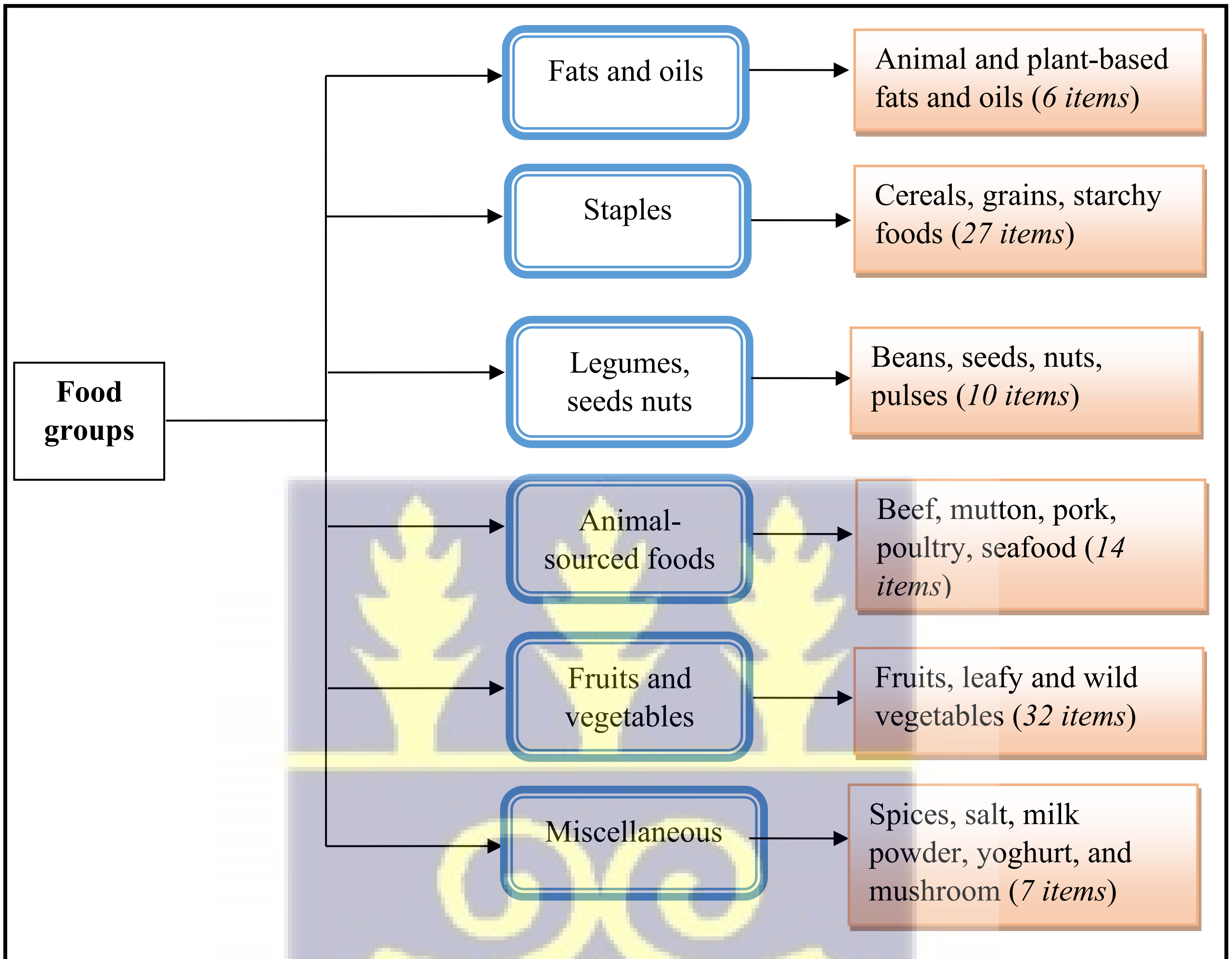


Figure 4.1: Food groups and subgroups considered within the scope of the study. Yoghurt, milk powder, and mushrooms were included under miscellaneous because of their low consumption rate in Ghana.

4.2.2 Data Acquisition and Processing

Data on the food composition of locally available foods were obtained from previous studies in Ghana (Nykänen *et al.,* 2018) and complemented with information from the FAO food composition table for West Africa (FAO, 2019). Zero was ascribed where there was no nutrient data for any food item in the database used for this study. A significant limitation of this work was the lack of country-specific data on the GHGE values of local food items in Ghana. Hence, secondary data on the GHGE of the ingredients were obtained from a database for product developers that contains representative data for different classes of food ingredients based on geographic origin and processing level. They were expressed as carbon dioxide equivalent (CO_2 eq.) for a kilogram (kg) of each ingredient and were further expressed on a 100g basis for equivalence. The data used for this study focused only on the GHGE values and did not consider other environmental factors like water use and land usage. The GHGE data was cleaned and categorised into food groups (staples, fruits and vegetables, protein-sourced foods, fats and oils, legumes, seeds, nuts, and miscellaneous) (Figure 4.1).

4.2.3 Nutrient considerations

The Dietary Reference Intakes (DRIs) for the lower and upper bounds for vitamins, minerals, and macronutrients were considered within the scope of this study. This, therefore, limited the study to the macronutrients (fat, protein, carbohydrates), and micronutrients (iron, zinc, iodine, folate, calcium, copper, vitamin A, vitamin C, vitamin E, vitamin B6, vitamin B12, thiamine, riboflavin, niacin, magnesium, phosphorus, selenium, zinc, sodium). The lower and upper requirements for these nutrients were defined based on the Recommended Dietary Allowances (RDA) for 97-98% of healthy pregnant and lactating populations defined by the Institute of Medicine (2000; 2001; 2011) and National Academies of Sciences, Engineering, and Medine (2019; 2023) (Table 4.2). Slight modifications were applied for mathematical suitability (Eqns 4.2 and 4.3).

4.2.4 Parameters and variables

The objective was to minimise carbon footprint (CO_2 eq./day). Thus, the aim was to obtain a list of ingredients that met defined requirements at a minimum CO_2 eq. The decision variables identified were the quantity of selected ingredients needed to give an optimal objective function value. The constraints were defined for the lower and upper bounds of the nutrient considered, and where necessary, rationing of ingredients and inclusion of essential ingredients like onions, tomatoes, and pepper.

4.2.5 Mathematical modelling

The linear programming (LP) mathematical algorithm was used to select a set of food ingredients that satisfied linear requirements of nutrients and acceptance at the minimum GHGE value. The primary purpose of the LP model was to minimise the overall GHGE of the chosen food items while (i) staying within the lower and upper limits for all nutrients, (ii) adhering to the specified restrictions on certain food items, and (iii) following the defined limits for some food groups. The mathematical equations (Eqn) used were as defined below.

$$Z = \sum_{j=1}^{n} g_j x_j \qquad \text{Eqn 4.1}$$

Subject to the defined linear constraints:

$$\sum_{j=1}^{n} a_{ij} x_j \geq l_i \qquad i = 1,2,3, \dots \dots \dots m \qquad \text{Eqn 4.2}$$

$$\sum_{j=1}^{n} a_{ij} x_j \leq u_i \qquad i = 1,2,3, \dots \dots \dots m \qquad \text{Eqn 4.3}$$

$$x_j \geq 0 \text{ (x is a continuous variable)} \qquad \text{Eqn 4.4}$$

$$FG_1 = p_1 * T \qquad \text{Eqn 4.5}$$

$$FG_2 = p_2 * T \qquad \text{Eqn 4.6}$$

$$FG_3 = p_3 * T \qquad \text{Eqn 4.7}$$

$$FG_4 = p_4 * T \qquad \text{Eqn 4.8}$$

$\text{Tomatoes} \geq 164\text{g}$ Eqn 4.9

$\text{Onions} \geq 76\text{g}$ Eqn 4.10

$\text{Pepper} \leq 50\text{g}$ Eqn 4.11

Where:

Z — the objective function to be minimised GHGE value

n — total number of food items

x_j — portions of food j represented in g

g_j — the carbon footprints ($CO2$ eq.) of food item j

a_{ij} — nutrient i in food item j

l_i — the lower bound for nutrient i (g or mg or kcal)

u_i — the upper bound for nutrient i (g or mg or kcal)

FG_i = the respective food groups (FOs, LSNs, ASFs, M, respectively)

FOs — fats and oils

LSNs — legumes, seeds and nuts

ASFs — animal — sourced foods

M — miscellaneous

p_i — the recommended percentage of the selected food items for *the* food groups

(the percentages specific to the study are 0.4% (FOs), 13.07% (LSNs), 9.5% (ASFs), and 2.77% (M), respectively).

T − the summation of food items x_j

4.2.6 Cultural acceptability

Limits were set on the contribution from the different food groups to ensure cultural acceptability (Eqs 4.5 to 4.8). Onions, pepper, and tomatoes are ingredients that are common in local Ghanaian diets. As such, constraints were included to select these ingredients if the algorithm did not select them based on the daily minimum requirements from the FBDG for Ghana (Eqns 4.9 to 4.11) (MoFA & GSPH, 2023). The optimisation process consisted of three levels. The first level involved imposing the nutrient requirements (Eqns 4.1 – 4.3). At the second level, both nutrient constraints and food group limits were imposed through Eqs 4.1 – 4.8. Finally, for the third level, nutrient constraints, limits on food groups, and the inclusion of three common ingredients were imposed using Eqns 4.1 – 4.11.

4.2.7 Software

The Pyomo package in Python was integrated with the CPLEX solver for optimisation in the Python programming language.

4.3 RESULTS AND DISCUSSION

4.3.1 RESULTS

The diet simulations yielded results that met all defined nutrients and dietary diversity requirements for lactating and pregnant women aged 19 to 50 (Table 4.1, Figure 4.2). The results indicate the possibility of adopting these dietary recommendations into practical, real-life dietary advice for Ghanaians. It is essential for nutritional requirements to be considered when diets that can reduce environmental impact are proposed.

The findings demonstrate that it is attainable to optimise a diet with minimum GHGE values for any target population, specifically pregnant and lactating women aged 19 to 50 (Figure 4.2). This suggests that it is feasible to translate these dietary guidelines into practical recommendations for healthy eating by pregnant and lactating women in Ghana.

The final minimum GHGE values obtained for the food baskets for pregnant and lactating women 19 to 50 years were 1.06 kg CO_2 eq./day and 1.48 kg CO_2 eq./day (Figure 4.2). The GHGE value of the food basket for lactating women was more than that of women at the pregnancy stage. Including the number of constraints to ensure more acceptable dietary patterns led to a gradual increase in the GHGE values.

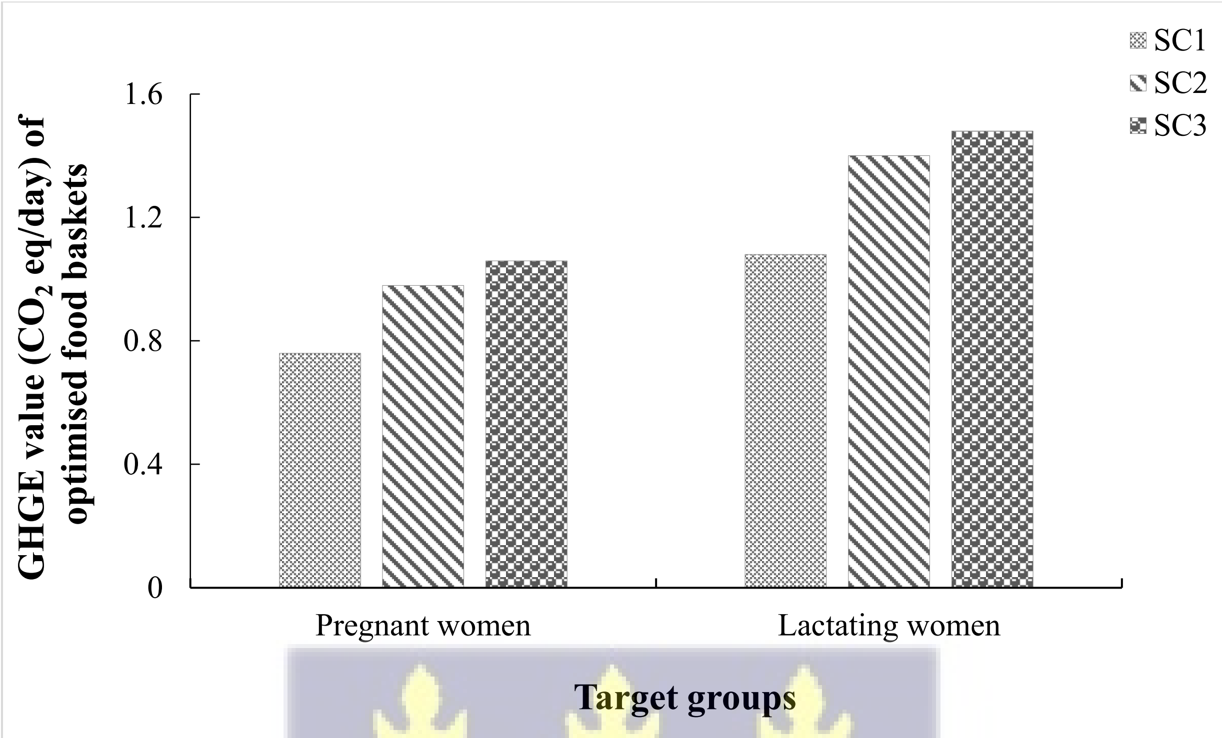


Figure 4.2: GHGE values of optimised food baskets for women at pregnancy and lactating stage aged 19 to 50.

SC1 - (i) nutrient constraints, SC2 – (i) nutrient constraints + (ii) constraints on animal-sourced foods, fats and oils, legumes, seeds and nuts, and miscellaneous, and SC3 - (i) nutrient constraints + (ii) constraints on animal-sourced foods, fats and oils, legumes, seeds, and nuts, and miscellaneous (iii) inclusion of tomato, onions, and pepper. SC – scenario.

The total number of items in the food baskets for pregnant and lactating women aged 18 to 50 years was 15 and 16, respectively (Table 4.1). The result shows the food items and their corresponding amount and GHGE values needed to meet the defined requirements. The total weights of the food baskets were 1370.68 g and 1472.11 g for pregnant and lactating women, respectively. The food baskets for both cases consisted of items classified under staples, legumes, nuts, fruits, and vegetables, and the animal-sourced category, with minimal contributions from fats and oils and miscellaneous (Table 4.1).

Table 4.1: Optimised food baskets for women at the physiological stages of pregnancy or lactation and aged 19 to 50 years.

	Pregnancy			Lactation		
Food Groups	**Food item**	**Amount (g)**	**GHGE value (kg CO_2 eq/100g)**	**Food item**	**Amount (g)**	**GHGE value (kg CO_2 eq/100g)**
Fats and oils	Palm oil	0.76	0.003	Palm Oil	3.66	0.02
	Vegetable oil	4.72	0.016	Vegetable oil	2.23	0.01
Total		**5.48**	**0.02**		**5.89**	**0.02**
Fruits and vegetables	*ademe/ayoyo* (jute mallow)	240.77	0.096	Apple	289.77	0.04
	Tomato	164.00	0.077	*Ademe/ayoyo* (jute mallow)	70.12	0.03
	Onion	76.00	0.019	Tomato	164.00	0.08
	Fresh Pepper	30.00	0.010	Carrot	35.46	0.00
				Onion	76.00	0.02
				Fresh Pepper	30.00	0.01
Total		**510.77**	**0.20**		**665.34**	**0.18**
	Groundnut	38.00	0.114	Groundnut	112.21	0.34

Legumes, seeds, and nuts	Sesame seeds	141.15	0.212	Sesame seeds	80.19	0.12
Total		**179.15**	**0.33**		**192.40**	**0.46**
Animal sourced foods	Smoked Herrings	5.08	0.009	Fresh *kpanla* (Barracuda)	64.96	0.37
	Anchovy	8.31	0.034	Snail	16.43	0.04
	Snail	89.71	0.197	Egg	58.46	0.27
	Egg	27.12	0.125			
Total		**130.21**	**0.37**		**139.85**	**0.68**
Staples	Cassava	507.10	0.067	Cassava	427.85	0.06
Total		**507.10**	**0.07**		**427.85**	**0.06**
Miscellaneous	Iodised salt	5.09	0.000	Iodised salt	5.03	0.00
	Yoghurt	32.88	0.076	Yoghurt	35.75	0.08
		37.97	**0.08**		**40.78**	**0.08**
Total		***1370.68***	***1.06***		***1472.11***	***1.48***

Figure 4.3 shows the contributions of the different food groups to the food baskets in both cases of women at the physiological stages of pregnancy and lactation. Fruits and vegetables contributed 37.26% to the food basket for pregnant women and 45.20% for lactating women, followed by staples, which contributed 37.00% and 44.36%. This was followed by legumes, seeds, and nuts, with 13.07% each in the food basket for pregnant and lactating women. Animal-sourced foods contributed 9.50%, miscellaneous 2.77%, and 0.4% fats and oils. For lactating women, animal-

sourced foods contributed 14.3% to the total weight of the food basket, followed by legumes, seeds, and nuts at 13.1%, miscellaneous at 2.8%, and fats and oils at 0.4%. The contribution from animal-sourced foods, miscellaneous, fats and oils were the same as recommended in the FBDG for Ghana (Figure 4.3).

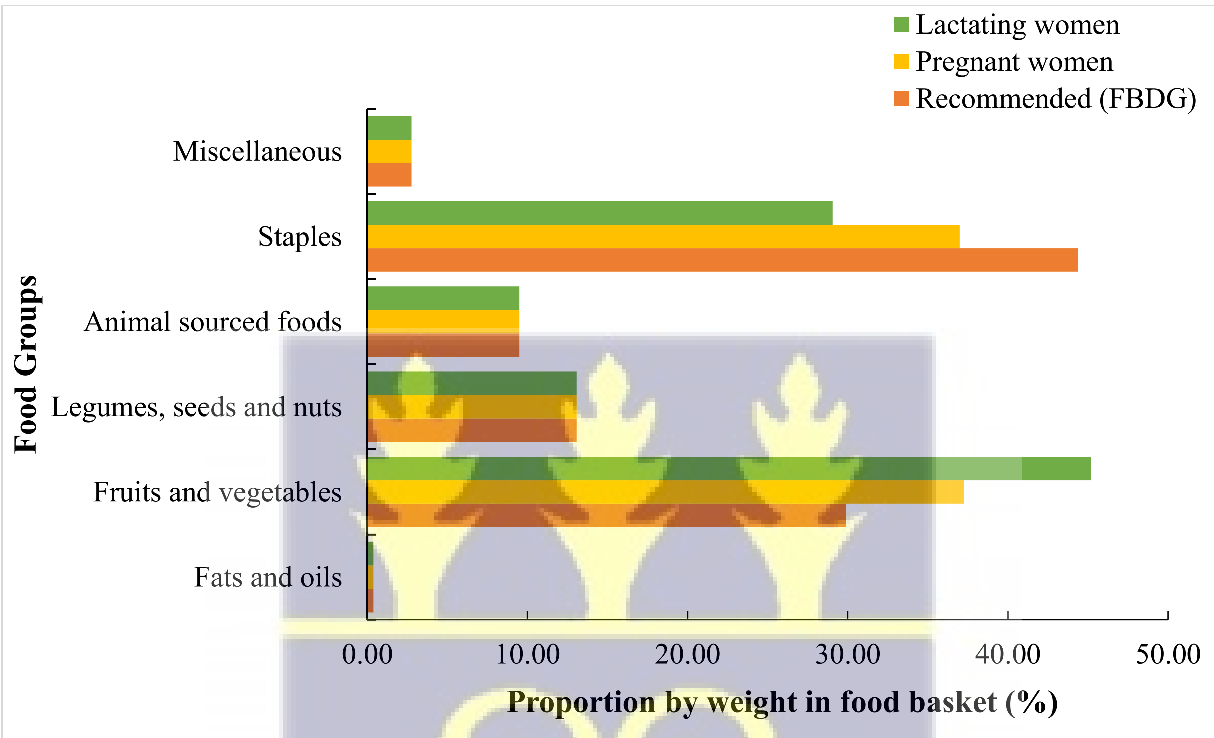


Figure 4.3: The proportion (by weight) of food groups and their contribution to the optimised food baskets for pregnant and lactating women aged 18 to 50, compared to recommended proportions from the FBDG for Ghana.

Table 4.2 summarises the nutritional values from the optimised food baskets for women in the physiological stage of pregnancy and lactation at 18 to 50 years. The nutrient values obtained stayed within the lower and upper limits defined without any violations. The baskets also provided the necessary macronutrients and micronutrients, such as magnesium, zinc, iron, and selenium.

The active constraints for the lower limits for the optimisation for pregnant women were vitamin B6 and iodine. Active constraints are constraints that directly influence the solution and define the bound

that directly influence the solution and define the boundaries within which the algorithm must operate. For the optimised food basket for lactating women, they were vitamin E, vitamin A-RAE (retinol activity equivalents), and riboflavin. The upper limit for sodium was active for both scenarios.

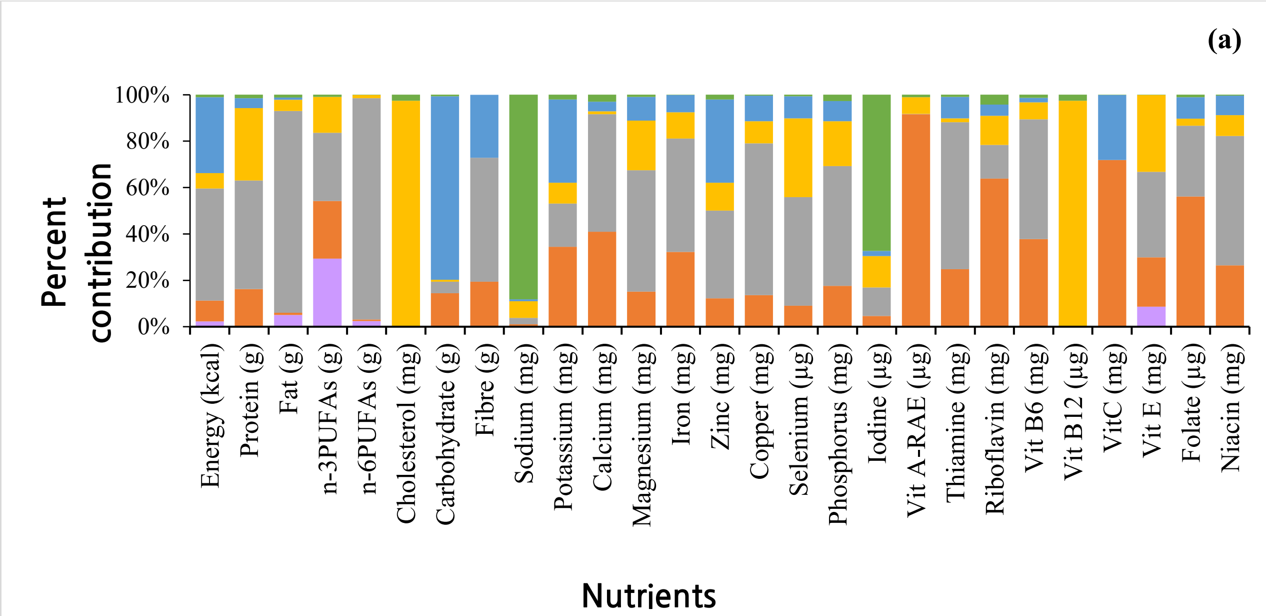
Table 4. 2: Nutrient constraints and the result of the nutrient values after optimisation

Nutrients		**Pregnancy**		**Lactation**	
		Recommended values	**Proposed minimum-GHGE diet**	**Recommended values**	**Proposed minimum-GHGE diets**
Energy	k/Cal	2200-3000	2200.00	2300-3000	2300.00
Protein	g	≥71	71.00	≥71	85.51
Fat	g	-	107.82	-	112.29
n-3 PUFAs	g	≥1.4	1.55	≥1.3	1.30
n-6 PUFAs	g	≥13	41.46	≥13	35.93
Cholesterol	mg	≤300	178.26	≤300	300.00
Carbohydrate	g	≥175	235.97	≥210	245.94
Fibre	g	≥28	44.29	≥29	46.23
Sodium	mg	1500-2300	2300.00	1500-2300	2300.00
Potassium	mg	≥2900	4809.43	≥2800	4862.52

Calcium	mg	1000-2500	2212.25	1000-2500	1263.46
Magnesium	mg	≥360	1089.89	≥310	862.23
Iron	mg	27-45	34.27	9-45	22.24
Zinc	mg	11-40	11.34	12-40	12.00
Copper	mg	1-10	4.15	1.3-10	3.72
Selenium	µg	60-400	106.21	70-400	95.78
Phosphorus	µg	700-3500	2040.19	700-4000	1782.49
Iodine	µg	220-1100	220.00	290-1100	290.00
Vit A-RAE	µg	770-3000	1015.57	1300-3000	1300.00
Thiamine	mg	≥1.4	2.20	≥1.4	2.84
Riboflavin	mg	≥1.4	2.12	≥1.6	1.60
Vitamin B6	mg	1.9-100	2.59	2-100	2.81
Vitamin B12	µg	≥2.6	2.60	≥2.8	3.96
Vitamin C	mg	85-2000	415.44	120-2000	365.74
Vitamin E	mg	15-1000	15.00	19-1000	19.00
Folate	µg	600-1000	600.00	400-1000	456.69
Niacin	mg	18-35	18.00	17-35	28.08

The range in the third column reflects the nutrients' lower and upper intake limits. To indicate nutrients that have only lower or upper limits, ≤ or ≥ was respectively used. RAE – retinol activity equivalent, n-3PUFAs – alpha-linolenic acid, n-6 PUFAs – linoleic acid. (Source: WHO & FAO, 2004; Institute of Medicine, 2000; 2001; 2011; National Academies of Sciences, Engineering, and Medicine, 2019; 2023).

The contribution of the food groups to the nutrient values obtained from the optimised food baskets is represented in Figure 4.4 Staples provided energy and carbohydrates while fruits, vegetables, legumes, seeds, and nuts supplied essential nutrients like thiamine, selenium, and iron.



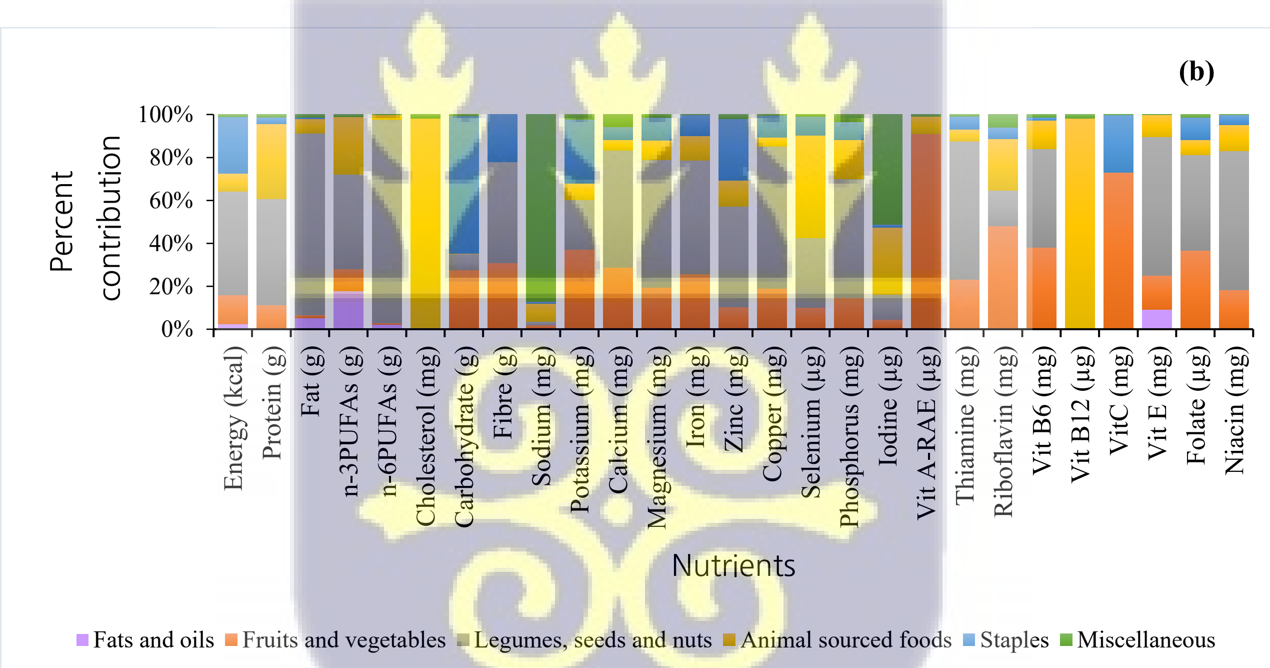


Figure 4.4: The proportion of food groups and their contribution to the nutrient values obtained for women aged 19 to 50 years in special physiological stages (a) pregnant and (b) lactating women.

4.3.2 DISCUSSION

The algorithm's robustness was clear in its multi-step approach to optimizing nutrient requirements and gradually incorporating additional constraints. This systematic method initially focused on nutrient optimisation and then added more complex requirements. Through rigorous testing, the algorithm consistently demonstrated high accuracy and reliability, producing results that met predefined criteria. These results were manually verified for a subset of cases before introducing more complex requirements, ensuring the algorithm's outputs remained valid and dependable throughout the process.

The process described in this paper used a combination of modelling, data-based elements, and shared knowledge of Ghanaian diets to achieve results (shared knowledge here refers to practicial understanding and grounded insights into common Ghanaian foods, cooking practices, and dietary habits beyond what datasets alone capture). The carbon footprint of food is an essential consideration in the effort to mitigate climate change. It was possible to obtain food baskets with low GHGE values for pregnant and lactating women aged 18 to 50 from the list of locally available foods. The results showed nutritional adequacy and acceptability from the selected ingredients for pregnant and lactating women with minimum GHGE values. This emphasises the need to include nutrient constraints in the optimisation process. According to Gephart *et al.* (2016), consumers are more likely to embrace diets that meet their nutrient needs to avoid any form of non-communicable diseases (NCDs) than accept diets that only have less environmental impact. From the results obtained, it can be deduced the optimised did not only meet nutrient needs but was acceptable because the food basket was made of ingredients that are common to the population group.

Since this is the first study to optimise food baskets for pregnant and lactating women using locally available foods in Ghana, no baseline is available to compare the results. Though some studies have been conducted on reducing the environmental impact of diets (Green *et al.,* 2015; Gephart *et al.,* 2016; Rose *et al.,* 2019; Brink *et al.,* 2022) in other geographical locations, most of them do not have defined a baseline or target for the diets that have a minimum environmental impact. Rose *et al.* (2019) reported a CO_2 eq. of 4.72 kg per person when food waste was considered. However, studies conducted by Macdiarmid *et al.* (2012) to optimise the carbon footprint of diets for adult women aged 19 to 50 in the United States assumed a 3.77 kg CO_2 eq/day baseline. Though carbon footprints differ based on geographical locations, results obtained in this study were 1.06 and 1.48 (kg CO_2 eq./day), which are lower than the baseline adopted by Macdiarmid *et al.* (2012). A study by Maillot *et al.* (2011) reported values of 3.6-4.2 kg CO_2 eq./day for French adults, which are higher than the results obtained from this study. Similarly, research conducted in the Netherlands by van Dooren *et al.* (2015) showed 1.56 kgCO_2 eq./day results for Dutch diets, a value close to that obtained for pregnant women and higher than those for lactating women. These differences could be due to the differences in food items available in the different settings and the constraints considered.

For the food basket for pregnant and lactating women, animal-sourced foods contributed the highest towards the GHGE value, 34.58% and 45.76%, respectively. This was followed by contributions from legumes, seeds, and nuts at approximately 31% each. Even though the weight of items from the animal-sourced food groups was 9.5% of the total weight of both food baskets, they contributed the highest to the total GHGE values. The high values of animal-sourced products are consistent with previous studies showing that animal-based foods have a higher carbon footprint than plant-based foods (Temme *et al.,* 2014; Drewnowski *et al.,* 2015; Masset *et al.,* 2015; Poore & Nemecek, 2018; Wang *et al.,* 2021) due to the higher energy and resources needed (Heller & Keoleian, 2015; Bryngelsson *et al.,* 2016). Studies by Macdiarmid *et al.* (2012), Temme *et al.* (2014), Drewnowski *et al.* (2015), and Brink *et al.* (2022) have suggested that reducing animal-sourced foods, specifically red meat, and shifting towards a more plant-based diet can lower the GHGE value of food baskets. Additionally, plant-based diets have positive health effects and can protect against heart disease (Alcorta *et al.*, 2021; Dominguez *et al.,* 2021).

The high contribution of fruits and vegetables to the food basket observed is not out of order from the EAT-Lancet Commission's recommendation of planetary diets. In a study conducted by Perigon *et al.* (2016) to reduce the greenhouse gas emissions of adult women's diets under various nutritional scenarios, fruits and vegetables significantly contributed to the food baskets obtained. Furthermore, food items like yogurt and some seafood products in the food baskets align with similar findings by Macdiarmid *et al.* (2012) and Ferrari *et al.* (2020). Indeed, different foods have a varying impact on carbon footprint (Auclair & Burgos, 2021).

The contribution from staples to the food baskets obtained cannot be overlooked as well. Though present, they were not optimised below the recommended percentage of 43 in the FBDG for Ghana. Masset *et al.* (2015) mentioned that in addition to the increased consumption of fruits, vegetables, and legumes, starchy foods should be considered in the recommendations for a planetary diet. However, their consumption should be in moderation.

A plant-based diet trend was recommended, aligning with the healthy planetary diet defined by the EAT-Lancet Commission (Willet *et al.,* 2019) and the Mediterranean diet (Davis *et al.,* 2015; Baroni *et al.,* 2018). Though slight variations exist for the Mediterranean diet for different geographical areas (Guasch-Ferré & Willet, 2021), it is generally considered as one that is more plant-based, encourages the consumption of more fruits and vegetables, nuts, legumes, cereals, some root crops, little fish, seafood, and dairy consumption, and little to no meat (Martínez-González, *et al.,* 2015; Davis *et al.,* 2015; Baroni *et al.,* 2018; FAO & WHO, 2019; Petkoska &

Trajkovska-Broach, 2021). Baroni *et al.* (2018) further indicated that these diets have been considered healthy and sustainable dietary patterns. Furthermore, a study on the benefits of the Mediterranean diet proved a positive correlation in preventing cardiovascular diseases (CVD) (Martínez-González, *et al.,* 2015).

The primary consideration for including commonly consumed ingredients in a Ghanaian diet was necessary to increase the level of acceptability. Even though the concepts of the Mediterranean and EAT-Lancet diets are the same and should be considered by many countries as a step to safeguard the environment, they should be adopted in a manner that considers the food cultures and traditions of the geographic setting (Tucci *et al.,* 2022).

The optimised diets had nutrient values within the lower and upper bounds for pregnant and lactating women aged 19 to 50. For pregnant women, the minimum constraints for vitamin B6, Vit E, and iodine were restrictive in the model, thus binding, even though they met the lower-level requirements. For lactating women, the binding nutrients were zinc, riboflavin, and vitamin E in both cases, sodium was binding at the maximum level. The constraints were crucial in obtaining the objective solution. For example, a reduction in the lower limit of vitamin B6 reduces the GHGE value for the food basket obtained for pregnant women. Similarly, increasing the upper limit for sodium reduces the GHGE value for the food baskets and vice versa. Although satisfying constraints for nutrients like zinc, iodine, and riboflavin increased the GHGE values of the food baskets, the requirements were satisfied in the optimisation problem. These micronutrients and their deficiencies are a public health concern (Arimond *et al.*, 2017; Appiah *et al.,* 2020; Sarfo *et al.*, 2020; Brink *et al.,* 2022).

The results could be incorporated into dietary guidelines for pregnant and lactating women in Ghana because the optimised diet met the established nutrient constraints. A study in the Juaboso district in Ghana in 2020 showed that 90% of maternal anaemia cases were due to inadequate dietary iron intake (Appiah *et al.*, 2020). The authors highlighted the need for good nutritional practices and increased sensitisation. Brink *et al.* (2022) state that only a few countries have incorporated environmental sustainability into their FBDGs. Therefore, this study will be a reasonable consideration for the recently released FBDG for Ghana, considering the country's commitment to environmental sustainability.

Even though carbon footprint has become an essential factor for dietary choices and patterns, it is not the only means of measuring sustainable diets. Therefore, there is a need for many considerations to be made to decrease the GHGE values of the population's diet while ensuring that required nutritional needs and what is acceptable to consumers are considered.

4.4 CONCLUSIONS

In conclusion, a linear programming approach was used to create food baskets with the minimum GHGE values for healthy women at the physiological stages of pregnancy and lactation from locally available foods in Ghana. The food baskets were designed to meet the target group's nutritional requirements and acceptability standards.

Results were 1.06 and 1.48 kg CO_2eq./day for pregnant and lactating women, respectively. It is necessary to define requirements for food groups and some common ingredients to ensure acceptability. Nutrient recommendations indeed remain the basis of diet optimisation to ensure nutrition security.

This study emphasises the importance of optimising diets to reduce the carbon footprint of food consumption. It also emphasises the significance of considering the greenhouse gas emissions of food items when making dietary choices. The findings from the study can be fused into the recently released food-based dietary guidelines, and it will be a good step towards improved nutrition for the defined population groups. Educating consumers on their dietary habits and raising awareness about the benefits of a plant-based diet that is mindful of the environment is essential.

Additionally, the study gives valuable insights into sustainable dietary choices that can be adopted in Ghana and potentially other West African countries that share similar food systems. Also, local food production and consumption can reduce the environmental impact of food production while supporting our local economies and promoting food security.

4.5 LIMITATION

One limitation was that the optimisation process yielded one optimal solution and did not provide insight into less optimal solutions that could have existed in the feasible region.

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CHAPTER FIVE

SIMULTANEOUSLY MINIMISING COST AND GREENHOUSE GAS EMISSION OF SUSTAINABLE DIETS FOR ADULT MALES AND FEMALES IN GHANA: AN OPTIMISATION STUDY

ABSTRACT

Introduction: Sustainable diets have recently gained global recognition, as food systems contribute about 25% to global greenhouse emissions (GHGEs). However, fulfilling the dimensions of nutritional adequacies, cultural acceptability, affordability, and environmental consideration is complex. Hence, synergies and trade-offs must be established. This study, therefore, sought to simultaneously minimise the cost and GHGE of diets for adult males and females who are 19 to 50 years old, while ensuring nutritional adequacy and maximum amounts of food per food group cultural acceptability from locally available foods in Ghana.

Method: A bi-objective optimisation method (epsilon constraint) was used. Cost and GHGE were solved individually using linear programming to obtain optimal solutions. The Epsilon constraint method was then used to solve cost and GHGE to generate optimal solution sets, with constraints defined on nutrients for nutritional adequacies and food groups for cultural acceptability. Pareto frontier was then generated to give a visual representation of the trade-off existing between cost and GHGE.

Results: A trade-off was established between cost and GHGE from the Pareto frontier developed: as cost increased, GHGE reduced, and vice versa. The correlation between cost and GHGE was strongly negative with values of -0.93 and -0.95 for results of adult males and females, respectively. Also, cost explained most of the variability in the GHGE values obtained, with co-

efficient of determination values of 0.87 and 0.90 for males, respectively. The findings from the study revealed that achieving optimal diets for both cost and GHGE entails a mix of dietary adjustments, emphasizing nutrient-rich, and environmentally friendly food choices. A variety of food items were included in the food baskets for all the optimal points, and they included staples, animal-sourced foods (seafood), fats and oils, fruits, and vegetables, miscellaneous and legumes, seeds, and nuts.

Implications: Findings from the study offer significant insights for policymakers, individuals, and food-related industries who aim to balance economic constraints and environmental responsibilities while promoting healthier and more sustainable diets.

Keywords: sustainable diets, minimum GHGE, trade-offs, nutrient requirements, epsilon constraint, diet optimisation.

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5.1 INTRODUCTION

Rapid population growth and increasing urbanisation have resulted in a change in the dietary habits of consumers, according to the World Health Organization (WHO, 2020). This change has raised concerns about its impact on the environment and the entire food system (Yin *et al.*, 2020; Steenson & Buttriss, 2021). These dietary changes do not only have an impact on the environment but can also affect consumers' health and jeopardise future food security (Rohmer *et al.,* 2019; Goulding *et al.*, 2020). This has been further compounded by the COVID-19 pandemic (Ibarrola-Rivas *et al.*, 2022), which has led to increased poverty and a significant increase in food prices (Laborde *et al.*, 2020; WHO, 2022). In addition, low-income consumers often choose energy-dense foods as they provide more energy for less cost (Gazan *et al.,* 2018; Nykänen *et al.,* 2018; Dizon *et al.*, 2019). However, such high-energy food choices including sugar drinks can contribute to obesity rates (Drewnowski, 2009). Additionally, the change in dietary patterns could be because most consumers do not receive advice on sustainable dietary choices (Lang & Mason, 2018). Despite the pressing health and environmental concerns, most consumers have yet to embrace a diet that promotes their well-being and environmental sustainability (Tufford *et al.*, 2023).

Globally, evolving dietary consumption trends are putting pressure on food systems, leading to poorer dietary health outcomes (Fanzo *et al.*, 2021). This requires a dietary shift towards nutritionally balanced diets that will reduce the pressure on the environment (Springmann *et al.*, 2021; Gazan *et al.*, 2022). Accessing culturally acceptable, affordable, and nutritious food is difficult because it is complex (Fanzo *et al.*, 2012; Fanzo, 2019). Furthermore, designing healthy diets classified as sustainable can be complex and time-consuming using trial and error methods. The Food and Agriculture Organisation (FAO) define a sustainable diet as "a diet that has a low environmental impact, nutritionally adequate, accessible, economically fair and affordable, and safe and healthy" (FAO, 2010). Sustainable diets are a growing concern worldwide (Land & Mason, 2018) because they link food security and climate change to the Sustainable Development Goals (SDGs) (Meybeck & Gitz, 2017; Downs *et al.*, 2023).

Even though many factors determine consumer food choices, one of the significant factors that have hindered access to nutritionally healthy and sustainable diets has been the issue of affordability (Rohmer *et al.,* 2019). An extensive literature search indicates little to no information about the affordability of sustainable diets in Ghana. In addition to these constraints, there is little to no literature on promoting sustainable eating patterns/habits (Verly-Jr *et al.,* 2021). Lucas *et al.* (2021) stated how consumers' dietary changes and actions to reduce food waste would impact the food systems positively. It is imperative that solving these complex dietary problems can reduce malnutrition and reduce the burden on the environment.

Diet optimisation is one of the best approaches to address dietary problems and ensure that sustainable diets are achieved for individuals or groups based on local and culturally acceptable foods (dos Santos *et al.,* 2017; Wilson *et al.,* 2019). Due to the practical nature of general optimisation problems, they have multiple conflicting objectives (Nakayama, 2005; Cui *et al.*, 2017), and though there may be procedures that can be implemented to solve them, it is not an easy task (Augusto *et al.*, 2012). The challenge lies in addressing the four crucial dimensions of nutrition, affordability, cultural acceptability, and environment. While significant progress has been made in solving dietary problems (Dibari *et al.*, 2012; Deptford *et al.*, 2017; Brixi, 2018; Nykänen *et al.*, 2018; Faksova *et al.*, 2019; Lauk *et al.*, 2020), little attention has been given to the environmental component (Lucas *et al.*, 2021). A systematic and meticulous approach is necessary to address the intricacies of dietary issues, which can be achieved by implementing optimisation methods. Over the past few years, mathematical optimisation techniques have become vital tools

(Lucas *et al.*, 2021). Multi-objective optimisation is a practical approach that enables decision-makers to consider several conflicting objectives simultaneously. This results in solutions that effectively balance all the objectives (Deb *et al.*, 2002; Coello *et al.*, 2007). These solutions, also known as Pareto optimal solutions, make it easy to conduct trade-off analysis among the objectives (Nakayama, 2005).

The epsilon (ε) constraint method is considered one of the best approaches to solving multi-objective optimisation problems (Chiandussi *et al.*, 2012). It is easy to construct and can solve and generate more efficient solution sets (Pareto optimal frontier) (Colten *et al.*, 2020) than the weighted sum approach (Mavrotas, 2009). Several researchers have studied the epsilon constraint method for multi-objective optimisation (Nezhad *et al.*, 2015; Javadi *et al.*, 2020). Recently, this method has gained popularity and has been used to solve some dietary problems (Eghbali-Zarch *et al.*, 2017; Colten *et al.*, 2020). This method optimises one objective while the other is constrained (Xiujian & Zhongke, 2004).

This study, therefore, used the bi-objective optimisation method to generate a solution set between minimum cost and greenhouse gas emission. The ε-constraint method was used to simulate sustainable diets in different population groups in Ghana, and they were classified as theoretical diets that simultaneously considered the dimensions of affordability (cost), health (nutrient requirements), environment (minimum greenhouse gas emissions), and cultural acceptability.

5.2 METHODOLOGY

5.2.1 Data acquisition and management

The study obtained a list of locally available foods in Ghana, including their nutrient composition and cost per 100g, from previous research by Nykänen *et al.* (2018) and additional data on food item cost from the Ministry of Food and Agriculture (MoFA). Current food prices were utilised by adjusting for inflation from February 2017 to February 2023 using CPI (Ghana Statistical Services, 2023). The GHGE values for food items were gathered from a private database for product developers. This database contains representative data for various classes of food ingredients, based on their geographic origin and processing level. The food items were then categorized into different groups, including animal-sourced foods, LSNs (legumes, seeds and nuts), fruits and vegetables, staples, miscellaneous, and fats and oils. Yogurt, milk powder, and mushrooms were classified as miscellaneous, as they are not commonly consumed in Ghana.

5.2.2 Nutrient considerations

The study focused on the Dietary Reference Intakes (DRIs) for vitamins, minerals, and macronutrients. The micronutrients that were considered were iron, zinc, iodine, folate, calcium, copper, vitamin A, vitamin C, vitamin E, vitamin B6, vitamin B12, thiamine, riboflavin, niacin, magnesium, phosphorus, selenium, zinc, and sodium. These nutrients are essential to public health in Ghana (Koryo-Dabrah *et al.*, 2021).

5.2.3 Defining Parameters and Variables

The objective was to minimise the cost and greenhouse gas emissions simultaneously. The variables were the weights of selected ingredients required. Requirements were defined for the lower and upper limits of the considered nutrients, as well as limits on the food groups for dietary diversification and acceptability purposes.

5.2.4 Mathematical modelling

Linear programming (LP) and the epsilon constraint methods were used to optimise the sustainable food baskets for the defined population groups in this study, as demonstrated in Figure 5.1.

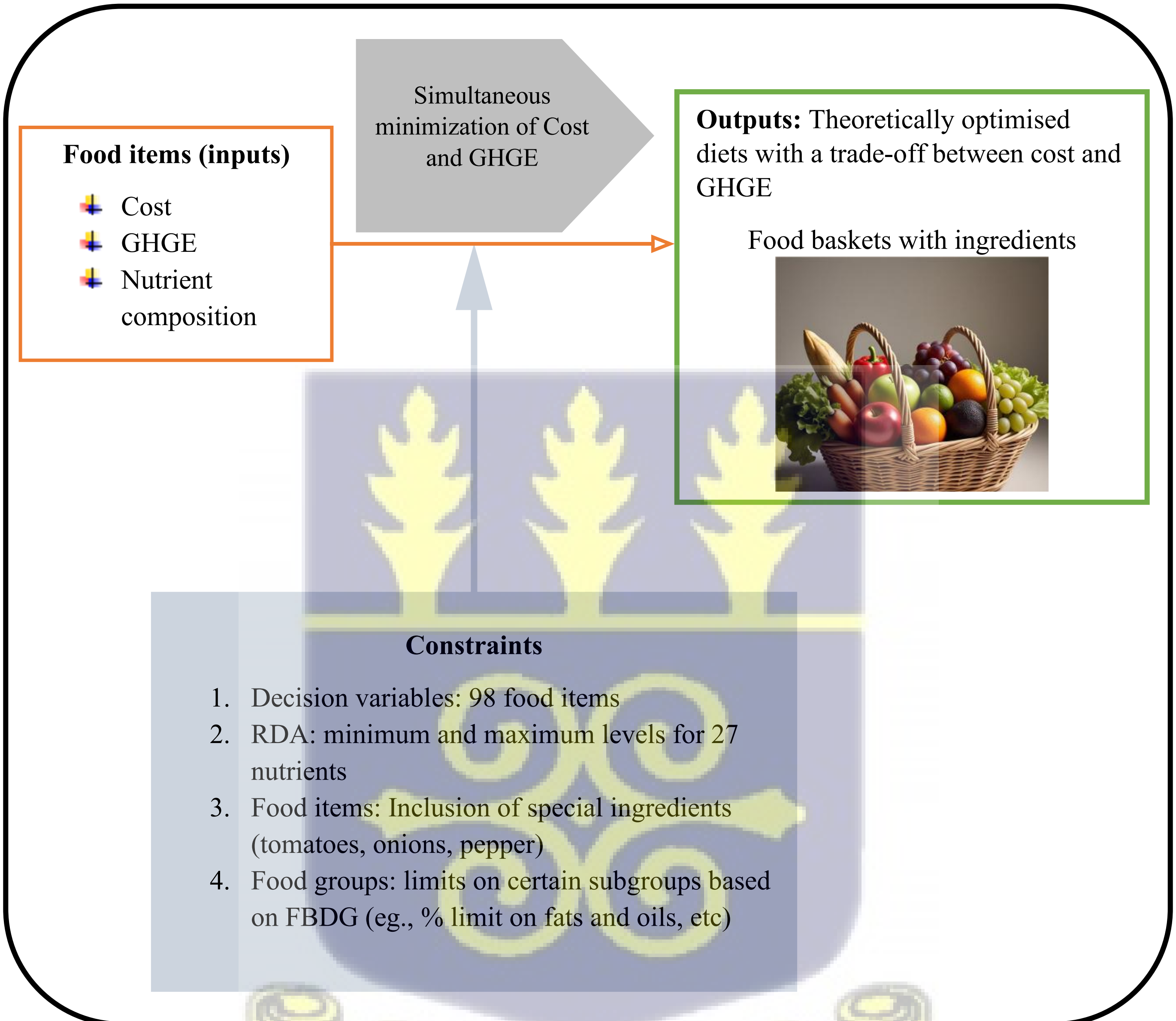

Figure 5.1: Overview of the elements of the ε-constraint optimisation process. GHGE – greenhouse gas emission, RDA – recommended dietary allowances, FBDG – food-based dietary guidelines.

The LP was used to obtain optimal diets for the target populations separately for each of the separate objectives as (i) diets with minimum cost and (ii) diets with minimum GHGE, both subject to nutrient (lower and upper limits) and acceptability (inclusion of three common ingredients and limits on food groups to prevent unrealistic portion sizes), as depicted in Equations (Eqns) 5.1 to 5.11.

$$\text{Minimise } f_{Cost} = \sum_{j=1}^{n} c_j x_j \qquad \text{Eqn 5.1}$$

$$\text{Minimise } f_{GHGE} = \sum_{j=1}^{n} g_j x_j \qquad \text{Eqn 5.2}$$

Subject to the defined constraints:

$$\sum_{j=1}^{n} a_{ij} x_j \geq l_i \qquad i = 1,2,3,\dots\dots\dots m \qquad \text{Eqn 5.3}$$

$$\sum_{j=1}^{n} a_{ij} x_j \leq u_i \qquad i = 1,2,3,\dots\dots\dots m \qquad \text{Eqn 5.4}$$

$$p_{11} \leq FG_1 \leq p_{12} * S \qquad \text{Eqn 5.5}$$

$$p_{21} \leq FG_2 \leq p_{22} * S \qquad \text{Eqn 5.6}$$

$$p_{31} \leq FG_3 \leq p_{32} * S \qquad \text{Eqn 5.7}$$

$$p_{41} \leq FG_4 \leq p_{42} * S \qquad \text{Eqn 5.8}$$

$$p_{51} \leq FG_5 \leq p_{52} * S \qquad \text{Eqn 5.9}$$

$$p_{61} \leq FG_6 \leq p_{62} * S \qquad \text{Eqn 5.10}$$

$$p_{71} \geq FG_7 \geq p_{72} * S \qquad \text{Eqn 5.11}$$

$$\text{Tomatoes } \geq 164\text{g} \qquad \text{Eqn 5.12}$$

Onions $\geq 76g$ Eqn 5.13

Pepper $\geq 30g$ Eqn 5.14

$X_j, l_i, u_i \geq 0$ (x is a continuous variable) Eqn 5.15

Minimise $f_{Cost}(x)$ Eqn 5.16

Subject to constraints:

$f_{GHGE}(x) \leq \varepsilon_1$ Eqn 5.17

Subject to:

Eqns 5.3 to 5.15

$$\varepsilon = f_{GHGE}{}^{min} + \frac{(f_{GHGE}{}^{max} - f_{GHGE}{}^{min})}{q} n, \qquad n = 1, 2, \ldots \ldots q$$ Eqn 5.18

$$\phi = \begin{bmatrix} f_1^*(x_1^*) & f_2^*(x_1^*) \\ f_1^*(x_2^*) & f_2^*(x_2^*) \end{bmatrix}$$ Eqn 5.19

f_{Cost} – the objective function to be minimised cost

f_{GHGE} – the objective function to be minimised, CO2 eq.

n – total number of food items in the LP analysis

x_j – portions of food j in g

c_j – the cost of food item j

g_j – the carbon footprints (CO_2 eq.) of food item j

a_{ij} – nutrient i in food item j

l_i – the lower bound for nutrient i

u_i – upper bound for nutrient i

FG_i – food groups (FG_1 – fats and oils, FG_2 – legumes, seeds, and nuts, FG_3 – animal – sourced foods, FG_4 – fruits, FG_5 – vegetables, FG_6 – miscellaneous, FG_7 – staples)

p_i – percentage of the selected food items for food groups i (p_1: 0.4 – 0.6%, p_2: 13.07 – 14%, p_3: 9.5 – 10%, p_4: 15 – 18%, p_5: 15 – 20%, p_6: 2.77 – 4%, and p_7: 33.4 – 44.26)

S – the summation of x_j

q – the number of iterations used to obtain the solution set

ε_1 – epsilon

f^* – the optimal value of each objective function

Equations 5.12 to 5.14 values were defined with guidance from the Food-based Dietary Guidelines for Ghana, based on the minimum daily intake for these ingredients MoFA & GSPH (2023). The minimum recommendation for onions was the same as defined, but that for tomatoes and pepper was relaxed where necessary, to obtain feasible solutions.

To obtain sustainable food baskets that included cost, GHGE, nutrition, and acceptability, the two single objectives (Eqns 5.1 and 5.2) were considered in one simultaneous model using the ε-constraint method. When more than one objective may conflict with the other, the ε-constraint method can generate a trade-off table for each decision-making (Eghbali-Zarch *et al.*, 2017; Nikas *et al.*, 2022). The cost was selected as the primary objective function while keeping GHGE as a constraint (Eqns 5.16 and 5.17). Nadir values (lowest or worst-case scenario values) were obtained for the objective functions (cost and GHGE, respectively). These values are essential in defining the limits for each objective function (Alves & Costa, 2009).

As Eghbali-Zarch *et al.* (2017) demonstrated, the range between optimal solutions obtained (for both cost and GHGE) and their corresponding nadir values were computed. The range was then divided into intermediate equidistant grid points (Mavrotas, 2009), $\varepsilon_1, \varepsilon_2, \ldots \ldots \ldots \varepsilon_n$, epsilon. The single bi-objective model was then solved with cost as the primary objective function while holding GHGE as a constraint, as defined in Eqns 5.16 and 5.17.

The value of ε was calculated using Eqn 5.18, and the minimum and maximum values were iteratively calculated using Eqn 5.19 as demonstrated by Javadi *et al.* (2020).

5.2.5 Obtaining results

Several experiments were conducted by coding in Python programming language to obtain feasible solutions to the optimisation problem.

5.2.6 Statistical analysis

Microsoft Excel was used analyse the data obtained from the optimisation exercise. The coefficient of correlation (r) and coefficient of determination (R^2) were calculated for the Pareto optimal trade-off graphs generated using Equations 5.20 and 5.21.

$$r = \frac{n\sum(xy) - \sum x \sum y}{\sqrt{[n\sum x^2 - (\sum x^2)]\,[n\sum y^2 - (\sum y^2)]}} \qquad \text{Eqn 5.20}$$

$$R^2 = (r^2) \qquad \text{Eqn 5.21}$$

n = number of data points

x = cost of food basket

y = GHGE of food basket

5.3 RESULTS AND DISCUSSION

5.3.1 Results

The epsilon constraint method was used to solve the dietary problem defined. Cost was optimised while holding GHGE as a constraint, and the algorithm was set to generate one hundred (100) solution set. This approach facilitates a comprehensive trade-off analysis between cost and GHGE, while meticulously considering nutritional adequacies and acceptability. Through the application of the multi-objective optimisation technique, the study aimed to identify food baskets that strike a delicate balance of cost and GHGE while adhering to nutrient specifications and some acceptability criteria for the population groups defined. The results were presented in tables and graphs.

Figure 5.2 represents the Pareto frontier- a visualisation of the interplay between cost and GHGE objectives for adult males and females aged 19 and 50. The graph shows the 2-dimensional (2D) representation where the x-axis denotes the cost objective function, while the y-axis signifies the GHGE objective function. Each data point within the graphical depiction corresponds to a solution that optimises the trade-off between cost and GHGE. It is important to note that minimising the cost of the food basket leads to an increase in GHGE and vice versa, highlighting the concept of Pareto optimality.

Every data point in Figure 5.2 represents nutritionally balanced and culturally acceptable diets because the nutrient and food group requirements stayed within the defined limits.

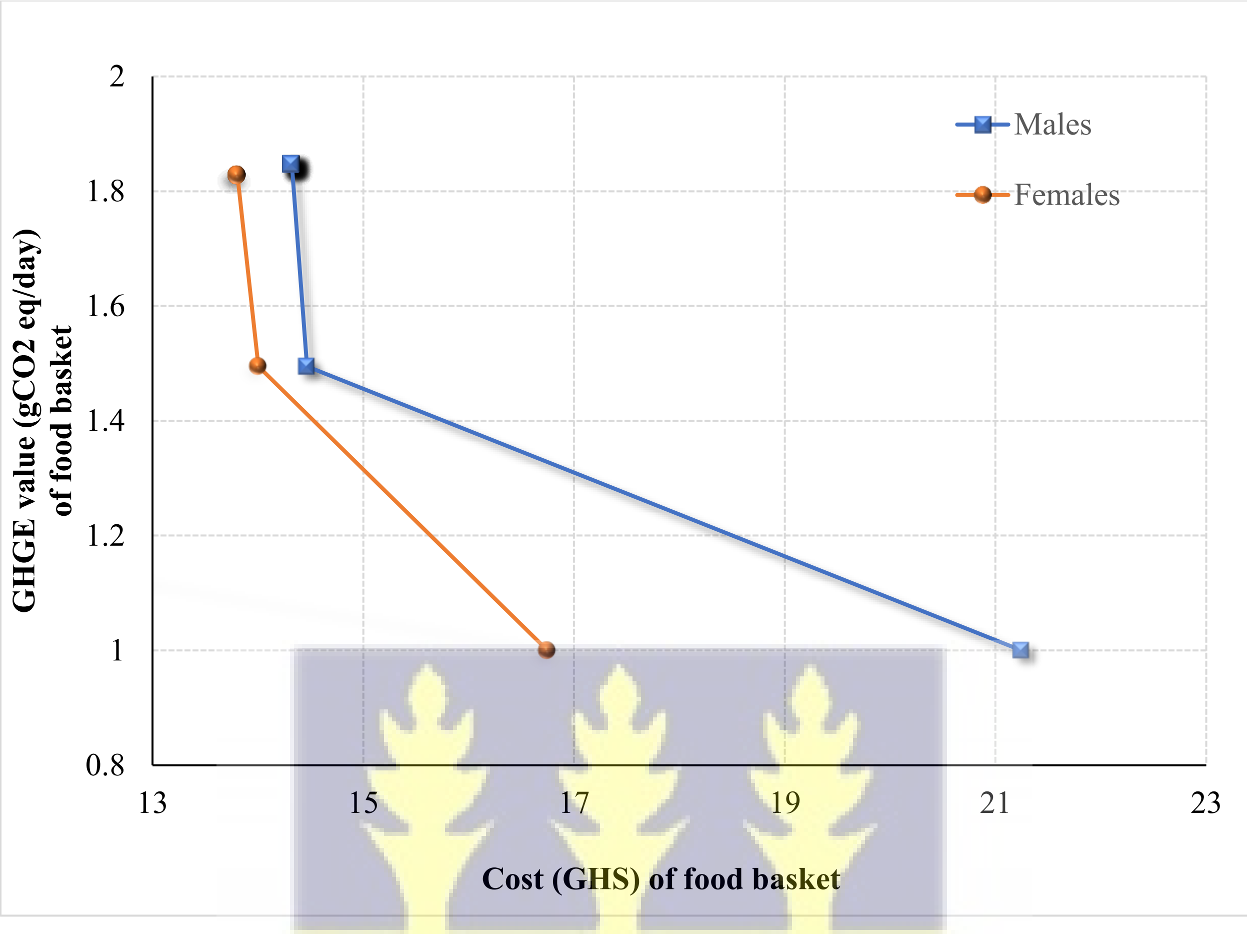

Figure 5.2: Pareto frontier showing the optimal solution sets for adults aged 19 to 50 years and above (a) males, and (b) females.

Table 5.1 shows a perfect negative correlation coefficient (r) and the proportion of variance (R^2) between the cost and GHGE objectives. The cost is a dependable predictor of GHGE, as it accounts for a significant portion of the variability in GHGE values. This emphasises the relationship between cost and GHGE, indicating that variability in cost is closely linked to corresponding changes in GHGE levels.

Table 5.1: Correlation and variability levels for Pareto frontier developed.

Target group	r	R^2
Males	-0.93	0.87
Females	-0.95	0.90

r - coefficient of correlation, R^2 - coefficient of determination

Table 5.2 summarises the pay-off generated between cost and GHGE for the different population groups considered within the study scope. From the trade-off table, it was observed that as the food basket cost increased, GHGE reduced moderately, and vice versa. This represents a conflict between the two objective functions: minimum cost and minimum GHGE.

Table 5.2: Trade-off table showing the Pareto set solution for cost and GHGE for adult males and females aged 19 to 50

Data set	Males		Females	
	f1	**f2**	**f1**	**f2**
1	21.25	1.00	16.75	1.00
2	14.47	1.49	14.01	1.49
3	14.32	1.85	13.81	1.83

f1- Cost (GHS) objective, f2 – GHGE (greenhouse gas emission) (CO_2 eq/day) objective

The contribution of the food groups remained within the defined limits (Equations 5.5 to 5.11) within the problem statement. However, deviations from the recommended intake levels outlined in the Food-Based Dietary Guidelines (FBDG) were observed across different food categories, as illustrated in Figure 3. For example, there was approximately +4 units deviations for vegetables from the recommendations from the FBDG, although this was captured in the modified equations

(5 to 11). Similarly, there was a reduction range of -4 to -6 units for staples across all the data optimal solution sets (points 1, 2, and 3) obtained (Figure 5.3).

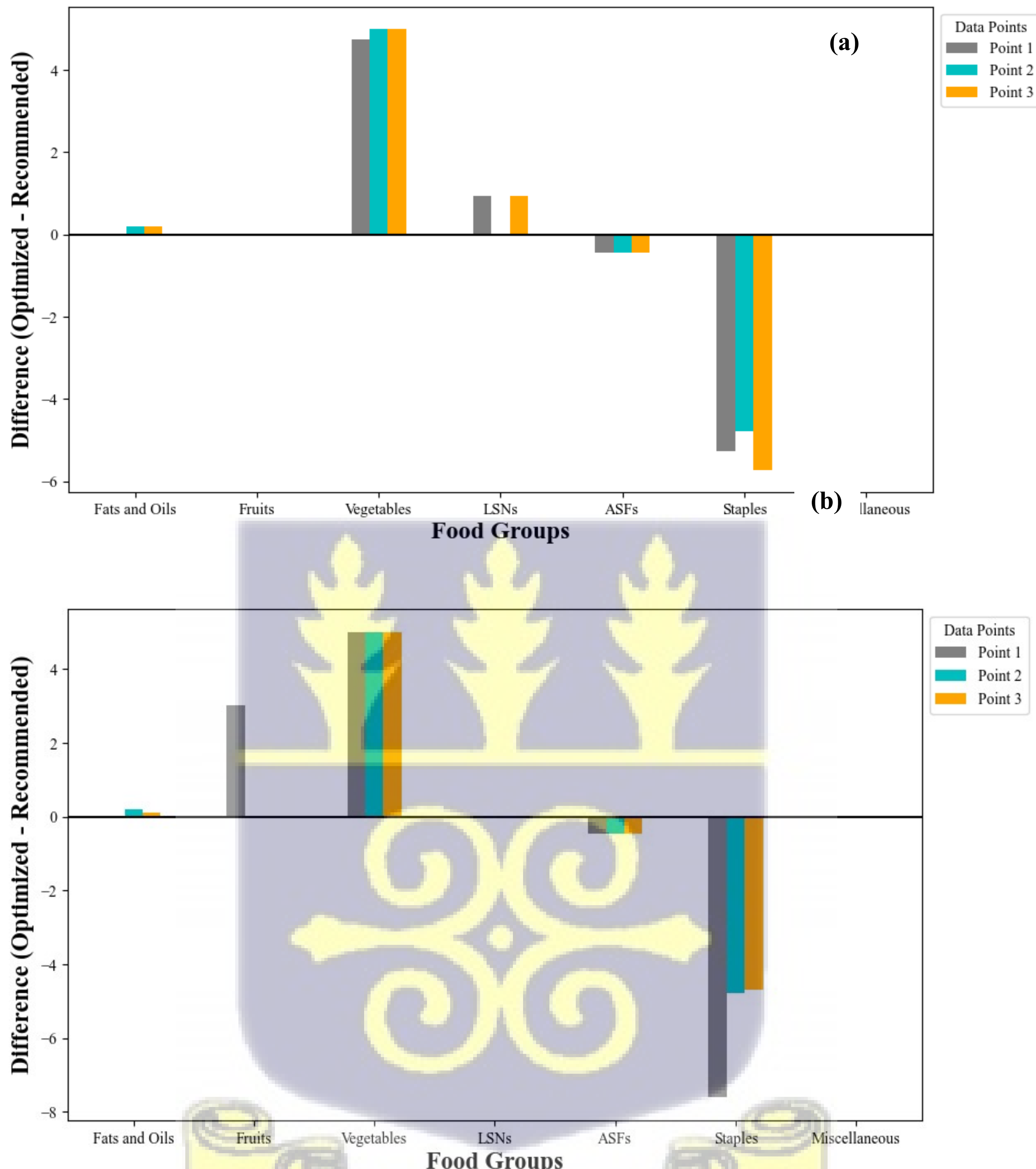

Figure 5.3: Deviations between the optimised and recommended food group contribution to the Pareto optimal sets (points 1, 2, and 3) obtained for adults 19 to 50 years (a) males and (b) females. ASFs – animal-sourced foods, LSNs – legumes, seeds, and nuts.

Figure 5.4 shows the contribution of the different optimal solution set points to the energy values obtained after the optimisation process for adult males and females aged 19 to 50 years. The optimised energy values were 2500, 2622.4, and 2500 kcal for the three Pareto optimal points for the food baskets for adult males. That for the female food baskets were 2355.5, 2400, and 2040 kcal for the three points. The colour spectrum in Figure 5.4 represents the intensity gradient, with darker red and blue colours indicating higher and lower values, respectively, and lighter colours indicating intermediate values. All other nutrients stayed within the established lower and upper limits.

The list of selected ingredients, their recommended amounts, GHGE, and cost values are presented in tables in Appendix I. Also included in Appendix I are the nutrient values obtained for the Pareto optimal point for adult males and females aged 19 to 50 years.

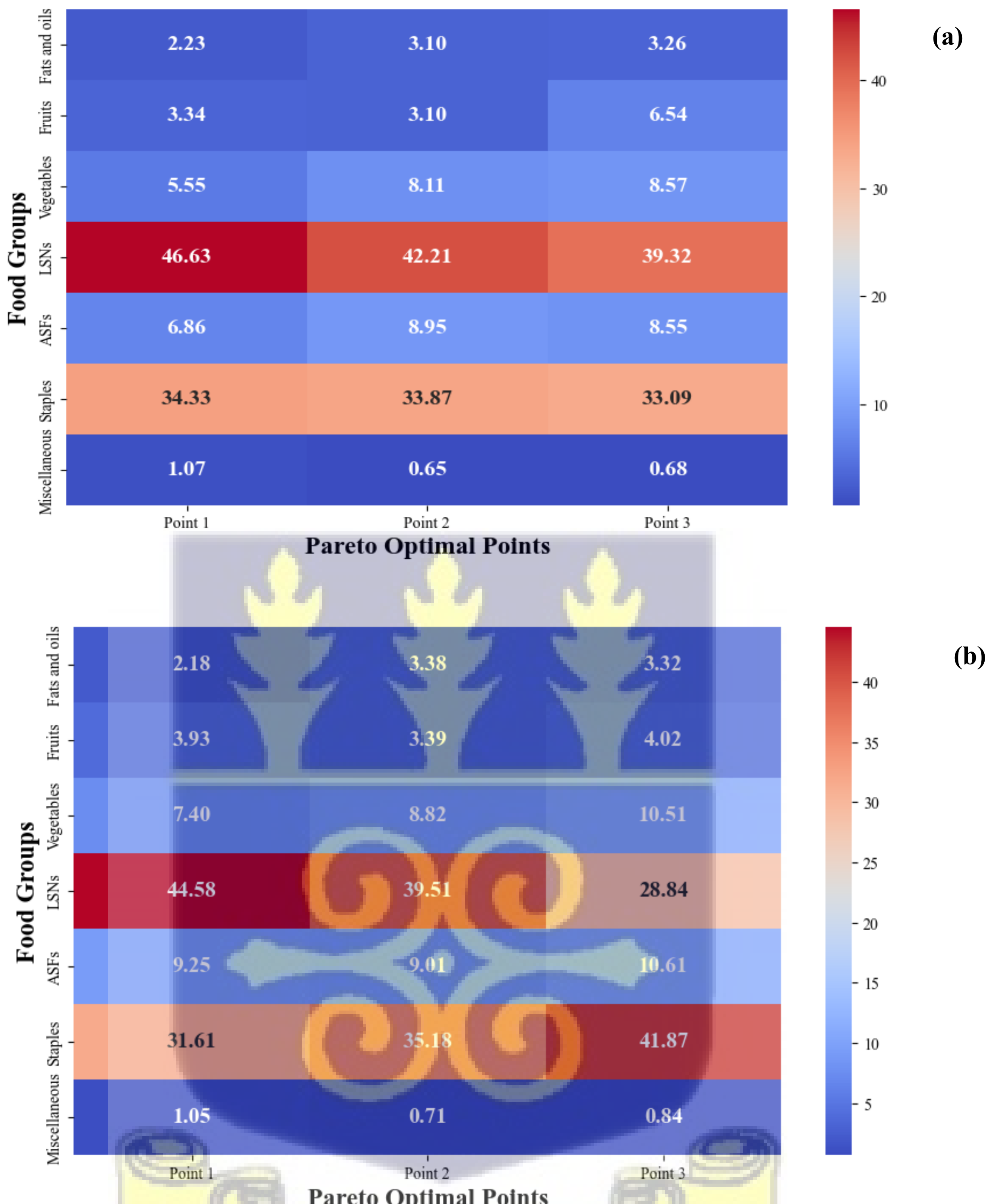

Figure 5.4: Contribution of the food groups to energy (k/Cal) values obtained for the optimised Pareto optimal solution sets (points 1, 2, and 3) for adults 19 years and above. (a) males and (b) females. LSNs – legumes, seeds, and nuts; ASFs – animal-sourced foods.

5.3.2 Discussion

The results emphasise the inverse relationship manifested in the trade-off between cost and GHGE. Thus, when the cost was minimised, GHGE increased; and vice versa. This implies that minimising the cost of the food basket may not be fully compatible with planetary boundaries for food production and consumption because the environmental component of that diet may be high. This trade-off aligns with observations made by other researchers (Moraes *et al.*, 2015; Reynolds *et al.*, 2019; Lucas *et al.*, 2021). The results support the highlights of Hendriks *et al.* (2023), who highlighted trade-offs existing in optimised diets, for affordability, climate, and the environment. Studies carried out by Lucas *et al.* (2021) also established an existing trade-off between diet affordability and environmental footprint. They found that the least expensive, nutritionally adequate diet did not necessarily result in the most environmentally sustainable diet, and vice versa. In a study where Moraes *et al.* (2015) modelled the trade-off between the cost of diets and methane emissions in dairy systems, they observed a reduction in methane emission when the cost of the diet increased, even though they did not generate a trade-off table and Pareto frontier. A study aimed at improving affordable, healthy, and sustainable diets found that as the cost increased, there was a slight decrease in greenhouse gas emissions. On the other hand, more affordable diets had a higher intensity of greenhouse gas emissions (Reynolds *et al.*, 2019). The trade-off between the cost and GHGE of a sustainable diet is a fundamental consideration in various industries and sectors.

Correlation is one of the basic statistical methods used to investigate the strength and direction of the relationship between two variables (Rizk, 2023). The established relationship between cost and GHGE of the optimised food baskets for adult males and females was significant (-0.93 and -0.95, respectively). The higher r values obtained, closer to -1, emphasised the strength of the relationship established. According to Kumari and Yadav (2018), correlation values range from -1 to 1, with values closer to +1 and -1 indicating strong positive and negative relationships, respectively.

Furthermore, the measured proportion of the variance between cost and GHGE was high from the values obtained (Table 5.1). Sharma (2005) indicated that R^2 is a valuable tool for interpreting the extent of the relationship between two variables. The greater the value of R^2, the better it explains the variation between two variables (Asuero *et al.*, 2006).

Balancing the cost of food and its impact on greenhouse gas emissions while also considering nutritional requirements is crucial for the overall well-being of individuals. Vermeulen *et al.* (2020) indicated that food affordability is central to ensuring dietary changes toward more sustainable ones. Neufeld *et al.* (2023) also emphasised the importance of prioritizing the availability and affordability of nutritious food in the necessary transformations to our food systems. Including nutritional adequacies in the complex trade-off between cost and GHGE was possible. Ensuring nutritional adequacy is a vital aspect of a sustainable diet as it promotes the health and well-being of individuals (Fong *et al.*, 2021). People are more likely to adopt and adhere to a diet that meets their nutritional requirements while being environmentally conscious. It is important to note that promoting sustainability in diets should not come at the cost of nutrition and vice versa.

Although one may say the ingredients selected by the algorithm are known to the people and may be challenging to put together for a meal, Downs *et al.* (2023) highlighted the fact that consumer dietary shift is instrumental in ensuring sustainable diets. That notwithstanding, the inclusion of limits on the food groups ensured that the food basket stayed close to the recommended limits proposed by the FBDGs for Ghanaians, which ensured diversity and acceptability. Consumer-facing strategies remain one of the effective multi-approach methods to make sustainable diet achievement possible. Tufford *et al.* (2023) also emphasised consumers' dietary choices as one of the critical points for the transition towards sustainable diets. Despite that, these dietary changes must be introduced to consumers without imposing unfamiliar foods on them. The inclusion of the food group constraints further ensured the selected ingredients' acceptability to the defined population groups.

5.4 CONCLUSION

Achieving sustainable diets necessitates a holistic approach that considers numerous factors. This study balanced the cost and GHGE associated with diets while ensuring they remained nutritionally sound and culturally acceptable. A strong negative correlation was observed between the cost and GHGE of the food baskets, with correlation coefficients of -0.90 and -0.93 for adult males and females, respectively. As the cost of the food basket increased, GHGE decreased, and vice versa. Moreover, the cost factor interpreted a significant proportion of the variability in GHGE, explaining 87% and 90% of the variability for adult males and females, respectively.

Using the epsilon-constraint method exemplifies an effective strategy for considering cost, environmental impact, acceptability, and nutrition in proposing sustainable dietary solutions. Furthermore, the study highlights the critical importance of considering nutrition and acceptability aspects in sustainable diets. By integrating these dimensions, the study offers invaluable insights into the development of sustainable dietary practices that strike a harmonious balance between economic, environmental, and socio-cultural dimensions.

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CHAPTER SIX

DEVELOPMENT OF AN INTERACTIVE PYTHON-BASED GRAPHICAL USER INTERFACE FOR SUSTAINABLE PRODUCT FORMULATION

ABSTRACT

Achieving cost-effective sustainable production has become a priority, for food product developers .as industries grapple with economic pressures. Sustainable food products can play a pivotal role in addressing consumer concerns related to environmental impact, social responsibility, and health. The adoption of a sustainable dimension to product development necessitates a comprehensive evaluation of nutritional content, affordability, and environmental impact, thus, posing a challenge for the food industry.

The study aimed to design the "*NourishCraft*," graphical user interface, a user-friendly interface that allows easy formulation of nutritious food products at minimum cost, minimum carbon footprint, or both. The model-based user interface leveraged Streamlit and Python libraries and considers affordability, nutrition, cultural acceptability, and the environment of a sustainable diet. Three models were developed previously for minimum cost, minimum GHGE, or both using the Python programming language and served as models that governed the operation of *NourishCraft*. By importing Streamlit, an open-source Python framework specifically designed to simplify the creation of interactive, data-driven web applications, codes were written to create *NourishCraft.*

A simple user interface was developed with a home page that introduces the purpose of the tool and provides options for either a nutritious product formulation at minimum cost, minimum greenhouse gas emissions, or a balanced approach for both. Users can select and define minimum and maximum limits for preferred parameters before they can run the interface. Results outputted

from running the interface are a list of the selected ingredients and the optimised objective value (for example, minimum cost). The interface has dropdowns, buttons and input sections, which allow users to interact with it. The interface is set to propose three more alternate solutions to the optimal solution, should they exist in the solution space.

This study has practical implications for being adopted for easy product formulations that integrate sustainability, affordability, and nutrition metrics, which can also be used for informed decision-making, and save product formulation time.

Keywords: Streamlit, nutritious, food formulation, model-based interface, sustainable diets, human-computer interactions (HCI).

6.1 INTRODUCTION

Global population growth is rapidly increasing and is expected to rise to about 10 billion by 2050 (Willet *et al.*, 2019). Additionally, global food systems are expected to provide optimal health for consumers and minimise the environmental impact (Ghammachi *et al.*, 2022). The rapid population growth is expected to exert pressure on the food systems over the coming decades, which will cause an imbalance of food resources. Furthermore, the increased consumption of food resources, particularly, meat, impacts the environment and consumers' health (Cederberg *et al.*, 2013; Tilman & Clark, 2014; Clark *et al.*, 2020; Ghammachi *et al.*, 2022). Indeed, the global burden of diet-related health issues, such as non-communicable diseases and obesity, is rising (Roth *et al.*, 2020).

According to Cederberg *et al.* (2013), limited technological potential is available to reduce food-related emissions; hence, understanding consumer consumption patterns is necessary to meet future climate targets. The concept of sustainable diets includes considerations of nutritional adequacy, environmental impact, cultural acceptability, accessibility, and affordability. Empowering consumers to make informed, sustainable food choices is essential in the search for a more resilient and equitable global food system (Willet *et al.*, 2019). Attwood *et al.* (2020) also emphasised the need for more research focused on developing behavioural change interventions that encourage consumers to adopt more sustainable dietary patterns. Consumers' dietary choices are instrumental sources of demand within the dynamic and multifaceted food systems (Pearson *et al.*, 2014).

Creating a user interface for consumers can help promote sustainable dietary patterns by proposing ingredient combinations that could meet their specific needs. However, developing a similar tool for industries can be more advantageous due to the significant impact and influence these industries have on the food supply chain. Hawkes *et al.* (2019) indicated the industry's pivotal role in shaping dietary patterns because of their control over food production, processing, distribution, and marketing. Targeting food industries as the end users for a sustainable diet graphical user interface (GUI) will allow for a more systematic and scalable approach to promoting sustainable dietary practices.

Furthermore, industries possess large-scale operations and supply chain influence, allowing them to strategically implement a GUI for sustainable diets that optimise affordability and promote environmentally friendly production processes (Heller *et al.,* 2013). This approach ensures that sustainability considerations are embedded throughout the supply chain, aligning with global sustainable development goals outlined by the United Nations (United Nations, 2015). Additionally, industries have a mass-scale impact on consumer choices, making them ideal agents for fostering the widespread adoption of sustainable dietary practices (Nestle, 2013). The growing consumer demand for more sustainable food options will offer industries a competitive edge while they advance their broader sustainability objectives. By so doing, the food industry will be better positioned to educate stakeholders within the supply chain, especially consumers, on the need for sustainable food systems. IPES-Food (2016) emphasises the need for shared knowledge and collaboration among stakeholders within the food supply chain. Hence, having a GUI within food industries will foster a collective understanding of the environmental impact of food choices made by consumers because producers can visualise any trade-off.

Recent technological advancements and human-computer interaction (HCI) principles have the potential to unravel the complexities of sustainable diets and products, offering users real-time guidance and informed decision-making. A tool that proposes sustainable options is an essential solution at the intersection of cost, nutrition, cultural acceptability, and environmental impact of diets in an increasing demand for sustainable diets. The recent advancements in technology, data availability, and advances in nutritional science have paved the way for a solution, which is: - a Graphical User Interface (GUI) for sustainable product formulation and development to support product formulation in a short time and an effective way. A GUI is a type of interface that allows users to interact with a computer through visual elements such as icons, buttons, and menus (Jansen, 1998) to make informed choices. Podržaj (2019) emphasised how GUIs are becoming increasingly important to human beings because computers have become part of our everyday lives.

The general steps to building a GUI include choosing a programming language and a framework that simplifies GUI creation. Create an intuitive and accessible interface by organising elements colour scheme, navigation and flow. In this study, the Streamlit-Python library was selected.

The Streamlit app is a rapidly growing open-source framework that enables the creation of interactive web applications quickly, making it an ideal choice for developing a user-friendly interface.

Streamlit is an open-source Python library that generates an interactive graphical visualisation using simple codes (Parker *et al.*, 2021; Ermer, 2023). Nápoles-Duarte *et al.* (2022) stated that researchers currently use Streamlit to share large data sets without needing front-end coding skills. According to Azarmi *et al.* (2021), Streamlit is gradually becoming the go-to tool due to its ability to prototype and deploy web applications without extensive knowledge and experience in web development. Streamlit makes interactions easy by providing input data, allowing parameters to be adjusted by using many input widgets, and finally receiving output results (Nantasenamat *et al.*, 2023). Additionally, the Streamlit framework can convert Python codes into interactive apps and makes it possible to build model-based apps rapidly (Pote, 2023).

To develop any web app using Streamlit's front end, one must understand the Python programming language (Nápoles-Duarte *et al.*, 2022). The usability of any GUI is vital during its development because it dramatically impacts user acceptance (Camargo *et al.*, 2018). Though many researchers have used Streamlit to develop web applications, it has rarely been used in the food industry. With the increasing demand for consideration of the environment, amidst consumers' demand for nutritious and affordable food products, there is a growing interest in a tool that simulates the complexity of sustainable diets and food products in virtual environments. The solution can be used by product developers who have little to no programming skills.

This study introduces *NourishCraft* GUI, which consists of a graphical user interface (GUI) that allows industry players to optimise sustainable product formulations.

6.2 METHODOLOGY

6.2.1 Definition of scope

The *NourishCraft GUI* was developed using Python programming language drawing on its free libraries, along with the dynamic features of Streamlit. The innovative GUI application was designed with object-oriented programming principles, creating a unique framework that seamlessly integrates Streamlit and offers an exceptional user experience. The GUI was designed to propose optimised food formulations that are nutritious, and culturally acceptable with minimum cost and/or minimum greenhouse gas emission (GHGE) values It is mainly intended for food product developers. It is designed to be user-friendly and does not require any previous coding experience.

6.2.2 Data source

The data set in this software demonstration consists of 75 locally available Ghanaian food items with their nutrient composition, cost, and greenhouse gas emission (GHGE) values expressed on a 100 g basis. The cost and nutrient composition were obtained from a previous study conducted by Nykänen *et al.* (2018) and complemented with data from the Ministry of Food and Agriculture (MoFA), Ghana, and the West African Food Composition table. Data on the GHGE of the food items were also obtained from a private database from the Nestle Research Center, Switzerland. The food items were categorised in the various categories defined in Table 6.1.

Table 6.1: Locally available food items in Ghana (n=75) included in the database for interface programming analysis.

Food groups	**Subgroups**	**Number of food items**
Staples	Cereals, grains, starchy foods	16
Legumes, seeds, and nuts	Beans, seeds, nuts (for example, peanut), pulses	8
Fruits and vegetables	Fruits, leafy, and wild vegetables	26
Animal-sourced foods	Beef, mutton, pork, poultry, seafood	14
Fats and oils	Animal and plant-based fats and oils	6
Miscellaneous	Spices, salt, and mushroom	5
Total		**75**

The GUI developed incorporated multi-class classification models. These models were trained to accurately identify 75 distinct food items along with their respective food groups, as detailed in Table 6.1.

6.2.3 Data processing

To ensure accurate implementation of the user interface, quality control and validation of the data were done. The input was verified for consistency before it was processed and displayed on the interface. Also, the data was normalized and optimised to improve model performance and facilitate more intuitive user interactions within the user interface.

6.2.4 GUI design and architecture

Streamlit widgets like sliders, sliders, buttons, and dropdowns complement the data processing method by enabling it for data transformation (Streamlit Inc., 2023). Subsequently, the visualizations were generated through Python libraries such as Matplotlib that was embedded into the Streamlit interface which enhanced the summarization capabilities of the GUI. Plotly properties of Streamlit were also used to develop a pie chart for easy visualisation of results generated. Figure 6.1 gives a schematic overview of how the interface interactions happen.

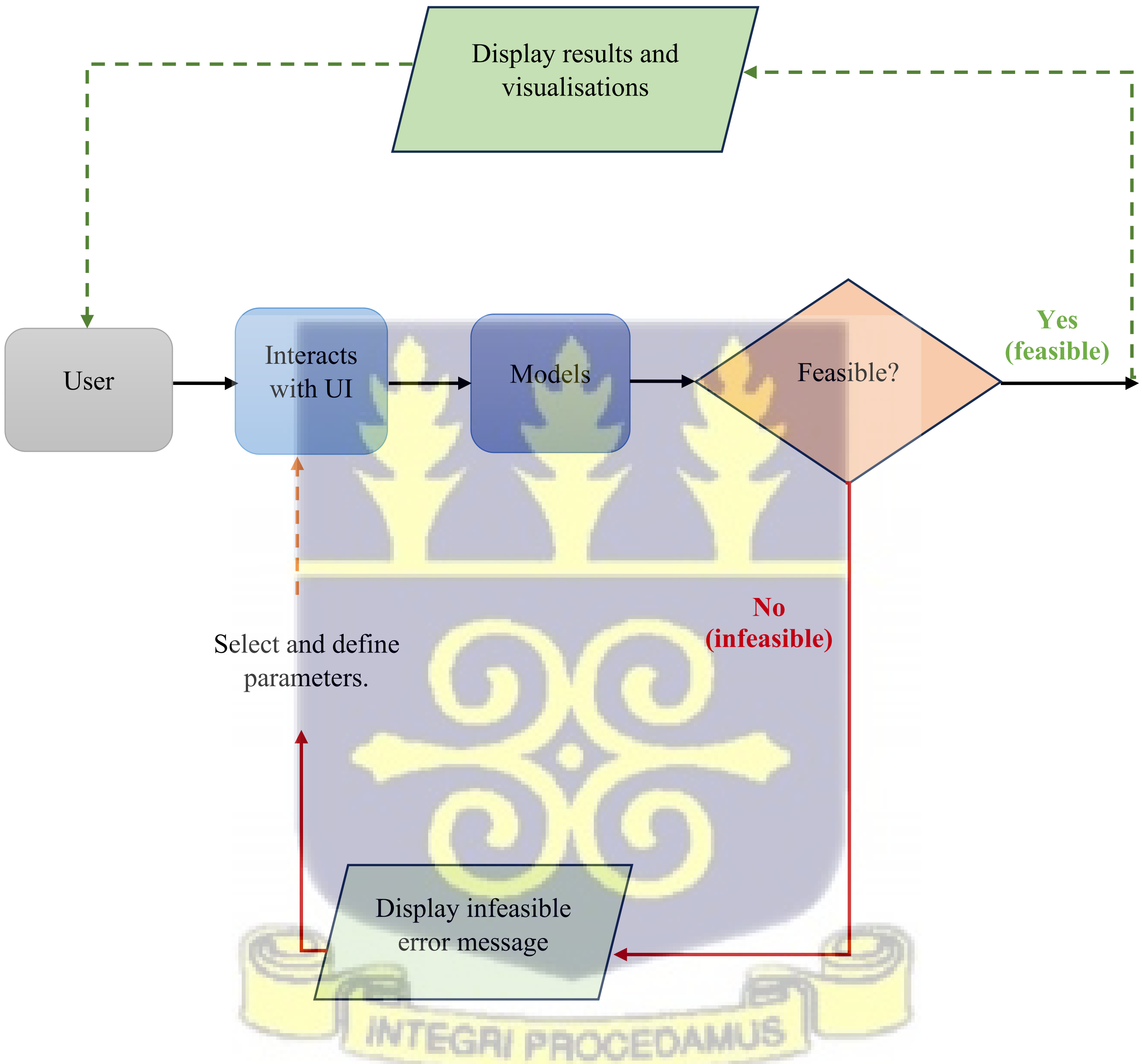

Figure 6.1: Schematic representation of the user interface cycle for creating and utilising *NourishCraft GUI.*

6.2.5 GUI functionalities and formulation recommendations

A fully functional user interface was created using Python (Visual Studio (VS) code environment) in which users can select their preferred nutrients and input all the related minimum and maximum requirements to output results.

Once a user launches the application, they are presented with a home page with a short introduction to the purpose of the GUI and a navigation guide. The user selects whether they aim to formulate ingredients that satisfy defined requirements either at minimum cost, minimum GHGE or minimising both cost and GHGE simultaneously. This is made possible with the aid of dropdowns, sliders, and text boxes. Once the user runs the interface after specifying all the requirements, the backend algorithm searches for the optimal formulation subject to the defined requirements to output the formulation. The optimal value of the optimisation problem is presented in a text box, followed by a graph and table to show the selected ingredients and their recommended proportions to the overall formulation. A table is used to propose basic unit operations to process the ingredients. Furthermore, a simple table shows the nutrient components that were selected and the resulting values after the ingredients were optimised. All tables and figures generated after a complete optimisation run can be downloaded and saved as applicable. The generation of these tables and figures serves as an additional enhancement of the interface.

6.2.6 Mathematical equations

The general formulae for the mathematical model running in the background to output results are based on minimisation (Eqn 6.1), subject to defined requirements (Eqns 6.2 to 6.5).

$$\text{Minimise } f(x^{(k)}) = c^{T}x^{(k)} \qquad \text{Eqn 6.1}$$

Subject to:

$L \le A_{x^{(k)}} \le U$ Eqn 6.2

$\sum_{j=1}^{n} x_j^{(k)} = 100$ Eqn 6.3

$x_j^{(k)} = 0$ for all $j \in S^{(k-1)}$ Eqn 6.4

$x_j^{(k)} \ge 0$ Eqn 6.5

$f(c^{(k)})$ – the objective function to be minimised

c – is a vector of coefficients $(c_1, c_2, \dots \dots . c_n)$

$x^{(k)}$ – is a vector of decision variables $(x_1, x_2, \dots \dots . x_n)$ for iterations $k = 3$

A – is a matrix of size $m * n$ where a_{ij} represents the amount of nutrient i in the food item j

L – a vector of minimum nutrient levels $(L_1, L_2, \dots \dots \dots L_n)$

U – a vector of maximum nutrient levels $(U_1, U_2, \dots \dots \dots U_n)$

$S^{(k-1)}$ – a set of indices corresponding to the ingredients selected in all previous solutions up to iteration $k - 1$

The requirements are set within the minimum and maximum nutrient parameters selected and defined (Eqn 6.2), and the summation of the ingredients to be selected (Eqn 6.3). An additional requirement was defined mathematically to exclude selected ingredients as the algorithm runs to generate alternate solutions (Eq 6.4).

6.2.7 Quality and Usability Study

The initial prototype of the user interface (UI) was shared with assessors using a structured methodology for feedback and improvement. A single-score usability scale for quick feedback (Bangor *et al.*, 2008) was used to enhance the usability and effectiveness of the UI. Access was given to assessors through a secured hosted platform via mail, with clear instructions to guide navigation and interaction with the UI. A total of eight participants assessed the *NourishCraft* GUI, as a sample size of 5 to 15 is considered sufficient to uncover usability issues and gather diverse perspectives for user interfaces (Nielson, 2000; Johnson & Onwuegbuzie, 2004; Ren *et al.*, 2010). The interface was shared with 10 people, and response was received from 8 participants. The evaluation utilised a 5-point hedonic scale to measure twelve key factors. The assessors had academic (37.5%) and research (62.5%) backgrounds and have basic knowledge on product formulation and development. A standardised feedback template created with Google Forms was used to capture the assessment details such as user-friendliness, functionality, design, etc. The assessment questions were designed to evaluate the practical and quality aspects of the user interface, such as ease of navigation and aesthetics. The questions broadly measured, effectiveness, and satisfaction as defined by Kortum & Bangor (2013).

A sample of the form used is shown in Appendix II. Results obtained from the assessment were used to validate and revise the UI.

6.3 RESULTS AND DISCUSSION

6.3.1 Interface and Features

Figure 6.2 shows the layout of the *NourishCraft* GUI developed. This intuitive interface empowers users to navigate seamlessly while providing comprehensive tools for defining the dietary requirements for the product to be developed. The left side shows the navigation to the home page, and subsequently, the three main objectives a user can access. The right hand allows the user to define constraints in terms of food groups and nutrient requirements.

Figure 6.2: An image of the *NourishCraft* GUI. A - sidebar for navigation for objective to optimise, B - the main content area for display. C – alternate page navigation to optimisation pages.

Once a user selects either of the three objectives (formulate product at minimum cost, formulate product at minimum environment impact, or balanced approach formulation for cost and environment), the content area enables him or her to select and define their preferred parameters using the drop-down and text functions. Figure 6.3 gives an overview of the layout once a page is selected.

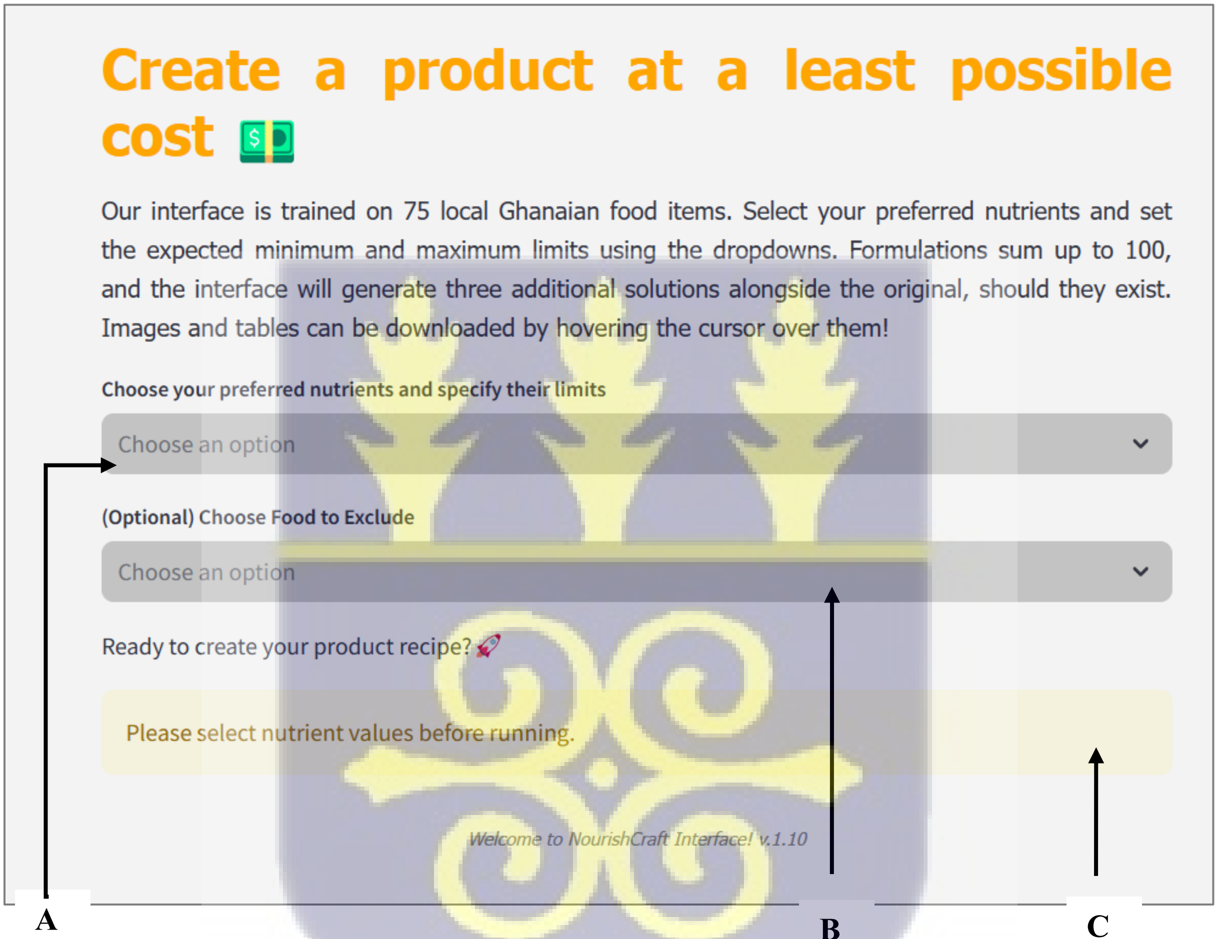

Figure 6.3: Content area for a selected objective.

A – a drop-down that enables a user to select and input limits for their preferred parameter(s). B – An optional dropdown that a user can use to drop a specific ingredient they would want to omit after an initial run. C – A validation check that prevents a user from running the interface only after selecting and indicating their preferred parameter.

Users can only run the interface after selecting the nutrients of interest and specifying their minimum and/or maximum limits. The development of a GUI for food formulation, such as the NourishCraft GUI, represents a significant advancement in dietary optimisation and nutritional management for food developers. This is because the GUI has the potential to support product formation in a short time. The GUI provides an easy-to-use platform for users to interact with complex systems, enabling user-friendly navigation and enhanced functionality.

The GUI was designed with principles of human-computer interaction and usability engineering in mind, prioritising simplicity and clarity. This enables users to easily navigate various features and functionalities (Kurniawan, 2004). The *NourishCraft* GUI features clear navigation menus and controls, which help guide users through the formulation process while ensuring accessibility to users. It enables user navigation by incorporating interactive elements and real-time feedback mechanisms.

Moreover, GUIs facilitate customisation and personalisation, allowing users to define their product formulation constraints and preferences according to their unique requirements and objectives. This level of customisation enhances user engagement and satisfaction, ultimately contributing to improved product formulation and encouraging healthier eating habits among consumers (Nielsen, 1993).

An even more interesting feature is the ability of the algorithm to propose alternative solutions, in addition to the initially proposed solution, if it exists within the solution space. The alternate solution for the initial optimal solution is set to 3 (Eqn 6.4). However, should the algorithm run and not find the three defined extra solution sets, it outputs whatever number it finds, and terminates the rest as infeasible. Additionally, users can use a dropdown button to exclude a particular ingredient if they do not want it to be selected, and then rerun for different formulations, only if they exist within the solution space (Figure 6.3B).

6.3.2 Independent testing

The assessment questions were designed to evaluate the practical and quality aspects of the user interface, such as ease of navigation and aesthetics. The responses broadly answered questions asked on usability assessment: efficiency, effectiveness, and satisfaction as defined by Kortum & Bangor (2013). Figure 6.4 summarises user assessment feedback on the various aspects of the interface.

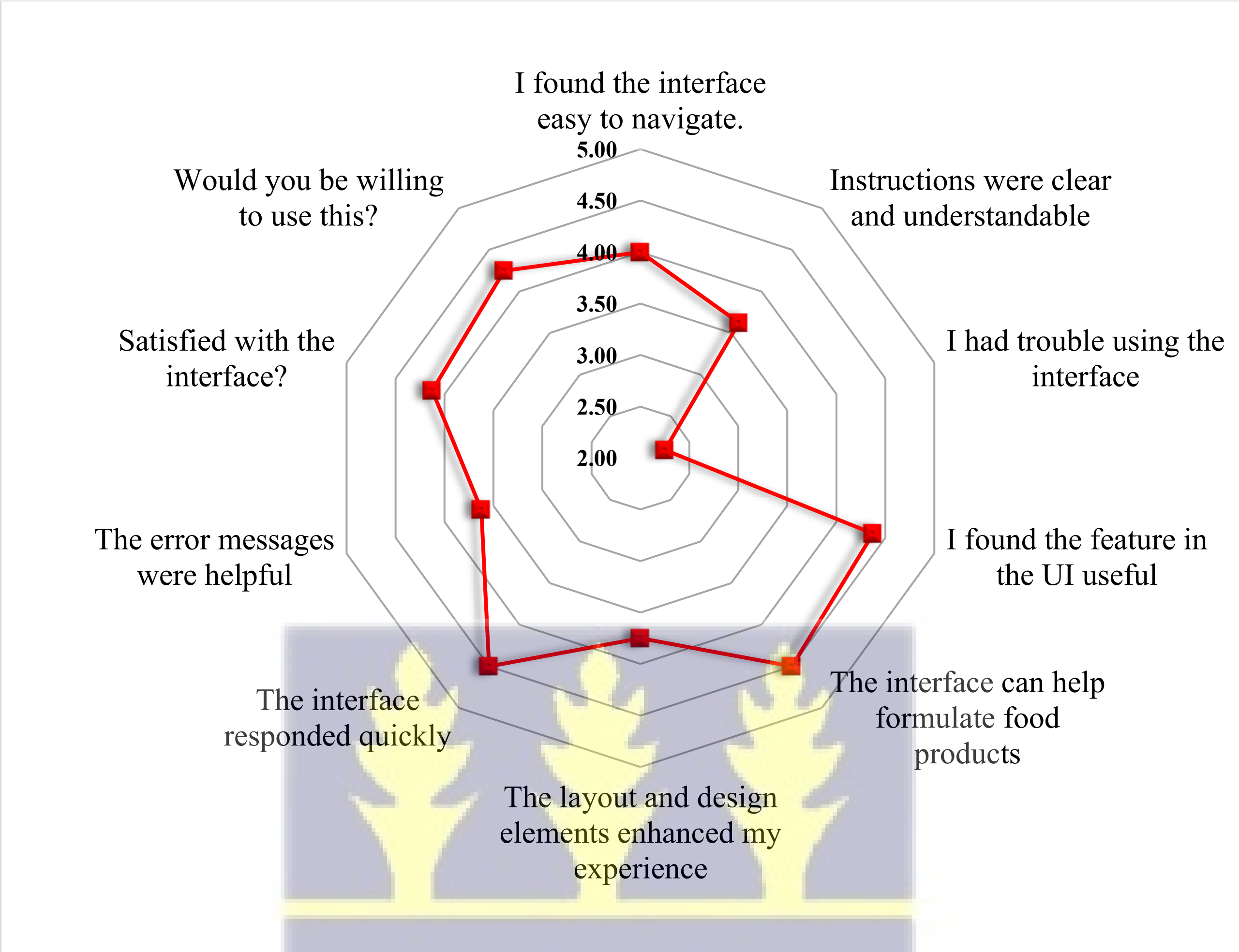

Figure 6.4: Radar chart representation of user interface assessment. Indicators were scored on a scale of 1 to 5. 1 – strongly disagree, 2 – disagree, 3 – neither agree nor disagree, 4 – agree, and 5 – strongly agree.

Overall, the UI received a favourable evaluation from the assessors, who particularly appreciated the ease of navigation, functionality, and prompt responsiveness. Hayat *et al.* (2015) indicated the need for usability testing, for the success and acceptance of a developed software. Hedonic scale assessment is important as descriptors make it easy for the subject to respond and for experimenters to analyse the results obtained (Lim, 2011). A notable strength identified was the efficiency of the interface to facilitate food formulation, coupled with its quick response time. This was particularly beneficial given the critical importance of time efficiency in user interactions with interfaces. Furthermore, the low mean score of 2.25 (± 0.43) for users encountering difficulties is a significant positive outcome. This low incidence of user difficulties indicates that the interface is highly intuitive and user-friendly, which is crucial for maintaining sustained user engagement and high satisfaction levels. The minimization of user challenges is an essential factor in ensuring the long-term adoption and effective use of the interface (Wolpaw *et al.*, 2002).

The interface scored above average for factors like the clarity of error messages, layout, and instructions (3.63 to 3.75). However, there is still room for improvement in these areas to enhance the robustness of the interface. The limitation with the clarity of error messages may be due to the algorithm's inability to identify which parameter is causing the infeasible solution. As an interim measure, an output message is generated for users when an infeasible solution occurs, advising them to re-evaluate their selected parameters and review their respective limits. Currently, the background model only outputs the infeasible expression without directly pointing to the exact parameter and its respective requirements that could contribute to this error. Additionally, to improve navigation, the links to the various pages needed for product formulation have been embedded in the main page as well as the side to make them more accessible to users (Figure 6.2C).

Additionally, positive feedback emphasised the satisfaction and potential of the UI to aid nutritious food product formulation. Some of these comments included "***The interface will help solve a lot of problems in food formulation***", and "***Great concept!! Well done, I like the fact that multiple/alternate formulations pop up***."

Additionally, the algorithm generates a graph that gives a visual representation of the selected ingredients and their different food groups, following the main food group classification from the Ghana food-based dietary guidelines (MoFA & GSPH, 2023), tables that indicate major unit operations that can be used to process the selected ingredients, the resulting outcomes, and their possible impact on nutrients.

Generally, the mathematical principles governing the functionality of the user interface can be adapted to different solution sets.

6.4 CONCLUSION

In conclusion, it was possible to develop a computer-aided tool to aid in formulating food products subject to some defined parameters, and this represents a significant step towards easing product development, with environmental considerations. The user interface named *NourishCraft* was developed with the properties of Streamlit (version 2023) and Python programming language and trained with about 75 locally available food items in Ghana. The food items in the database have their cost values, greenhouse gas emissions, and nutritional values for 27 nutrients, normalised for easy processing.

This sought to simplify food formulation processes while promoting eco-friendly choices. *NourishCraft* highlights the potential of technology to foster healthier, more sustainable food choices from the food processors' view to consumers. The algorithm requires the selection of nutrient parameters and their respective lower and upper limits. Once a user has selected preferred parameters and run the interface, feasible output for an optimal solution, including three extra solutions, is outputted, should there be a feasible solution(s) in the solution space. Selected ingredients are represented in a table with their respective amounts, to yield nutrient values that satisfy the requirements defined. The results obtained are downloadable, once a user hovers their cursors over them.

The GUI has the potential to contribute significantly to research, particularly in designing products that can be considered sustainable. Furthermore, this can lead to significant improvements in designing food products because the application can be extended beyond the initial dataset used to test the GUI. This can result in further collaboration and innovation with other researchers.

6.4.1 Limitations

One potential limitation is the inability to offer details on how these unit operations can be integrated to form a complete process flow. Additionally, it is not possible for the cost component of the ingredients to be updated in real time, using the interface. However, it can be updated in the background data, to reflect in the interface output. Alternatively, another improvement could be in the adoption of an advanced economic model that enhances the update of the cost component of the food items.

It should be noted that the data used in *NourishCraft* GUI is currently limited to Ghana, although it can be expanded to cover other geographical areas.

Additionally, another problem is the interface's inability to indicate an exact parameter selected that contributes to an infeasible solution space.

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CHAPTER SEVEN

DEVELOPMENT AND EVALUATION OF AN OPTIMISED BREAKFAST MIX FOOD FOR CHILDREN AGED 10 TO 18 YEARS

ABSTRACT

Introduction: Starchy foods and legumes are crucial in enhancing nutritional security when combined with starch-rich foods. However, developing products that are not only nutritious but also sustainable is a great hurdle. Traditional food formulation methods rely on a trial-and-error approach, which involves multiple adjustments and can be both cost-intensive and time-consuming. Additionally, there is a growing demand for more efficient and systematic procedures to develop healthier and more nutritious food options. More importantly, a call for more computer-aided approaches to ease product formulation. Hence, the study aimed to use *NourishCraft* GUI an interface developed to aid product formulation) to formulate a nutrition product for children 10 to 18 years.

Methodology: The "*NourishCraft*" interface developed for product formulation was used to obtain formulations, using one-third of the recommended dietary allowance (RDA) for adolescents aged 10 to 18. The formulation was made into a drum-dried instant product.

The AOAC methods were used to *analyse* the product for proximate analysis, and the Kjeldahl method for protein content. Functional properties, bulk density, swelling capacity, and water absorption capacity of the final product were assessed. The colour of the product was analysed using the Hunter lab equipment.

Aerobic microbial load, total coliforms, Enterobacteriaceae, yeast, and mould were assessed by pour plating on Plate Count Agar (PCA), Violet-Red Glucose Agar (VRGA), MacConkey agar, and Potato Dextrose Agar (PDA), respectively.

A consumer acceptability test was conducted using a 9-point hedonic scale using 89 untrained panellists aged 12 – 18 years, at the Staff Village Basic School, Legon.

Results: The product formulation resulted in two optimisations. The second, consisting of cassava, coconut, millet, and Bambara beans, was selected in ratios of 27.64: 14.22: 25.44, and 32.70, respectively. The optimised formulation contained 300 kcal of energy, 45 g carbohydrates, 10.00 g protein, and 4.29 mg of iron.

The drum-dried composite constituted 434.21 ± 0.35 kcal of energy, 73.75 ± 0.07 g carbohydrate, 11.64 ± 0.01 g protein, and 3.47 ± 0.02 g iron. The interface predicted above 60% of the nutrient composition, with a minimum prediction of 61.02% for carbohydrates and an over-prediction of 123.63% for iron.

The final product's bulk density, swelling capacity, and water absorption capacity were 0.38 ± 0.03 g/ mL, 10.28 ± 0.36 mL/g, and 693.50 ± 38.10% respectively. The L*, a*, b*, and ΔE values for colour were 72.81 ± 0.48, -0.80 ± 0.12, 14.68 ± 0.11, and 24.84, respectively. The drum-drying process had an impact on the functional and colour properties of the final product.

Sensory acceptability was scored above average with a value of 7.82 ± 1.21 for overall likeness. The aroma attribute was scored 8.09 ± 1.19, flavor 8.02 ± 1.39, aftertaste 7.76 ± 1.55, mouthfeel 7.83 ± 1.22, and appearance 7.57 ± 1.45. There was no statistically significant difference among the attributes assessed for acceptability ($p = 0.132$).

Implication: *NourishCraft* GUI has the potential to support nutritious and acceptable food formulations and can predict above 60% accuracy.

Keywords: Optimisation, acceptability, cereals, legumes, human-computer interaction

7.1 INTRODUCTION

Malnutrition (undernutrition, micronutrients, overnutrition) affects almost all countries and remains a persistent issue in developing countries (Prasadajudio *et al.,* 2023). Children are some of the most vulnerable groups affected because 9 to 13 years is a crucial phase for an individual's physical, cognitive, and emotional growth (Raza *et al.,* 2020; Prasadajudio *et al.*, 2023). As children around this age move from childhood to adolescence, their nutritional needs become more complex. Azupogo *et al.* (2020) stated that a quarter of the Ghanaian population is 10 to 19 years old. Azupogo *et al.* (2020) further indicated that a higher prevalence of stunting was found among adolescent males who are 15 to 19 years old, whereas for adolescent females, overweight was prevalent in Ghana. The adolescence stage is usually characterized by unhealthy dietary habits, as adolescents engage in fast food, skip meals such as breakfast, and snack on unhealthy food choices (Nsiah-Asamoah, 2017; Wiafe *et al.,* 2023). Ochola and Masibo (2014) emphasised that most children go to school without eating breakfast, and this has necessitated interventions that improve their nutritional status.

The dietary habits of children and adolescents are often governed by what is served in their homes (Onyango, 2003; Renzaho & Burns, 2006). In Africa, for example, cereals and legumes contribute significantly to the population’s dietary habits. Kumar *et al.* (2022) indicated the significance of grain legumes in achieving nutritional security, as they contribute to household diets when complemented with other starch products. However, there is a need to ensure that food products meet the nutritional requirements of consumers.

Therefore, there is a need for innovative solutions that address dietary quality, affordability, and environmental sustainability. Additionally, inadequate nutrition can be a major contributing factor to health problems, and access to affordable and nutritious foods can be a means to lessen this problem (Musina *et al.*, 2017). Hargreaves *et al.* (2022) indicated the need to increase the availability and affordability of healthy foods to promote adolescent nutrition.

There is a need for food systems transformation to focus on children and adolescents to foster a healthier future generation (Vermeulen et al., 2020). According to Raza *et al.* (2020), ensuring that children and adolescents access nutritious, safe, affordable, and sustainable diets remains a major global developmental challenge.

Modern-day scientists and food industries are tasked with ensuring the provision of safe, nutritious, and palatable products as consumers are becoming more aware of the association between diet and health (Bower, 2013). Nehir El and Simsek (2012) further emphasised the role of the food industry in promoting healthy diets and new products aligned with healthy dietary guidelines. Most food industries, irrespective of size have research and development (R&D) departments that are tasked with ensuring the innovation of quality, and safe products that meet consumer nutritional requirements. Most importantly, they must optimise the product formulation before manufacturing to save costs and maximise resources (Musina *et al.*, 2017).

Furthermore, a bigger challenge even lies in formulating products that will save cost but be tagged as sustainable. During the product development process, food formulation plays a crucial role, especially with the growing demand for healthier and more nutritious options among consumers. The typical method for developing formulations for food products is the trial-and-error approach which involves a lot of retrials and readjustments, which can be cost-intensive and time-consuming (Sheibani *et al.*, 2018; Donkor *et al.*, 2023). Arteaga *et al.* (1994) indicated the application of response surface methodology (RSM) and mixture design among other techniques used for formula optimisation in product development. Additionally, Minitab is a statistical software tool that is often used in generating mixture designs during product development but lacks optimization algorithms like linear program and requires statistical expertise to use effectively (Montgomery, 2017).

Linear programming can be employed to overcome many formulation hurdles. There is a need for a deep understanding of the mathematical aspects of linear programming, and that can be challenging. The development of a graphical user interface (GUI) for easy product formulation, with consideration for the environment, cost, nutritional adequacy, and cultural acceptability is a remarkable achievement. The model-based GUI, which was trained with 75 locally available ingredients in Ghana, can be used to easily formulate products, subject to some defined requirements (or constraints). The interface, *NourishCraft*, is designed with three core pages to support optimised food product formulation:

1. **Cost Optimisation Page**: This page formulates food products that minimise cost.
2. **Environmental Optimisation Page**: This page prioritizes minimising the environmental impact (measured by greenhouse gas emissions, or GHGE) in the product formulation process.
3. **Balanced Optimisation Page**: This page provides a balanced formulation approach, considering minimum cost and environmental impact, respectively.

Each page offers targeted optimisation to help users meet specific formulation goals in a streamlined, efficient way.

This study, therefore, aimed to develop and evaluate a product for children 10 to 18 years by utilizing the graphical user interface developed purposely for a food product formulation at a minimum cost, to assess nutritional and acceptability requirements. A product was developed from the formulation, and proximate, physicochemical, microbiological, and sensory analyses were conducted.

7.2 MATERIALS AND METHODS

7.2.1 Product formulation

The model-based user interface was developed based on 75 food items locally available in Ghana. The objective was set to minimise the cost of the food product formulation. The constraints were defined based on one-third of the nutrient requirement for energy, protein, carbohydrates, and iron for adolescents 10 to 18 years. The source of the nutrient requirements was defined based on recommendations from the Institute of Medicines (2019). The constraints defined for the selected nutrients following the recommendations from the Institute of Medicines are summarized in Table 7.1.

Table 7.1: Nutrient requirements that were used to formulate the product per 100 g.

Nutrient	Minimum	Maximum
Energy (kcal)	300	600
Carbohydrate (g)	45	130
Protein (g)	10	46
Iron (mg)	3	11

(Source: Institute of Medicines, 2019)

Interacting with the user interface using the parameters defined in Table 7.1 resulted in two formulations: - an optimal solution, and an alternate solution, as represented in Table 7.2 and both formulations come at the same cost and meet the defined nutrient requirements.

Due to extensive work available on maize and soya beans, the second formulation was selected for product development (Table 7.2).

Table 7.2: Formulation obtained from the *NourishCraft* after optimisation

Formulation 1			Formulation 2		
Ingredient	Amount (g)	Cost (GHS)	**Ingredient**	Amount (g)	Cost (GHS)
White maize	82.53	0.51	**Coconut**	14.22	0.06
Soya beans	17.47	0.16	**Bambara beans**	32.70	0.46
			Millet	25.44	0.26
			Cassava	27.64	0.09
Total	***100***	***0.67***	***Total***	***100***	***0.67***

The cost of the ingredients in the database was adjusted to reflect inflation rates as of February 2024

7.2.2 Procurement of raw materials

The ingredients generated using the *NourishCraft* GUI were coconut, Bambara beans, millet, and cassava. Three kilograms (3 kg) of Bambara beans, two (2 kg) kilograms of millet, five (5 kg) kilograms of cassava, and 5 pieces (5.6 kg) of coconut were procured from the Adjei Kojo market in the Greater Accra region and transported to the Food Process Engineering laboratory of the University of Ghana for storage and processing. Samples were put in zip lock bags, labelled with their names and dates, and kept under refrigerated conditions for further processing. Figure 7.1 represents the ingredients purchased for the product development process.

Figure 7.1: The raw ingredients obtained for product formulation based on the *Nourishcraft* optimisation (a) coconut, (b) cassava, (c) millet, and (d) Bambara beans.

7.2.3 Sample preparation

7.2.3.1 Coconut

The mature coconuts were cracked, the fluid drained away and the flesh removed using a sterile knife. washed and dried. The flesh was washed under running water (room temperature) and cut into smaller sizes to allow blending. The chopped pieces were blended with water in a ratio of 1:3 using a commercial lab size blender, and the blend was squeezed to extract the juice.

7.2.3.2 Bambara beans

The Bambara beans were washed and soaked for 8 hours at room temperature. They were then dehulled to remove the outer hulls to access the cotyledons. The beans were dried at 60 °C (Biobase forced air drying oven, model: BOV-V230F) for eight hours and milled into a fine powder using a hammer mill (Brook Crompton, model: 2-TDA905J).

7.2.3.3 Millet

The millet was cleaned and sorted to remove any dirt and foreign particles. It was soaked for 8 hours and dried at 60 °C (Biobase forced air drying oven, model: BOV-V230F) for 8 hours and milled using the hammer mill (Brook Crompton, model: 2-TDA905J) to obtain fine powder for further processing.

7.2.3.4 Cassava

The cassava was washed under running water to remove dirt and any physical impurities. They were peeled, washed thoroughly, and chopped into chunks. The chunks were dried at 70 °C (Biobase forced air drying oven, model: BOV-V230F) for 6 hours. The dried chunks were milled using a hammer mill (Brook Crompton, model: 2-TDA905J) to obtain a fine powder for further processing.

7.2.4 Mixing and drum drying

The Bambara flour, millet flour, and cassava flour were combined to a final weight of 3 kg. The coconut juice (3 ltrs) was then added, followed by water 3 ltrs, to achieve a total solid-to-liquid ratio of 1:2. The ingredients were thoroughly mixed by continuously stirring to create a smooth and uniform mixture. The slurry mixture was drum-dried (ANDRITZ Gouda drum dryer, E5/5) at 140 °C at 6 rpm into flakes and milled into flour.

Figure 7.2 provides a schematic representation of the process flow followed for the product development.

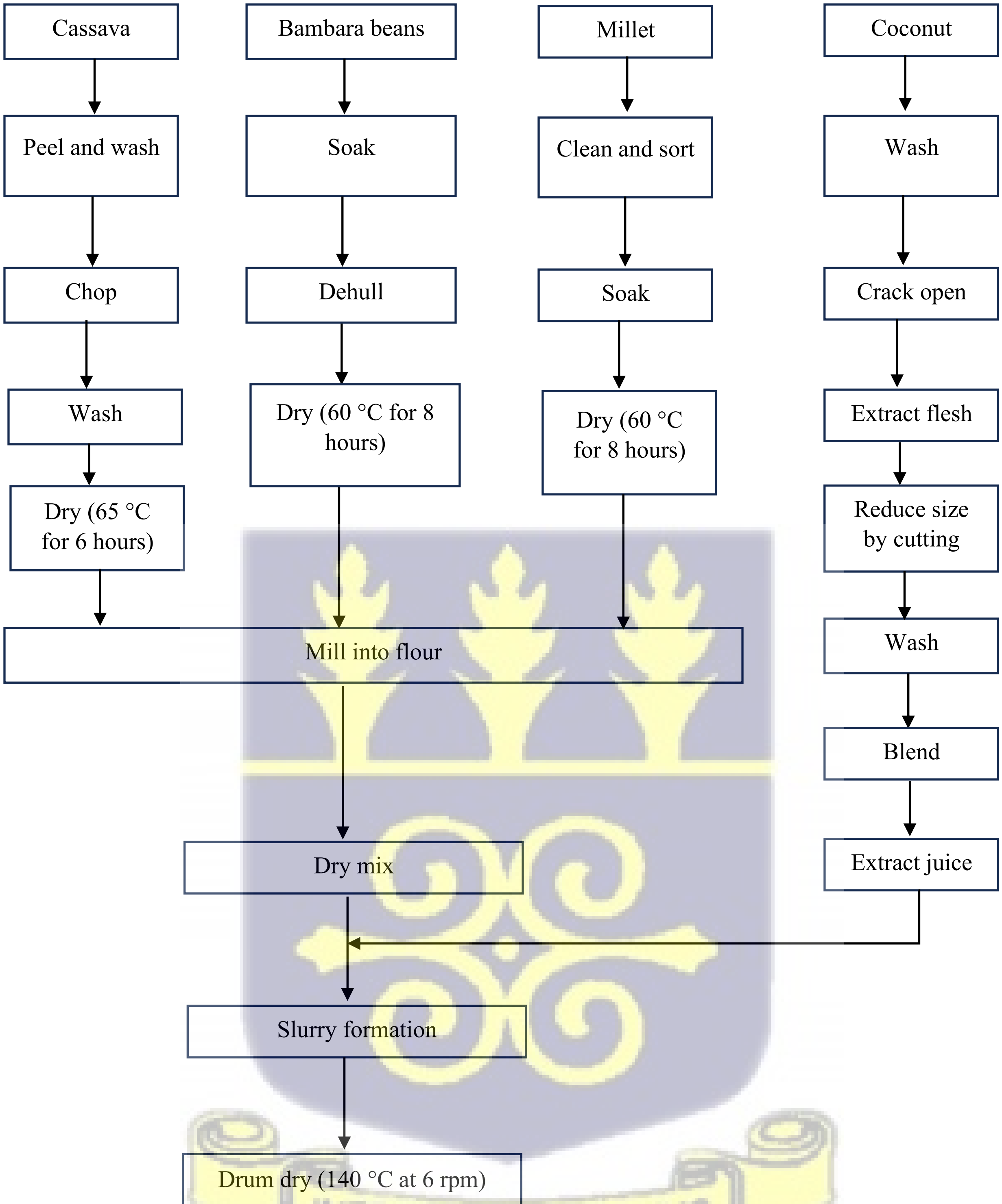

Figure 7.2: Process flow for drum-dried root-legume-cereal blend

7.2.5 Product analyses

7.2.5.1 Microbial analyses

The microbial analyses were conducted in the Microbiological research laboratory of the Food Research Institute, Legon. Finished product samples were kept in Ziploc bags, placed in clean containers and transported to the laboratory under hygienic conditions and stored at refrigerated conditions (2 – 8 °C) for not more than 24 hours before use. Microbial analyses were conducted for specific microorganisms (total plate count, total coliforms, Enterobacteriaceae, yeast and mold) to certify the safety of the product, before sensory analyses.

7.2.5.1.1 Agar preparation

The agar powder plate count agar (PCA) (Oxoid, UK), violet-red bile glucose (VRBG) agar (Oxoid, UK), MacConkey agar (Oxoid, UK), and Dichloran Rose Bengal Chloramphenicol (DRBC) agar (Oxoid, UK) were each weighed into sterile media bottles, dissolved in one litre of distilled water, autoclaved at 121ºC for 15 minutes and immediately cooled in a water bath at 45 °C. The specific quantity of agar used was as described by the manufacturer.

7.2.5.1.2 Enumeration

Using the pour plate technique, ten (10) grams of the finished product was aseptically weighed into sterilized stomacher bags. Ninety (90) mL of sterilized buffered peptone water was added, and the mixture was homogenized using a Stomacher blender. One (1) mL homogenized mixture was pipetted aseptically into sterile disposable petri dishes in duplicates. To each plate, 15 mL of molten agar was added and swirled gently to ensure even distribution. The plates were then allowed to solidify at room temperature. Once solidified, the plates were incubated at 35 – 37 °C for up to

120 hours for the different enumerations. After incubation, the plates were examined, and colony counts were performed. Aerobic microbial counts were conducted using PCA (V. Azanza, 2005), total coliforms were analysed using MacConkey agar (Thunberg *et al.,* 2002), Enterobacteriaceae using VRBGA (Paulsen *et al.,* 2008), and yeast and mould counts were assessed using DRBCA (Beuchat & Mann, 2016).

7.2.5.2 Compositional analyses

7.2.5.2.1 Proximate analyses

The moisture, ash, fat, and crude fibre contents of the raw ingredients and finished products were determined following the standard procedures of 934.01, 923.03, and 996.06 AOAC (2006). Protein was measured using the Kjeldahl method, as specified by AOAC 955.04 (AOAC, 2006).

Carbohydrate (CHO) content was determined by difference as described in AOAC (1990).

$$\text{Total (CHO)} = 100\% - \text{sum(moisture} + \text{protein} + \text{fat} + \text{fiber} + \text{ash) per 100g sample}$$

7.2.5.2.2. Energy

The energy content of each sample was determined based on the Atwater factor, and computed by multiplying the quantities of carbohydrates, fats, and proteins by their energy values: 9 kcal/g for fat and 4 kcal/g for both carbohydrates and proteins, as recommended by the FAO (2003).

7.2.5.2.3 Iron content

Iron content was determined by the 2,2 Bipyridyl colourimetric method. With modifications from the method described by Pujare *et al.* (2020), 5 ml of 2,2, Bipyridyl reagent was added to the sample, and allowed to sit at room temperature. Absorbance was estimated calorimetrically at 520 nm using the spectrophotometer, and the concentration of iron was calculated from a standard graph by extrapolation. The result was expressed on a dry weight basis in a mg/ 100 g sample.

7.2.5.2.4 Cyanide content

As described by Cumbana *et al.* (2007) and Njankouo *et al.* (2019), cyanide contents were determined in the raw cassava and the drum-dried product. The sample was placed in a sealed bottle containing a phosphate buffer (pH 6), enabling the cyanide to be released and absorbed by the picrate paper over 24 hours at 30 °C. The picrate paper was placed inside the bottle containing the phosphate buffer. The observed colour changes in the picrate paper indicated the presence of cyanide, and the absorbance was measured at 510 nm from a standard curve, cyanide content was calculated in ppm.

7.2.5.3 Physicochemical analyses

7.2.6.3.1 Colour analysis

The colour of the samples was evaluated using the Minolta Chroma meter on the L*C* h colour space. The chroma meter was calibrated with a standard white tile (L*= 97.63; a*= -0.48; b*= 2.12). The colour of the samples was recorded in L*, a*, and b* parameters, where L* denotes brightness, a* green to red (-a and +a), and b* blue to yellow (-b and +b), respectively. The total colour difference (ΔE) was calculated from the L*, a*, and b* values of the slurry and drum-dried product using the formula below

$$\Delta E = \sqrt{\Delta a^{*2} + \Delta b^{*2} + AL^{*2}} \quad (1)$$

7.2.6.3.2 Tapped bulk density

With slight modifications to the method described by Laryea *et al.* (2017), 10 g of the drum-dried product was placed in a 10 mL graduated cylinder and packed by gently tapping the cylinder on the laboratory bench. The final volume of the product was recorded in millilitres, and the bulk density was calculated using the formula below (Eqn 2). Samples were analysed in triplicates.

$$\text{Bulk density}\left(\frac{\text{g}}{\text{mL}}\right) = \frac{\text{Weight of sample}}{\text{Volume occupied by sample}} \qquad (2)$$

7.2.6.3.3 Swelling capacity

With slight modifications to the method described by Adepeju *et al.* (2024), the swelling capacity of the drum-dried product was determined by filling a 100 ml graduated cylinder with the sample up to the 10 ml mark. Distilled water was added up to the 50 ml mark, and the cylinder was sealed and mixed by turning it upside down. The suspension was then allowed to stand on the laboratory counter for 1 hour, and the swelling capacity was determined as a factor of the initial weight, using the formula below (Eqn 3). Samples were analysed in triplicates.

$$\text{Swelling capacity}\left(\frac{\text{mL}}{\text{g}}\right) = \frac{\text{volume occupied by sample}}{\text{Initial weight of sample}} \qquad (3)$$

7.2.6.3.4 Water absorption capacity

One (1) g of drum-dried sample was weighed into a graduated centrifuge, and 10 mL of distilled water was added. The mixture was shaken for 5 minutes to ensure dispersion and centrifuged for 30 minutes at 3500 rpm. The volume of the supernatant was decanted and measured, and the weight of the sediment and centrifuge was weighed. The water absorption capacity (WAC) of the product was calculated using equation (4) (Laryea *et al.,* 2017). Samples were analysed in triplicates.

$$\text{WAC} = \frac{\text{Weight of sample after centrifuge} - \text{Intital weight of sample}}{\text{weight of sample}} * 100 \qquad (4)$$

7.2.6 Consumer acceptability test

7.2.6.1 Panel recruitment

A consumer test was used to assess the acceptability of the product developed using untrained panellists from the Staff Village Basic School in Legon. Before conducting the sensory assessment, with permission from the school authorities (Appendix III), pupils were given parental consent and recruitment forms (Appendix III). Only pupils whose consent forms had been approved by their parents or guardians on the assessment day participated in the sensory assessment.

7.2.6.2 Assessment

A total of 89 participants took part in the test because those were the participants who had consent from their parents/ guardians. They were adolescents between the ages of 12-18. They received orientation on the test setup and instructions for assessing the samples. Assessors were asked to observe the samples provided, smell it, take a sip and swirl around their mouths. Water was also provided to rinse their palates when needed. Ratings were used to assess appearance (color), aroma (smell), flavour, mouthfeel (sweetness, smoothness), and aftertaste (sensation of the product after swallowing) using a 9-point hedonic scale with words shown in Table 7.3 and a simple questionnaire (Appendix III).

Table 7.3: 9-point hedonic scale with words and numbers

Scale	***Expression***
1	Dislike extremely
2	Dislike very much
3	Dislike moderately

4	Dislike slightly
5	Neither like nor dislike
6	Like slightly
7	Like moderately
8	Like very much
9	Like extremely

For each 10 g sample, 40 mL of water, liquid milk, and sugar solution were added (10 g drum-dried product + 25 mL water + 13 mL milk + 2 g sugar), and mixed evenly with the solid flour sample. Each participant was served 50 mL of sample in 80 cc disposable cups. The assessment results were collated for analyses and discussions.

7.2.7 Cost analyses

The predicted cost was compared to the actual market cost at the time of conducting the study. The samples purchased were weighed, and their cost was determined as an equivalent amount optimised per 100 g formulation. With modifications from Chichernea, (n.d.), percentage difference and cost deviation ratios were calculated following the formulas (equations 5 and 6, respectively) shown below.

$$\text{Percent deviation} = \left(\frac{\text{Actual Cost} - \text{Optimised Cost}}{\text{Optimised Cost}}\right) * 100 \qquad (5)$$

$$\text{Cost deviation ratio} = \frac{\text{Actual cost}}{\text{Optimised cost}} \qquad (6)$$

7.2.8 Statistical analysis

Microsoft Excel (version 2408) was used to analyse the data obtained, expressing the data as means and standard deviations. One-way analysis of variance (ANOVA) and Tukey's test was used to ascertain any statistical difference at an alpha value of 5%. Results from the microbial analysis were represented as mean log CFU/g ± standard deviation. The spider web was used to show the results of the sensory analyses conducted. A one-sample t-test was used to compare the optimised nutrient values to the analysed values. All nutrient and microbial analyses were conducted in duplicates, whereas the functional and physical properties were conducted in triplicates.

7.3 RESULTS AND DISCUSSION

7.3.1 Formulation

The formulation obtained from the optimisation processing using one-third of the RDA of the critical nutrients for the selected target group resulted in the inclusion of coconut, Bambara beans, millet, and cassava in ratios of 14.22: 32.70: 24.44: and 27.64, respectively.

The selection of cassava, Bambara beans, millet, and coconut served as a complement to achieving the defined targets for energy, protein, carbohydrate, and iron. Cassava and millet are staple foods in Ghana that offer complementary nutritional benefits when they are consumed with other foods to achieve a more balanced nutrient profile (Baffour-Ata *et al.*, 2021; Kodwo *et al.,* 2023). The selection of Bambara beans in the formulation is mainly due to the inclusion of the protein parameter. Cassava and millet are food items that serve as high-energy sources, Bambara bean legumes are high in energy and serve as key protein sources for most diets. Hillocks *et al.* (2012) classified Bambara beans as foods with highly balanced protein and micronutrients.

The FAO/WHO (2001) indicated that most staples lack some essential micronutrients, hence necessary to be complemented by micronutrient-rich foods. The high protein content of legumes is a promising trait that makes them ideal candidates for product reformulation with foods that are generally lower in protein (Binou *et al.,* 2020; Amoah *et al.,* 2023).

The nutritional composition of the tuber-legume-cereal-fruit blend product suggests that it is well-balanced and has the potential to contribute to the dietary needs of adolescents (Table 7.4). With a moisture content of 1.65%, high energy value, and significant protein and iron levels, the product can be suitable as a complementary food to support adolescent growth and development. The product could also be valuable in school feeding programs or as a supplementary food to enhance the overall nutritional status of adolescents, particularly in areas with limited access to diverse diets.

7.3.2 Compositional analysis

Table 7.4 presents the results for macronutrients (carbohydrate, protein) energy, iron, and cyanide for the raw and formulated sample. Carbohydrate content ranged from 8.12 ± 0.11 g/100 g in coconut to 77.94 ± 0.45 g/100 g in millet, with the final product containing 73.75 ± 0.07 g/100 g. Protein content was highest in Bambara beans (17.14 ± 0.08 g/100 g) and lowest in cassava (1.70 ± 0.03 g/100 g). The final product had a protein content of 11.64 ± 0.01 g/100 g.

Energy values ranged from 173.82 ± 0.63 kcal/100 g in cassava to 434.21 ± 0.35 kcal/100 g in the final product, with millet also providing a high energy value of 366.00 ± 0.70 kcal/100 g. Iron content was highest in millet (8.78 ± 0.22 mg/100 g), while cassava had a cyanide content of 17.64 ± 0.20 mg/kg. The final product contained 3.47 ± 0.02 mg/100 g of iron and 0.63 ± 0.04 mg/kg of cyanide. The reduction of the cyanide content in the final product after processing was significant ($p < 0.05$).

Table 7.4: Compositional analysis of raw ingredients and the final drum-dried product

Sample	Proximate						Energy	Mineral	Chemical
	Moisture	CHO (g/ 100 g)	Protein (g/100 g)	Crude fibre (g/ 100g)	Ash (g /100g)	Fat	Energy (kcal/ 100g)	Iron (mg/ 100g)	Cyanide (mg/ kg)
Coconut	$37.82^{b} \pm 0.23$	$8.12^{e} \pm 0.11$	$8.23^{c} \pm 0.05$	$3.38^{a} \pm 0.33$	3.02b ± 0.13	$39.45^{a} \pm 0.10$	$420.41^{b} \pm 0.67$	$4.63^{b} \pm 0.06$	-
Bambara beans	$10.58^{c} \pm 0.06$	$61.69^{c} \pm 0.08$	$17.14^{a} \pm 0.08$	$1.39^{bc} \pm 0.05$	6.33a ± 0.11	$2.89^{d} \pm 0.01$	$341.25^{d} \pm 0.06$	$0.66^{d} \pm 0.05$	-
Millet	$10.75^{c} \pm 0.24$	$77.94^{a} \pm 0.45$	$3.68^{d} \pm 0.06$	$1.92^{b} \pm 0.05$	1.33d ± 0.06	$4.40^{c} \pm 0.25$	$366.00^{c} \pm 0.70$	$8.78^{a} \pm 0.22$	-
Cassava	$55.50^{a} \pm 0.08$	$40.44^{d} \pm 0.11$	$1.70^{e} \pm 0.03$	$0.91^{cd} \pm 0.06$	0.88e ± 0.01	$0.59^{e} \pm 0.01$	$173.82^{e} \pm 0.63$	$0.55^{d} \pm 0.02$	$17.64^{a} \pm 0.20$
Drum-dried product	$1.65^{d} \pm 0.02$	$73.75^{b} \pm 0.07$	$11.64^{b} \pm 0.01$	$0.63^{d} \pm 0.04$	$2.05^{c} \pm 0.01$	$10.30^{b} \pm 0.06$	$434.21^{a} \pm 0.35$	$3.47^{c} \pm 0.02$	$0.63^{b} \pm 0.04$

Values are presented in mean ± SD. The means that have the same superscript in the same columns are not statistically significant ($p > 0.05$).

The moisture content of 1.65% is relatively low, which is advantageous for the shelf stability of the product. Low moisture levels inhibit the growth of microorganisms and reduce enzymatic activities, thereby extending the product's shelf life (Fellows, 2022).

With a carbohydrate content of 73.75 ± 0.07% and an energy value of 434.21 ± 0.35 kcal, the product can provide a significant energy source, vital for adolescents with high energy demands due to rapid growth and active lifestyles.

The interface prediction accuracy for energy, carbohydrates and protein were lower, and that of iron was higher, and significantly different statistically ($p < 0.001$) (Table 7.5). The ad hoc analysis comparing the optimised and analysed nutrient values showed significant. The analysed energy and carbohydrate values were substantially higher (~44.7% and ~63.9%, respectively) than the optimised targets, suggesting potential inefficiencies in the formulation process or variability in ingredient composition. Protein levels were also higher (~16.4%), though the difference was less pronounced. Conversely, iron content was ~19.1% lower than the optimised value, indicating a possible shortfall in meeting nutritional targets for this micronutrient. These discrepancies highlight the challenges of translating theoretical optimisation into practical outcomes, possibly due to factors such as ingredient variability, or processing effects. Verdouw et al. (2016) indicated that although optimisation optimisation models allow for better decision-making based on real-time data, they may not fully account for the complexity and unpredictability of read-world scenarios. Additionally, these differences could be mainly due to seasonality, which can be seen in the lower values of the ingredients in the database used for the optimisation compared to the analysed nutrient values of the ingredients purchased for the product development (Appendix II). Furthermore, the unit operations used in processing the ingredients could have also contributed to the difference in the nutrient values between the optimised and the actual nutrient values obtained after analysis. For example, the juice extraction process used in processing the coconut could have resulted in some energy and carbohydrates being removed with the chaff.

The cyanide content in cassava is a critical factor when considering its use in food products due to the potential toxicity of cyanogenic compounds, which can lead to health issues if not adequately processed. In this case, the raw cassava had a mean cyanide content of 17.64 ± 0.20 mg/kg, which is significantly high, especially since it can pose risks of cyanide poisoning when consumed in large quantities or frequently. Cassava naturally contains cyanogenic glycosides, which can release hydrogen cyanide upon enzymatic breakdown (Nambisan, 2011). Therefore, processing methods are essential in reducing cyanide levels in cassava-based foods (Brimer, 2015).

The reduction in cyanide content to 0.63 mg/kg ± 0.04 in the final product shows a reduction above 90% in the final product. The WHO indicated that cyanide levels up to 10 ppm or 1 mg/kg in food is acceptable and is not associated with acute toxicity (Odoemelam *et al.,* 2020). Additionally, the combination of unit operations such as peeling, washing, and drying (thermal), contributed significantly to the reduction in the cyanide concentration observed.

The nutrient values from the optimised formulation were compared to the values analysed in the drum-dried product (Figure 7.3), and the percentage predictions were tabulated in Table 7.5. The *NourishCraft* interface predicted 69.09% of the actual energy content, 61.02% of carbohydrates, 85.91% of protein, and 123.63% of iron.

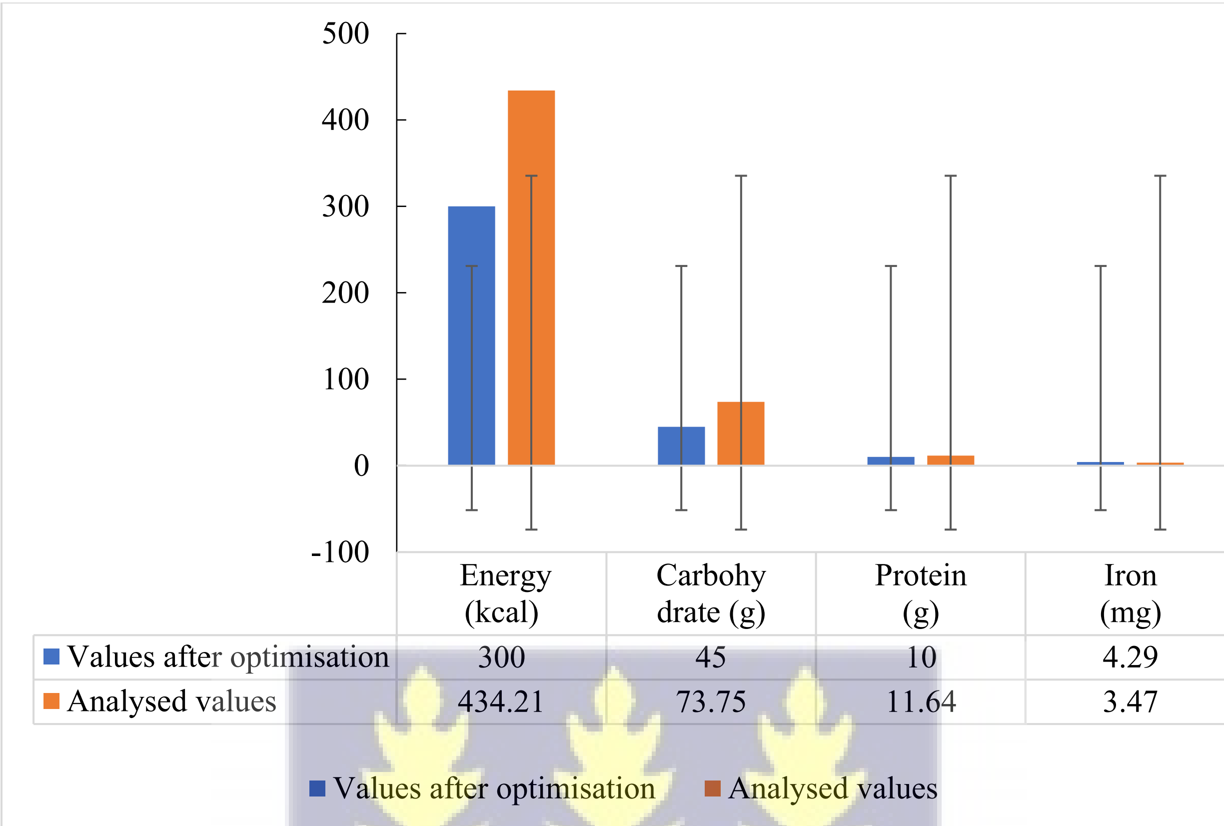

Figure 7.3: Nutrient values obtained from optimisation against actual values *analysed* after product development, on a per g/ 100 g basis.

Table 7.5: Comparison of optimised nutrient values with actual *analysed* values and percent predictions

Nutrients	Values obtained after optimisation	Actual values analysed	Model Prediction (%)	t- Statistics	p-Value
Energy (kcal/ 100 g)	300	434.21 ± 0.35	69.09	536.88	<0.001

Carbohydrate (g/ 100g)	45	73.75 ± 0.07	61.02	575.00	<0.001
Protein (g/ 100g)	10.00	11.64 ± 0.01	85.91	234.29	<0.001
Iron (mg/ 100 g)	4.29	3.47 ± 0.02	123.63	-58.57	<0.001

% prediction was calculated as a ratio of the optimised vs the actual, expressed as a %

7.3.3 Functional properties

The bulk density of the drum-dried sample was 0.38 ± 0.03 g/mL, which indicates a porous structure. When drum-drying, the food material is applied to the dryer in a thin film, and this undergoes rapid evaporation of moisture and the formation of air pockets as the food material dries (Joardder *et al.,* 2015). The swelling capacity was determined to be 10.28 ± 0.36 mL/g, which shows the sample's ability to increase in volume to water, that is, one gram of sample can absorb water and swell to about 10.28 mL in volume, taking up more space than its original volume. The water absorption capacity was 693.50 ± 38.10 % (Table 7.6), signifying a high potential for water retention.

Table 7.6: Functional properties of the drum-dried product

Parameter	Value
Bulk density (g/mL)	0.38 ± 0.03
Swelling capacity (mL/g)	10.28 ± 0.36
Water absorption capacity (%)	693.50 ± 38.10

The bulk density of 0.38 ± 0.03 g/mL observed in the drum-dried product was lower than the values reported by Igbabul *et al.* (2013) (0.69 – 0.71 g/cm^3) Otondi *et al.* (2020) (0.45 – g/cm^3 – 0.63 g/cm^3), and Adepeju *et al.* (2024) (0.39 – 0.45 g/cm^3). Although the studies conducted by Igbabul *et al.* (2013), Otondi *et al.* (2020), and Adepeju *et al. (*2024) did not use the same ingredients as used in the current study, their studies considered about one or two of the ingredients used in this study. The differences in the results from the different studies could mainly be due to the different formulations. Fast (1990) indicated that bulk density shows the transformation of food ingredients, from a denser to a lighter state. Low bulk density is often desired in instant foods as it allows for quicker rehydration and easy mixing (Adebowale *et al.,* 2005) and can affect mouthfeel and consumer perception (Akubor & Badifu, 2004).

The swelling capacity of 10.28 ± 0.36 mL/g indicates the ability of the flour particles to absorb moisture and increase in volume. High swelling capacity can be advantageous in instant products as it can provide a desirable texture and increase consistency when water is added (Adebowale *et al.,* 2012). Swelling capacity is influenced by the structure of starch granules, protein, and fiber content, and these factors contribute to the water-binding ability of a food material (Ikegwu *et al.*, 2009). The high-water absorption capacity and swelling capacities observed in the drum-dried sample could be due to weaker bonding forces in their granules (Eriksson *et al.,* 2014; Tharise *et al.,* 2014). Eriksson *et al.* (2014) also indicated high swelling and water absorption capacities for processed cassava flour.

The low bulk density, high swelling capacity, and excellent water absorption suggest that the final blend will offer convenience and sensory appeal, making it suitable for quick preparation applications.

7.3.4 Colour

The slurry showed an L* value of 94.81 ± 0.00, indicating high lightness, while the drum-dried sample had an average L* value of 72.81 ± 0.48, suggesting a darker appearance after drum drying. The ΔE value between the slurry and the drum-dried sample was 24.84, highlighting a difference in the two analysed samples due to processing. The slurry was lighter, whereas the drum-dried product was darker with an increased yellowness.

The slurry appeared lighter, whereas the drum-dried product was darker with increased yellowness. These changes can be attributed to Maillard reactions and caramelisation during drum drying, which are non-enzymatic browning processes that occur at high temperatures and result in the formation of brown pigments (Martins et al., 2000). Additionally, the loss of moisture during drum drying can concentrate pigments and alter light reflectance, contributing to the darker appearance (Fellows, 2017). The increased yellowness may also result from the degradation of heat-sensitive compounds, such as carotenoids (from the Bambara beans), which can undergo oxidation or isomerisation during thermal processing (Rodriguez-Amaya, 2016). These findings align with highlights made by Pathare et al. (2013) who indicated the significant impact of thermal processing on the color of food products, often leading to darker and more yellowish hues due to chemical and physical transformations (Pathare *et al.*, 2013). Understanding these changes is crucial for optimizing processing conditions to achieve desired product characteristics while minimising undesirable color alterations.

Table 7.7: Colour attributes of slurry and the drum-dried samples

Sample	L*	a*	b*	ΔE
Slurry	$94.81^{a} \pm 0.00$	$-0.13^{a} \pm 0.00$	$3.17^{b} \pm 0.00$	-
Final product	$72.81^{b} \pm 0.48$	$-0.80^{b} \pm 0.12$	$14.68^{a} \pm 0.11$	24.84

Values are presented are mean ± SD. The means with the same superscript in the same columns are not statistically significant ($p > 0.05$).

In food products, colour is a critical attribute influencing consumer acceptance and preference (Neves *et al.*, 2021). The lower L* value of the drum-dried composite indicated a significantly darker appearance compared to the slurry, likely due to the blending of the differently coloured ingredients and the thermal drying processing, resulting in a more toned brown and heterogeneous appearance compared to the individual components. This can be seen in the decrease in the L* value of the slurry after drum-drying (Table 7.7).

Also, the increase in the b* value of the slurry and drum-dried product reflected a more intense yellow colouration after processing, this yellow colouration is evident in the product (Figure 7.3). The elevated yellow colouration can be attributed to the combination of pigments from the millet, cassava, and Bambara beans. This colouration is evident in the ΔE (24.84) value obtained, subsequently influencing consumer perception.

The high ΔE value in the composite indicates a significant change between the slurry and the final drum-dried product which is more yellowish. The darkening could have been due to the formation of brown compounds through Maillard reactions during the drying process (Soison *et al.,* 2014). The Maillard reaction is a chemical reaction between amino acids and reducing sugars and contributes to the development of a darker hue in cooked food (Bhatt & Jyothi Lakshmi, 2022). Although this variation may affect consumer appeal, the product can be positioned as a distinct option with a unique nutritional profile, turning its difference into a potential market advantage.

7.3.5 Microbial analyses

The microbial analysis of the drum-dried product showed varying levels of colony-forming units (CFU) across different media. The aerobic plate count was observed to be 6.35 * 10^4 (log 4.81) CFU/ mL, and that of yeast and mould was 2.00*10^1 (log 1.30) CFU/ mL. However, VRBGA and MacConkey agar showed no detectable microbial growth for Enterobacteriaceae and total coliforms, respectively (Table 7.8).

Table 7.8: Microbial quality of the drum-dried product

Aerobic plate count	Enterobacteriaceae	Total Coliforms	Yeast and mould
4.81 ± 0.01	ND	ND	1.30 ± 0.00

The low aerobic microbial contamination and yeast and mould levels across the tested microorganisms were within the recommended safe limit of 10^4 to 10^6 CFU/g, and 10^3 CFU/g respectively, as recommended by the Ghana Standards Authority (GSA) (2020) for processed flour products. The absence of growth on VRBG and MacConkey agar further demonstrates the effectiveness of the unit operations in controlling coliform bacteria, and Enterobacteriaceae contamination. This is particularly significant, as coliforms and Enterobacteriaceae are considered hygiene indicators in food products (Jay *et al.*, 2008). The absence of these microorganisms suggests that the raw materials were of good microbiological quality and that hygienic processing conditions were maintained throughout production. Furthermore, the results are consistent with the findings of Rahman *et al.* (2016) and Forsido *et al.* (2021), who reported similarly low microbial counts in thermally processed composite flour.

Additionally, drum drying applies high temperatures over a short duration, which could potentially reduce the microbial load of a product by lowering the moisture content (Ekpa *et al.,* 2019; Alp & Bulantekin, 2021; Courtois, 2024) which is known to inactivate most vegetative bacteria and yeast cells, thus enhancing the product's microbiological safety.

These results suggest that the product meets the food safety standards for microbial quality, although if not handled well there could be the risk of post-processing contamination. The absence of Enterobacteriaceae and coliform growth on MacConkey and VRBG further supports the drum-drying process's effectiveness in maintaining the product's microbiological safety.

7.3.6 Acceptability assessment

From Figure 7.4, the mean acceptability attribute scores showed that aroma received the highest score with an average value of 8.09 ± 1.19, indicating that it was the most appreciated attribute among the tested attribute qualities. The flavour attribute followed with a score of 8.02 ± 1.39, mouthfeel scored 7.83 ± 1.22, aftertaste scored 7.76 ± 1.55, appearance scored 7.57 ± 1.45, and overall acceptability was scored 7.82 ± 1.21, reflecting a balanced and acceptable profile in the sensory attributes assessed.

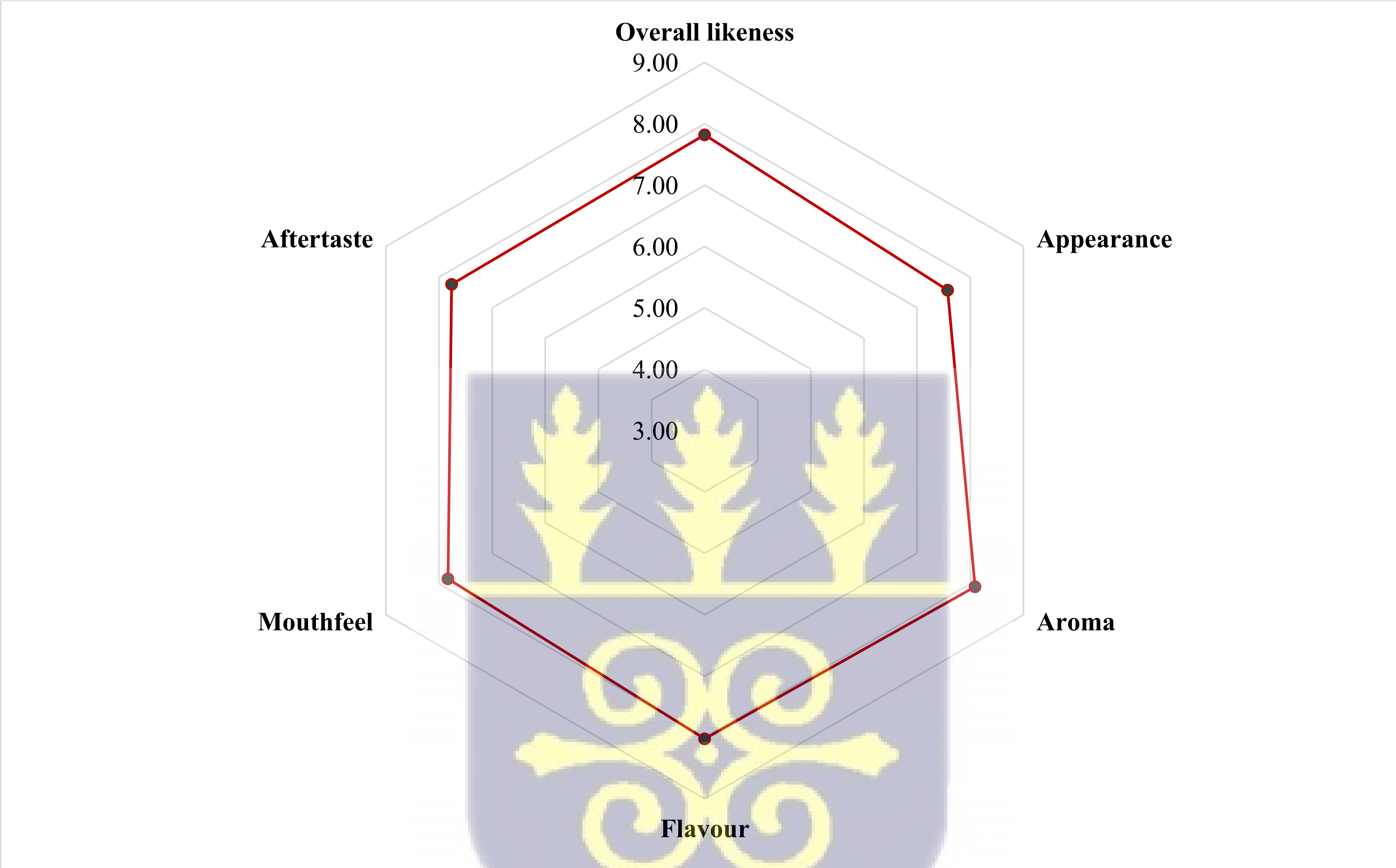

Figure 7.4: Sensory scoring of the drum-dried product

Lawless and Heymann (2010) indicated that a sensory score of ≥ 7.0 for a 9-point hedonic scale indicates good acceptability and are considered a pass for consumer products.

Hein *et al.* (2008) indicated that acceptance and preference of sensory properties of foods are among the most important criteria for determining food choice. The sensory evaluation of the drum-dried product made from cassava, Bambara beans, millet, and coconut showed positive acceptability because all the attributes tested scored above 7 on the 9-point hedonic scale. The positive response in the sensory results suggests that it could be a viable option for enhancing food security and nutrition in various contexts.

7.3.7 Cost estimate analysis

Table 7.9 compares the optimised cost of the formulated ingredients with the actual market prices. The percentage cost difference revealed that Coconut had the highest cost increase (133.33%), followed by Bambara Beans (80.43%), Millet (57.69%), and Cassava (11.11%). The cost deviation ratio showed that actual costs were significantly higher than optimised costs, with Coconut having the highest deviation (2.33 times the optimised cost).

Table 7.9: Comparison of optimised cost with actual purchased cost and percent predictions

Ingredient	Optimised cost (GHS)	Actual cost (GHS)	% difference	Cost deviation ratio	Rank (highest increase)
Coconut	0.06	0.14	133.35%	2.33	1 (highest increase)
Bambara beans	0.46	0.83	80.43%	1.80	2
Millet	0.26	0.41	57.69%	1.58	3
Cassava	0.09	0.10	11.11%	1.11	4 (lowest increase)

The cost of the ingredients in the database used for the optimisation has the inflation rates adjusted to February 2024. Actual values of ingredients were calculated by using a simple ratio after weighing the total samples obtained.

Although the output from the interface aligns reasonably well with the current market price for cassava, the discrepancies in the output for coconut and Bambara beans especially, reflect the dynamic nature of food prices and the complexities of market conditions. One significant factor contributing to the observed differences is the impact of inflation on food prices. Hendrix & Haggard (2015) indicated how global food prices have risen significantly since the 2000s.

The prices of foods are particularly sensitive to inflationary pressures, which can cause substantial fluctuations over short periods. For instance, in recent years, inflation rates in many developing countries, including Ghana, have been relatively high, leading to increased food prices and reduced household purchasing power. Olusola *et al.* (2022) indicated that inflation is a macroeconomic problem that Ghana is currently dealing with, and it is the most concerning economic situation.

Allen & Prosperi (2016) further highlighted that other causes of inflation could be climate change, changes in dietary patterns, shifting trade patterns, and increasing demand for biofuels.

The observed difference between the optimised cost (0.06) and the actual cost (0.14) of coconut for example, may reflect the influence of recent price surges due to inflation, which the model did not fully capture since it was based on historical price data.

7.4 CONCLUSION

In conclusion, it was possible to formulate a nutritious product that met nutrient requirements for energy, protein, carbohydrates, and iron for adolescents aged 10 to 18 years old with the aid of the *NourishCraft* GUI. The interface formulation included Bambara beans, cassava, coconut, and millet at a minimum cost of GHS 0.67 per 100 g.

The product had unique functional properties with a bulk density of 0.38 ± 0.03, swelling capacity of 10.28 ± 0.36, and water absorption capacity of 693.50 ±38.10%. The drum-drying process resulted in a colour change, reducing the lightness of the product and increasing the yellowish component.

Furthermore, the thermal processing applied effectively reduced the microbial load, ensuring safety and quality.

Consumer acceptance evaluated using a 9-point hedonic scale indicated acceptance of the product, with an overall likeness score of 7.82 ± 1.45, suggesting its potential market viability.

The interface's predictions for key nutritional components—carbohydrates, protein, and energy—were lower than the actual *analysed* values. However, the *NourishCraft* GUI proved its potential to aid in formulating a nutritious product at a minimum cost. Nevertheless, inflation rates and price fluctuations must be considered in real-world scenarios. While the tool shows promise for cost savings in product development, integrating economic factors is essential to maximise its effectiveness and reliability in diverse market conditions.

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CHAPTER EIGHT

8.0 GENERAL CONCLUSION AND RECOMMENDATIONS

8.1 CONCLUSIONS

The study showed how mathematical modelling can help solve complex dietary challenges. Using advanced techniques, specifically, linear programming and bi-objective optimisation, the study developed nutritionally adequate, culturally acceptable, affordable, and environmentally sustainable diets for diverse demographic groups. Furthermore, using programming languages such as Python and their libraries for human-computer interactive (HCI) interfaces enabled the development of an interface to facilitate the creation of sustainable food products.

Linear programming was used successfully to design food baskets meeting nutrient and cultural requirements for both adolescent males and females. Linear programming proved to be a useful method for designing balanced and cost-effective diets for teenage boys and girls, and least GHGE diets for women at the physiological stages of pregnancy and lactation. While there are no inherent limitations to this optimisation approach, it is important to factor in the typical foods consumed by a particular group, as well as any restrictions on the quantity of food from each food group to ensure acceptability.

Similarly, it is crucial to propose affordable dietary options for various demographic groups while considering the environment. The results obtained for food baskets with minimal environmental impact (GHGE) showed the possibility of using linear programming to propose diets that have minimum carbon footprints.

More importantly, considering the complexity of sustainable diets defined within the context of the study, it became important to tie in these four dimensions (affordability, nutrition, acceptability, and the environment) to establish the relationship and any possible trade-offs or synergies. Results from applying the multi-objective modelling approach, specifically, the epsilon constraint method established a negative correlation between cost and the environment, subject to nutrient, and acceptability requirements.

Using the Python libraries and Streamlit app, it was possible to develop a simple interactive interface to aid sustainable product formulation. The interface offered simple interactive elements to ease product formulation and present results with tables and charts that are downloadable by the users.

The interface was validated by using it to formulate a sustainable product for adolescents, based on one-third of their recommended dietary allowance. It was possible to obtain a formulation at a minimum cost, with a prediction accuracy ranging from 40 to 90% for cost, and predictions of 61.02 – 123.63% for the nutrients defined. The formulation was made up of coconut, millet, Bambara beans, and cassava, in ratios of 14.22: 24.44, 32.70: and 27.64, on a per 100 g basis, respectively. A drum-dried composite was produced from the formulation. Overall acceptability was scored above average, indicating acceptance of the product made from the formulation

8.2 RECOMMENDATIONS FOR FUTURE WORK

8.2.1 Policy

1. It is necessary to take a stakeholder approach to educate consumers about the benefits of transitioning to sustainable diets. This can be done through social media community workshops and educational materials. Policymakers, researchers, and health institutions need to collaborate to effectively communicate the importance of sustainable diets, the reasons for it, and their advantages and disadvantages to the public. For example, the Ministries of Health and Education can incorporate the findings from the study in the on-

going school feeding program. Furthermore, government and other stakeholders need to empower healthcare workers to advocate for the proposed dietary patterns among pregnant and lactating women. Additionally, a user interface developed to assist in sustainable product formulation can be implemented in selected industries, monitored, and continually improved to reach a wider audience.

2. The findings from the study can be fused into our recently released food-based dietary guidelines, and it will be a good step towards improved nutrition for the defined population groups. Furthermore, educating consumers on their dietary habits and raising awareness about the benefits of a plant-based diet that is mindful of the environment is essential.
3. Furthermore, the findings can be translated into school feeding programs to ensure that the nutritional needs of school-going children are met. While the results obtained were based on mathematical simulations and may not precisely reflect real-world situations, it is still essential to explore their potential implementation to promote the adoption of sustainable diets.

8.2.2. Research

1. Other methods such as the weighted sum approach can also be used for a multi-objective comparison to assess their compatibility with the findings from the epsilon approach used in this study.
2. Additionally, the user interface developed to assist in sustainable product formulation can be implemented in selected industries, monitored, and continually improved to reach a wider audience. The developed interface can be further explored by integrating big data analytics, which can provide deep insights and improve operational efficiencies. This

innovative approach should be tested in collaboration with food industries to further validate its effectiveness and scalability in real-world applications.

3. Further work can be conducted to factor in the inflation rate to allow real-time access to the cost of the ingredients in the database.

APPENDICES

APPENDIX I

Appendix I. 1: Nutrient values for each Pareto optimal set point after optimisation for adult males aged 19 to 50.

Nutrient	Units	Recommended	Optimised values		
			Point 1	Point 2	Point 3
Energy	kcal	2500-3000	2500.00	2622.39	2500.00
Protein	g	≥56	64.27	70.17	75.67
Fat	g	ND	108.30	121.07	114.85
n-3PUFAs	g	≥1.6	1.60	1.60	1.60
n-6PUFAs	g	≥17	17.00	17.00	17.00
Cholesterol	mg	≤300	141.98	300.00	300.00
Carbohydrate	g	≥130	321.81	319.91	296.51
Fibre	g	≥38	42.25	56.77	60.29
Sodium	mg	1500-2300	2300.00	2300.00	2300.00
Potassium	mg	≥3400	5091.12	5549.69	6080.12
Clacium	mg	1000-2500	1000.00	1000.00	1000.00
Magnesium	mg	≥420	987.46	1083.25	1090.03
Iron	mg	8-40	29.53	29.26	27.23
Zinc	mg	11-40	13.46	15.10	14.53
Copper	mg	0.9-10	4.27	4.73	4.42
Selenium	µg	55-400	83.56	103.16	118.96

Phosphorus	mg	700-4000	1529.90	1587.66	1677.20
Iodine	µg	150-1100	150.00	166.45	160.43
Vitamin A-RAE	µg	900-3000	907.93	1213.17	1329.68
Thiamine	mg	≥1.2	2.11	2.51	2.31
Riboflavin	mg	≥1.3	1.30	1.30	1.30
Vitamin B6	mg	1.3-100	2.12	2.54	2.80
Vitamin B12	µg	≥2.4	4.90	5.13	3.13
Vitamin C	mg	90-2000	336.96	360.83	323.40
Vitamin E	mg	15-1000	18.42	16.82	16.72
Folate	µg	400-1000	400.00	553.99	576.68
Niacin	mg	16-35	16.00	25.15	35.00

Appendix I. 2: Nutrient values for each Pareto optimal set point after optimisation for adult females aged 19 to 50 years.

			Optimised values		
Nutrient	**Units**	**Recommended**	**Point 1**	**Point 2**	**Point 3**
Energy	kcal	1800-2400	2355.49	2400.00	2024.23
Protein	g	≥46	55.21	66.05	72.42
Fat	g	ND	113.78	103.01	65.96
n-3PUFAs	g	≥1.1	1.50	1.10	1.10
n-6PUFAs	g	≥12	12.00	12.00	12.00
Cholesterol	mg	≤300	300.00	300.00	300.00
Carbohydrate	g	≥130	284.44	310.37	292.44
Fibre	g	≥25	47.39	56.92	61.56
Sodium	mg	1500-2300	2300.00	2300.00	2300.00
Potassium	mg	≥2600	4641.67	5561.32	5978.66
Clacium	mg	1000-2500	1000.00	1000.00	1000.00
Magnesium	mg	≥320	844.46	942.64	832.84
Iron	mg	18-45	27.07	26.91	22.31
Zinc	mg	8-40	13.10	13.94	12.52
Copper	mg	0.9-10	4.09	4.04	2.94
Selenium	µg	55-400	72.07	100.83	121.08
Phosphorus	mg	700-4000	1347.14	1437.93	1496.26
Iodine	µg	150-1100	150.00	168.29	160.14
Vitamin A-RAE	µg	700-3000	1013.18	1196.47	1306.30

Thiamine	mg	≥1.2	2.21	2.42	2.27
Riboflavin	mg	≥1.1	1.30	1.23	1.16
Vitamin B6	mg	1.3-100	2.19	2.52	2.55
Vitamin B12	µg	≥2.4	9.03	4.22	3.05
Vitamin C	mg	75-2000	337.32	364.13	364.39
Vitamin E	mg	15-1000	15.00	16.89	16.81
Folate	µg	400-1000	441.68	556.16	613.50
Niacin	mg	14-35	14.00	25.28	35.00

Appendix I.3: Optimised ingredients with their respective amounts, cost, and GHGE values for the 3 Pareto optimal set obtained for adult males aged 19 to 50.

Point 1				Point 2				Point 3			
Ingredients	**Amount (g)**	**Cost (GHS)**	**GHGE**	**Ingredients**	**Amount (g)**	**Cost (GHS)**	**GHGE**	**Ingredients**	**Amount (g)**	**Cost (GHS)**	**GHGE**
Smoked Herrings	26.46	1.02	0.04	Fresh salmon (Mackerel) fish	21.76	0.68	0.13	Fresh *kpanla* (Barracuda)	27.22	0.71	0.16
Fresh *kpanla* (Barracuda)	17.24	0.45	0.10	Fresh *kpanla* (Barracuda)	37.26	0.97	0.21	Egg	55.70	1.39	0.26
snail	82.14	4.39	0.18	Egg	56.79	1.41	0.26	Smoked tuna	53.72	1.06	0.59
Egg	14.29	0.36	0.07	Smoked tuna	20.53	0.40	0.23	Sunflower oil	2.41	0.09	0.01
Groundnut Oil	0.52	0.01	0.00	Sunflower oil	9.04	0.35	0.03	Vegetable oil	6.64	0.13	0.02
Vegetable oil	5.68	0.11	0.02	Oranges	225.99	0.88	0.03	Oranges	142.80	0.56	0.02
Oranges	232.26	0.90	0.03	melon seeds	32.94	0.68	0.13	avocado	83.68	0.48	0.08
Groundnut	16.45	0.35	0.05	Oil palm nut	163.98	1.25	0.13	Soya Bean	49.18	0.46	0.15
Bambara Bean	33.78	0.48	0.03	Iodised salt	2.81	0.02	0.00	melon seeds	34.23	0.71	0.14

Sesame seeds	40.14	4.82	0.06	Ginger	38.93	0.46	0.02	Oil palm nut	127.97	0.97	0.10
Oil palm nut	126.41	0.96	0.10	White maize	20.77	0.13	0.02	Salt, iodised	2.98	0.02	0.00
Salt, iodised	2.52	0.02	0.00	Cassava	574.49	1.90	0.08	Ginger	38.84	0.46	0.02
Yogurt	40.37	1.36	0.09	Dried pepper	20.00	0.70	0.03	Cassava	582.50	1.92	0.08
Cassava	604.38	1.99	0.08	Tomato	164.00	1.87	0.08	Dried pepper	20.00	0.70	0.03
ademe/ayoyo (jute mallow)	45.77	0.34	0.02	Dried okro	41.32	1.67	0.10	Tomato	164.00	1.87	0.08
Dried Pepper	20.00	0.70	0.03	Onion	76.00	1.10	0.02	Dried okro	41.97	1.70	0.10
Tomato	164.00	1.87	0.08					Onion	76.00	1.10	0.02
Onion	76.00	1.10	0.02								

Appendix I.4: Optimised ingredients with their respective amounts, cost and GHGE values for the 3 Pareto optimal set obtained for adult females aged 19 to 50.

Point 1				**Point 2**				**Point 3**			
Ingredients	Amount	Cost	GHGE value	Ingredients	Cost	GHGE value	Amount	Ingredients	Amount	Cost	GHGE value
Smoked Herrings	49.94	1.93	0.08	Fresh salmon (Mackerel)	0.27	0.05	8.84	Fresh *kpanla* (Barracuda)	23.69	0.62	0.14
Anchovy	3.97	0.12	0.02	Fresh *Kpanla* (Barracuda)	1.15	0.25	43.98	Egg	55.42	1.38	0.26
Fresh *kpanla* (Barracuda)	13.30	0.35	0.08	Egg	1.43	0.27	57.42	Smoked tuna	57.25	1.13	0.63
Snail	8.84	0.47	0.02	Smoked tuna	0.51	0.29	25.95	Sunflower oil	7.47	0.29	0.02
Egg	53.21	1.32	0.25	Sunflower oil	0.34	0.03	9.03	Oranges	226.01	0.88	0.03
Groundnut Oil	0.53	0.01	0.002	Oranges	0.88	0.03	225.75	Soya bean	123.51	1.16	0.37
Sunflower oil	5.18	0.20	0.02	Soya Bean	0.34	0.11	36.23	Oil palm nut	73.42	0.56	0.06

Oranges	257.09	1.00	0.03	Melon seeds	0.13	0.03	6.48	Iodised salt	3.18	0.02	0.0
Sesame seeds	19.45	2.33	0.03	Oil palm nut	1.17	0.12	153.99	Ginger	38.56	0.45	0.02
Oil palm nut	167.23	1.27	0.13	Iodised salt	0.02	0	2.93	Cassava	596.88	1.97	0.08
Iodised salt	1.92	0.01	0	Ginger	0.46	0.02	38.76	Dried pepper	20.00	0.70	0.03
Yogurt	37.65	1.27	0.09	Cassava	1.96	0.08	594.62	Tomato	164.00	1.87	0.08
Cassava	524.33	1.73	0.07	Dried pepper	0.70	0.03	20.00	Dried okro	41.35	1.67	0.10
Dried Pepper	20.00	0.70	0.03	Tomato	1.87	0.08	164.00	Onion	76.00	1.10	0.02
Tomato	164.00	1.87	0.08	Dried okro	1.66	0.10	41.00				
Dried okro	25.66	1.04	0.06	Onion	1.10	0.02	76.00				
Onion	76.00	1.10	0.02								

APPENDIX II

User experience assessment: Food formulation interface (google.com) **(**Link to the Google document used to assess the user interface).

Appendix II. Table 1.1: Indicators for user interface assessment and average scores

Assessment indicator	Average score	Standard deviation
I found the interface easy to navigate.	4.00	0.71
Instructions were clear and understandable	3.63	0.70
I had trouble using the interface	2.25	0.43
I found the feature in the UI useful	4.38	0.48
The interface can help formulate food products	4.50	0.50
The layout and design elements enhanced my experience	3.75	0.43
The interface responded quickly	4.50	0.50
The error messages were helpful	3.63	1.22
Are you satisfied with the interface?	4.13	0.60
Would you be willing to use this?	4.25	0.66

Indicators were scored on a scale of 1 to 5. 1 – strongly disagree, 2 – disagree, 3 – neither agree nor disagree, 4 – agree, and 5 – strongly agree.

APPENDIX III

Appendix III.1: Letter submitted to the Head of Staff Village Basic for the sensory test

NFS SENSORY LABORATORY

DEPARTMENT OF NUTRITION AND FOOD SCIENCE

P.O. BOX LG 134, LEGON, GHANA

EMAIL: sensory@ug.edu.gh TEL: 0240436872

11th October, 2024.

To the Principal / Headteacher

Staff Village Basic School

Legon.

Dear Sir/Madam,

INVITATION TO PARTICIPATE IN A FOOD TASTE TEST AS PART OF A RESEARCH STUDY

The Sensory Evaluation Laboratory under the Department of Nutrition and Food Science, University of Ghana is recruiting students between ages 12 – 18 years (i.e. J.H.S. 1 to 3) to participate in a taste test on an instant drum-dried breakfast tuber-legume-cereal product.

We would like to invite your school to participate in a research study scheduled from September **16th to September 18th, 2024.** Your students can take part on any one day of your choice within this period, at a time that suits you.

By accepting our invitation to participate in the study, we will recruit willing and eligible participants from your school and carry out the test on your school premises.

Interested students will be required to get approval from their parents by having their parents complete a questionnaire and assent form. Only students with approval from their parents will participate in the test. Participation by students is purely voluntary.

The taste test will involve the pupils tasting an instant breakfast cereal-legume product to assess how much they like or dislike it on an anchored scale. The pupils will be guided on how to use the scale. We consider that this will be an exciting learning experience for your pupils.

Participation in the study is completely voluntary for your school and the students. A small token will be given to the participating students for their time which will not be monetary or equivalent to paid work.

The project has been approved by the Ethics Committee for Basic and Applied Science, University of Ghana-Legon. For further details about the study and/or to accept to be part of the study please contact me by email sensory@ug.edu.gh or phone 0542122672.

Yours faithfully,

Cecille Wendy Aboagye

(Senior Technologist)

Appendix III.2: PARENTAL CONSENT FORM

Title: Improving sustainable and affordable nutrition using artificial intelligence (AI)

Supervisors:

Professor Firibu Saalia, Dr. Nicole S. Affrifah

Sensory Supervisor:

Dr. Maame Yaakwaah Blay Adjei

Investigator:

Leticia Donkor

Address:

Department of Nutrition and Food Science, School of Biological Sciences, College of Basic and Applied Science, University of Ghana, Legon, Accra.

General Information about Research

Your child has been invited to participate in a sensory evaluation involving an instant breakfast product. During the test, your child will be given one product to taste and assess how they like or dislike the product using a 9-point hedonic scale. Your child will be given guidance on how to proceed with the test and use the scale correctly. They will also be required to answer questions about their food consumption patterns as well as provide basic demographic information about themselves. The test is planned to take place at your child's school premises. Arrangements have been made with the school to ensure that this study does not unduly disrupt your child's normal class schedule.

This form is to obtain your assent for your child to participate in the study. Your child will be asked to give their consent to be part of the study. Your child may choose not to be part of the study even though you have agreed for them to participate, this is ok, and they will not be forced to participate. Also, your child will not be made to participate if you do not assent although they provide consent to be part of the study. These conditions are set to ensure that your child feels comfortable enough to participate in the study. Permission has been sought from the school authorities to conduct the test.

Possible Risks and Discomforts

In general, food taste tests are non-invasive and should not be a source of risk to your child's health or person. Unless your child is allergic to cassava, bamabara beans, millet, coconut or milk products for which they will not be included in the study, then the test does not pose a risk to your child's health.

Possible Benefits

By participating in this food taste test, your child will be contributing immensely to the development and improvement of nutritious breakfast products in Ghana. This is a huge emotional benefit to your child as they will have a sense of achievement to contributing significantly to scientific research.

Alternatives to Participation

Should your child choose not to participate in this study or for other reasons your child is excluded from this study by the researcher, there will be other opportunities to participate in sensory evaluation research at the Department of Nutrition and Food Science, University of Ghana. If you allow us, we will contact you regarding other studies similar to this one.

Confidentiality

You should be assured that the data your child provides in any sensory evaluation will be kept confidential by the sensory research team. He/she will never be personally identified in any work published as a result of his/her participation in any sensory study without you and his/her prior consent. Also, the information provided by your child is anonymous.

Compensation

You should understand that there is no economic benefit to you or your child for participating in a sensory study, only the emotional benefit of knowing that he/she has contributed significantly to the development and improvement in the quality of the products tasted. This benefit cannot be overlooked. However, at the end of the study, your child will be given a small token to show our appreciation for his/her time spent on the project.

Additional Cost

There is no additional cost to you for your child participating in a sensory study organized by the Department of Nutrition and Food Science.

Voluntary Participation and Right to Leave the Research

Although we would like your child to complete any sensory project you agree for them to participate in, you should know that his/her participation is purely voluntary, and he/she has the right to withdraw from the study without giving you or us any explanation and without any penalty to him/her. His/her withdrawal from this test will not negatively affect his/her personal relationship with the investigator, your child's school, or the University of Ghana as a whole.

Notification of Significant New Findings

To preserve the scientific quality of the data we collect in food taste tests, we are unable to disclose too much information about the products we test at the onset of the project. However, if your interest in the product is raised through your child's participation in the project, we can provide additional information about the product to you at the end of the project. You will have to leave your details with the investigator to share such information about the product with you at the end of the study.

Contacts for Additional Information

For information and questions about this study in particular or any sensory evaluation test in general, please contact:

Dr Maame Yaakwaah Blay,

Department of Nutrition and Food Science,

University of Ghana

Email: mybadjei@ug.edu.gh

Tel: 0545525974

Your Child's Rights as a Participant

The Ethics Committee for Basic and Applied Science (ECBAS) has reviewed and approved sensory studies in foods at the Department of Nutrition and Food Science. This study falls one of such studies. If you have any questions about your child's rights as a research participant, you can contact the ECBAS Office through the address below

Administrator, Ethics Committee for Basic and Applied Sciences

College of Basic and Applied Sciences

University of Ghana

P. O. Box LG 68

Legon – Accra

Tel: +233242759315

Email: janoku@ug.edu.gh

PARENT/ GUARDIAN AGREEMENT

The above document describing the benefits, risks and procedures for the sensory evaluation of foods has been explained to me. I have been given an opportunity to have any questions about the research answered to my satisfaction. I agree to let my child participate as a volunteer.

_______________________ ____

Date Name and signature or mark of parent/guardian

If parent/ guardian cannot read the form themselves, a witness must sign here:

I was present while the benefits, risks and procedures were explained to the parent. All questions were answered, and the parent has agreed to let their child/ward take part in the research.

_________________ ____

Date Name and signature of witness

I certify that the nature and purpose, the potential benefits, and possible risks associated with participating in this research have been explained to the above individual.

________________ ____

Date Name & signature of person who obtained consent

Appendix III.3: RECRUITMENT QUESTIONNAIRE

RECRUITMENT QUESTIONNAIRE

INTRODUCTION

Good day to you.

We are conducting a research study on the application of artificial intelligence (AI) in supporting affordable nutrition and would like to include your ward. It will involve the team from the Sensory Evaluation Laboratory at the Department of Nutrition and Food Science, University of Ghana to come to your school on 16th - 18th October 2024 to conduct a taste test. A consumer sensory taste test involves the use of all your basic senses to evaluate and assess a food's characteristics and tell whether one likes or dislikes it. The test will take roughly about 5-10 minutes to complete.

You will receive a token as a thank you for your time and helping us with the project.

Please fill out this questionnaire truthfully and to the best of your ability.

2. Possible risks: Unless you are allergic to certain foods and ingredients used in processing breakfast cereals the general testing of the samples is non-invasive and should not be a source of risk to health.

Please circle the appropriate responses.

1. Are you willing to take part in a sensory test involving ready to eat breakfast cereal
   a. Yes
   b. No

Could you please provide us with the following details?

2. NAME : ………………………………
3. CONTACT NUMBER (optional): …………………………………
4. Please indicate your gender
   a. Male

b. Female

5. What is your age range?

   a. 12 - 15

   b. 16 - 18

   c. Above 18

6. What is your ethnicity?

   a. Akan coastal (Fante, Nzema Ahanta etc)

   b. Akan forest (Akuapem, Akyem, Ashanti's Sefwi, Bono, etc)

   c. Ewe

   d. Ga/Adangbe

   e. Guan

   f. Northerner

   g. Other, please specify…….

7. What education stage are you in?

   a. Lower primary

   b. Upper primary

   c. Junior high school

   d. Prefer not to mention

   e. Other, please specify……...

8. Which of the following are you allergic or intolerant to? Choose all that apply

   a. Cassava

   b. Bambara beans

   c. Millet

   d. Coconut

   e. Milk

   f. None of the above

9. On a scale of 1-7 (where 1 is "Not at all" and 7 is "very much", generally, how excited are you about breakfast meals?

   a. Not enthusiastic at all
   b. Moderately not enthusiastic
   c. Slightly not enthusiastic
   d. Neither enthusiastic nor non-enthusiastic
   e. Slightly enthusiastic
   f. Moderately enthusiastic
   g. Very enthusiastic

10. How often do you consume ready-to-eat breakfast cereal (e.g. cornflakes, cheerios, instant hausa koko, yumvita, cerelac?

    a. Everyday
    b. At least three times a week
    c. At least once a week
    d. Once every two weeks
    e. Once a month
    f. Less than once a month

11. Who purchases ready-to-eat breakfast cereal in your household? Choose all that apply

    a. Myself
    b. My parents
    c. My siblings
    d. Other, please specify……………………………

12. Why do you consume ready-to-eat breakfast cereal? Choose all that apply

a. Health benefits

b. Nutritional benefits

c. Price

d. Quality

e. Quantity

f. Taste

g. Convenience

h. Your parents offer them to you

Thank you for your patience in answering these questions.

Appendix III.4: SENSORY QUESTIONNAIRE

PROJECT CHERRY INSTANT BREAKFAST CEREAL CONSUMER ACCEPTANCE TEST

Welcome Panellist name!

The sample has been reconstituted with water to form aslurry. Please rate the following liking attributes for the sample BC111:

OVERALL LIKING

Considering everything about Sample BC111, how much do you like or dislikeit **overall**?

Dislike Extremely	Dislike Very Much	Dislike Moderately	Dislike Slightly	Neither Like nor Dislike	Like Slightly	Like Moderately	Like Very Much	Like Extremely

APPEARANCE LIKING

How much do you like or dislike the **appearance** of the sample?

Dislike Extremely	Dislike Very Much	Dislike Moderately	Dislike Slightly	Neither Like nor Dislike	Like Slightly	Like Moderately	Like Very Much	Like Extremely

AROMA LIKING

How much do you like or dislike the **aroma** of the sample?

Dislike Extremely	Dislike Very Much	Dislike Moderately	Dislike Slightly	Neither Like nor Dislike	Like Slightly	Like Moderately	Like Very Much	Like Extremely

FLAVOUR LIKING

How much do you like or dislike the **flavour/taste** of the sample?

Dislike Extremely	Dislike Very Much	Dislike Moderately	Dislike Slightly	Neither Like nor Dislike	Like Slightly	Like Moderately	Like Very Much	Like Extremely

MOUTHFEEL LIKING

How much do you like or dislike the **mouthfeel (texture in the mouth)** of thesample?

Dislike Extremely	Dislike Very Much	Dislike Moderately	Dislike Slightly	Neither Like nor Dislike	Like Slightly	Like Moderately	Like Very Much	Like Extremely

AFTERTASTE LIKING

How much do you like or dislike the **aftertaste/afterfeel** in the mouth?

Dislike Extremely	Dislike Very Much	Dislike Moderately	Dislike Slightly	Neither Like nor Dislike	Like Slightly	Like Moderately	Like Very Much	Like Extremely

Please comment on anything that you **liked** about sample BC111

Please comment on anything that you disliked about sample BC111

Please drink some water to cleanse your palate