Developing a nutrient profiling model for categorising food and beverages in Ghana: a multimethod study

By

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A doctoral thesis

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“And eat and drink but be not excessive.

Certainly, He (Allah) likes not those who commit excess”.

(Al-A’raf 7:32)

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PhD research supervisors

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Dedication

To my family, for all the love and encouragement

To my beloved Huzur, for the support with prayers

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Conferences and publications

Conferences

Abdul-Haq, Z., Halliday, V., Pradeilles, R., Laar, A. & Holdsworth, M. (2018). Poster Presentation. Defining and categorising healthy or unhealthy food: a systematic review. ScHARR PGR Conference, Sheffield, UK.

Abdul-Haq, Z., Halliday, V., Pradeilles, R., Laar, A. & Holdsworth, M. (2018). Oral and poster presentation. Defining and categorising healthy or unhealthy food: a systematic review. Agriculture, Nutrition and Health (ANH) Academy Week and Conference, Accra, Ghana.

Abdul-Haq, Z., Halliday, V., Pradeilles, R., Laar, A. & Holdsworth, M. (2018). Defining and categorising healthy or unhealthy food: a systematic review. ScHARR PGR Conference, Sheffield, UK.

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Publications

1. Defining and categorising healthy or unhealthy food: a systematic review. Target journal: *Public Health Nutrition* (In Preparation).
2. Validation of a nutrient profiling model for use in Ghana. Target journal: *Nutrients* (In Preparation)
3. Experts' classification of food in comparison to the classification by a validated Nutrient profile model for use in Ghana. Target journal: *Journal of Human Nutrition and Dietetics* (In Preparation)

Preface: a personal reflection

My particular interest in seeing the global burden of nutrition-related non-communicable diseases (NR-NCDs) reduced is forged by my educational and professional background in public health, specifically in the field of nutrition. After qualifying as a Community Nutritionist from the University for Development Studies in Ghana, I worked at the Greater Accra Regional Hospital (the Ridge Regional Hospital) in Ghana for five years. There, I learnt to work within the communities to support them in making informed decisions regarding their nutrition.

In my role as a public health nutritionist at the hospital, I worked alongside dietitians, public health nurses, and community health nurses in both the hospital and community settings. I observed that most of the nutrition cases were associated with overweight, obesity, diabetes, hypertension and stroke. The underpinning causal factors of these cases seemed to include urban poverty, low health literacy, low nutrition literacy and the lack of food regulations focusing on healthy and unhealthy food consumption in Ghana.

From my observation, a nutritional shift is currently taking place in Ghana, which is being propelled by rapid urbanisation. This urbanisation occur alongside acculturation and modernisation, which have been shown to impact the prevalence of NR-NCDs. Many of the NR-NCDs with which my colleagues and I dealt presented various common contributing factors linked to unhealthy foods. Hence, a mix of pre-transitional disease conditions related to poverty, the emerging chronic illnesses and the human immunodeficiency virus (HIV) all manifested themselves as different forms of malnutrition (undernutrition, as well as overweight and obesity) especially amongst the vulnerable groups such as women and children living in the poor urban communities. According to national statistics, the prevalence of NR-NCDs including type 2 diabetes, coronary heart diseases and stroke, has further increased drastically in Ghana to become among the top ten leading causes of death (Ghana Statistical Service, 2015; Institute for Health Metrics and Evaluation, 2021). Studies have linked this to the rapid nutrition transition in the country (Bosu, 2015; Haggblade et al., 2016). This evidence, coupled with my daily encounter with patients suffering from type 2 diabetes and related conditions, piqued my interest to pursue further studies specific to research in NR-NCDs. For this reason, post completion of my Master's degree in Public Health Nutrition at the University of Southampton, I enrolled in a PhD programme at the University of Sheffield. When I contacted my supervisor, I was glad to be informed that she would be coordinating a project related to the dietary transition in Ghanaian cities. After a discussion about the project, I was keen to develop my PhD around the definition and classification of the healthiness of foods in the Ghanaian context because currently no national or uniformly applied validated criterion exists in Ghana for defining and categorising the healthiness of foods and beverages, which is required for a number of public health nutrition interventions. I was deeply excited as it was dear to my heart and I wanted to pursue this further. My research aims to develop a validated and reliable nutrient profiling model that will assist in informing policy makers towards the reduction of the current NR-NCDs burden in Ghana.

Abstract

Background: Increasing evidence has recognised the double burden of malnutrition in Ghana. However, the development of reliable and validated nutrient profiling models tailored to categorise the nutritional quality of foods and beverages is required to implement policies or interventions, such as taxing or controlling the advertising of unhealthy foods.

Aim: The aim of this PhD was to explore how foods are classified as "healthy" or "unhealthy" and to critically appraise the validity of nutrient profiling models in order to develop a reliable and validated model that will assist in implementing nutrition policy in Ghana.

Methods: The PhD involves a multimethods study (i.e., three studies): In **Study 1**, a systematized literature review was conducted to identify the "terms" for defining food as "healthy" or "unhealthy" and to critically appraise the validity and public health applications of the different methods for classifying foods and beverages. Based on the review findings, **Study 2** used secondary data analysis of food composition data to develop the Ghanaian Nutrient Rich Food Index (NRF11.3). Regression analysis was used to explore the optimal combination of nutrients needed for inclusion. The internal consistency of the nutrients included was assessed. In addition, the optimal cut-off points for sensitivity and specificity were determined. In **Study 3**, a primary quantitative survey of Ghanaian Nutrition experts was conducted to assess the convergent validity of the nutrient profiling model.

Results: Study 1 found that 38 different "terms" were used to define food as healthy (n=16) or unhealthy (n=22). "Nutrient-dense" and "healthier" were common terms for healthy foods, while "energy-dense nutrient-poor" and "less healthy" were common terms for unhealthy foods. Three comparative methods were commonly used for categorising food: "food-based" (n=18), "nutrient-based" (n=35) and "food processing" (n=3). The nutrient-based approach used nutrient profiling models with explicit definitions of nutritional quality that were subject to construct validity testing. Evidence from this review identified the Nutrient Rich Food Index, amongst other nutrient profiling models, as easily adaptable for use in the Ghanaian context.

In **Study 2**, regression analysis indicated that a nutrient profiling model subsequently named the Ghanaian Nutrient Rich Food (NRF 11.3 index) with 11 positive and three negative nutrients was the optimal model to use in the classification of Ghanaian foods and beverages (Adjusted R^2=0.999, p<0.001). In **Study 3,** analysis of survey findings with Ghanaian nutrition experts found a statistically significant and strong positive correlation (R_s = 0.549 p<0.001) between the Ghanaian NRF11.3 index profiling and the experts' ranked scores for classifying foods.

Conclusions: The Ghanaian NRF11.3 index is a reliable and validated nutrient profiling model adapted for use in Ghana. It will assist policy makers in implementing interventions requiring the identification of "healthy" and "unhealthy" foods that could contribute towards the overall reduction in nutrition-related non-communicable diseases in Ghana, for example, in identifying which foods and beverages should or should not be advertised to children.

Key words: Ghana, multimethods, nutrient profiling, nutrition policy, nutrition-related non-communicable diseases

Abbreviations

BIC	Bayesian Information Criterion
DV	Daily Value
DRVs	Daily Reference Values
ED	Energy Density
EDNP Foods	Energy-Dense, Nutrient-Poor Foods
FAO	Food and Agricultural Organization
FCTs	Food Composition Tables
FDA	Food and Drug Administration
GDHS	Ghana Demographic and Health Survey
HIC	High-Income Countries
IHME	Institute of Health Metrics and Evaluation
KFCT	Kenyan Food Composition Table
LMIC	Low and Middle-Income Country
NCDs	Non-communicable Diseases
NR-NCDs	Nutrition-Relate Non-communicable Diseases
NRF11.3	The Ghanaian Nutrient Rich Food Index
PROSPERO	International Prospective Register of Systematic Reviews
PRISMA	Preferred Reporting of Systematic Reviews and Meta-Analyses
RDIs	Reference Daily Intake
ROC	Receiver Operating Characteristics
SPSS	Statistical Package for the Social Sciences
SPIDER	Sample, Phenomenon of interest, Design, Evaluation, Research type
SSA	Sub-Saharan Africa
TFCT	Tanzania Food Composition Table

UK	United Kingdom
UN	United Nations
WAFCT	West African Food Composition Table
WHO	World Health Organization

Definition of terms

Across-the-board	A nutrient profile model that uses the same algorithm to classify all foods, regardless of the food category. This type of model aims to promote healthier categories of foods (e.g. legumes and vegetables) instead of healthier versions of foods within food categories (e.g. low-fat yoghurts).
Algorithm	A series of operations that can be followed to obtain a solution or result. In nutrient profiling, this refers to the underlying set of instructions that determine the classification of a food based on its nutritional composition.
Nutrient to limit	A nutrient component which contributes towards a negative weighting in the context of a specific model.
Nutrient profiling	"The science of categorising foods according to their nutritional composition for reasons associated with preventing disease and promoting health" (World Health Organization, 2011b)
Positive nutrient/food	A nutrient or food component which has a positive weighting in a nutrient profiling algorithm.
Negative nutrient/food	A nutrient or food component which has a negative weighting in a nutrient profiling algorithm.
Reference base	This is the standard amount of food usually calculated per 100 grams, 100 kcal, or a serving.
Scoring model	A nutrient profile model that produces a score for each food so that a ranking can be produced for any list of foods (e.g. from "healthiest" to "least healthy").

Threshold model A type of nutrient profile model that can only be used to produce a classification of food (e.g. as “healthy” or “unhealthy”) and cannot be used to produce a ranking of foods.

Summary of thesis organisation

Chapter One: Background

This chapter presents the study context and wider narrative to highlight the need for this PhD. It describes the main public health challenge, i.e. the increased consumption of "unhealthy" foods and its link to the global obesity/nutrition-related non-communicable diseases (NR-NCDs) epidemic, and the criteria for defining and categorising "healthy" and "unhealthy" foods globally; thus, the background to this PhD research. The narrative of the main concepts includes background information of the case study country, Ghana which is a lower- middle-income country (LMIC) in West Africa undergoing a nutrition transition. Then the necessity to identify a validated and context-specific nutrient-profiling model for defining food as "healthy" and "unhealthy" is deliberated. The chapter concludes with the questions, aims and objectives of the research. This is also shown in a study framework clearly illustrating the structure and plan of the thesis.

Chapter Two: Systematized review (Study One)

This chapter presents a systematized literature review; summarising how "healthy and unhealthy" foods are defined and categorised, tracing the historical development of the definition of food and critically appraising the methods currently used in practice to classify food items as healthy and unhealthy. Other follow-up sections and subsections give insights into the strengths, weaknesses and validity/reliability of the different categorisation methods identified. Further to this, the range of applications of the different food categorisation methods in policy, intervention and research are highlighted. Literature on the types of malnutrition (e.g. NR-NCDs) that these different food categorisation methods are aimed at preventing is highlighted.

Thus, the literature review chapter aims to provide a systematic and critical appraisal of the methods used for defining and categorising food as “healthy” and “unhealthy”.

Chapter Three: Methodology

This chapter explains the multimethods approach taken in this PhD and presents the epistemological and ontological position of the researcher. An account of the procedures or methods undertaken to provide insights into the research questions and objectives outlined in each study is discussed in this chapter.

Chapter Four: The development of the Ghanaian NRF11.3 index (Study 2 Phase 1)

This chapter summarises and discusses the results of phase one of the second study of this PhD. This includes the steps undertaken to develop the Ghanaian Nutrient Rich Food index “NRF11.3”, i.e., the procedure and results. A description of the datasets used in the study is first presented, i.e., the 2017/2018 “Drivers of Food Choice (DFC) and the Leveraging Evidence for Interventions and Policy to Prevent Diet-Related NCDs (TACLED) in Ghana” (Holdsworth et al., 2020). Second, the study settings for the DFC/TACLED data are described and the sampling methods used are indicated. Subsequently, an overview is given of the development of the NRF11.3 index, with the principal decisions and considerations in the developing process of the NRF11.3 index recounted. Using regression analysis, the optimal combination of nutrients required in the Ghanaian NRF11.3 index for classifying Ghanaian foods is determined. Then the steps involved in the profiling of individual food items using the NRF11.3 index are described.

Chapter Five: The reliability, optimal cut-off point, sensitivity and specificity of the Ghanaian NRF11.3 index

Chapter five describes the second phase of Study 2, the performance and reliability, of the newly developed Ghanaian NRF11.3 index. The key objectives of this chapter include:

- To obtain an estimation of the reliability of the Ghanaian nutrient profiling index (i.e., internal consistency and inter-rater reliability).
- To determine the sensitivity, specificity and optimal cut-off point for the Ghanaian nutrient profiling index in order to identify its performance.

First, the reliability of the Ghanaian NRF 11.3 index is tested for internal consistency by calculating the Cronbach's Alpha. Next, the nutrient profiling scores of Ghanaian food items using the newly developed Ghanaian NRF11.3 index are compared to a context-specific "reference model". Thus, Study 2 Phase 2 establishes the optimal cut-off, sensitivity and specificity of the Ghanaian NRF11.3 in order to determine the performance of the Ghanaian NRF11.3 index using Receiver Operating Characteristics (ROC) curves and Kappa statistics. A discussion and summary of the study finally concludes this chapter.

Chapter Six: Convergent validity study (Study Three)

This chapter describes the adapted model's validation by "Nutrition experts" through an online survey. (i.e., Ghanaian nutrition experts' were invited to classify commonly consumed foods and beverages on a 5- Likert scale in order to identify where there is/is no consensus between the experts' classification and the adapted nutrient profile model's classification). This chapter sets out the proposed design and procedures for the data collection, management and analysis. Thereafter, the results are presented and discussed with reference to the relevant literature. A summary of the findings concludes this chapter.

Chapter Seven: Discussion, conclusions and recommendations

The findings from the three studies in this PhD are combined in this chapter, within the context of the background literature and with the main purpose of discussing the overall research findings from the three studies. The complementarity of the three studies provides comprehensive evidence for adopting a context-specific profiling model for defining and categorising "healthy" and "unhealthy" food items in the Ghanaian context and for informing the nutrition policy geared towards the prevention of NR-NCDs. The strengths, limitations and implications for policy are also related in this chapter

CHAPTER ONE: BACKGROUND TO THE STUDY

The chapter elucidates a broader narrative to highlight the relevance of this research and provides an overview of the study context. It situates the research within the context of relevant literature by discussing the main subject areas, i.e., the increased consumption of "unhealthy foods" and its link to the global obesity and NR-NCD epidemic. Within the narratives, the contextual background of Ghana is presented. Next, the need to identify a validated and context-specific nutrient-profiling model for defining Ghanaian food as healthy and unhealthy is discussed. The chapter concludes by identifying the research gaps and stating the research aims, objectives and questions that the thesis seeks to explore. A study framework is used to illustrate this research.

1.1 The public health nutrition context: global, regional and local

1.1.1 Global context

In the 21st century, some of the largest health challenges globally are linked to imbalances in energy and nutrient intake (Popkin, 2015; NCD Risk Factor Collaboration, 2016; Shekar, 2020; Global Nutrition Report, 2021; Wells, 2021; Popkin, 2022). When these imbalances occur over time, in a person's diet it can manifest as malnutrition, including undernutrition (i.e. problems related to deficiencies) and overnutrition (i.e. overweight or obesity) and resulting NR-NCDs (NCD Risk Factor Collaboration, 2016; Swinburn et al., 2019; World Health Organization, 2021).

Historically, undernutrition has been characterised as the world's most serious nutritional health concern, including stunting, wasting and micronutrient deficiencies (Caballero, 2007; Popkin et al., 2020; Wells, 2021). Although the Global Hunger Index (GHI) shows a significant decrease in all parts of the world since 2000, progress is slowing (Global Nutrition Report, 2021). Recent statistics on the prevalence of undernutrition, a component of the GHI, revealed a significant increase in 2020, which is of concern. According to a forecast by the United Nation's FAO, "taking COVID-19 into account, approximately 8% (657 million individuals) will in 2030 be undernourished, 30 million additional individuals than if the pandemic had not occurred" (FAO, 2021). Undernutrition is expected to worsen as a result of climate change, culminating in an even bigger disease burden linked to inadequate diets, especially amongst the most vulnerable groups (Swinburn et al., 2019; International Food Policy Research Institute, 2022).

In addition to this, the current obesity pandemic has altered malnutrition patterns (Shekar, 2020; Wells, 2021; Popkin, 2022). Since the early nineteen-eighties, high-income countries (HICs) have experienced a dramatic increase in the prevalence of overweight and obesity, which is rapidly gaining ground in low-middle-income countries (Popkin, 2007, 2022).

Obesity is a predisposing risk factor for NR-NCDs (i.e. type 2 diabetes, cardiovascular illness and some forms of cancers) that contribute to mortality and morbidity worldwide (GBD 2015 Obesity Collaborators, 2017). This modifiable risk factor has been linked to unhealthy diets typified by the excessive consumption of ultra-processed foods (Monteiro et al., 2013) and sugar-sweetened drinks that contain excess saturated fats, salt, added sugar and maybe energy-dense (Popkin, 2015, 2022).

The World Health Organization reported startling key malnutrition statistics in 2016, revealing that "nearly half a million (462,000,000) adults are underweight, while 1.9 billion people" worldwide are suffering from overweight or obesity (World Health Organization, 2017b, 2021).

In conjunction with this, the Lancet commission report on the Global Syndemic of obesity, undernutrition and climate change and the 2021 Global Nutrition Report reaffirmed that the majority of countries worldwide are challenged and struggling to cope with the double-burden of malnutrition (Swinburn et al., 2019; Global Nutrition Report, 2021) that is causing poorer health globally.

There is also compelling research evidence linking foetal undernutrition and the risk of obesity later in life (Wells, 2021) and malnutrition disproportionately impacts LMICs (GBD 2015 Obesity Collaborators, 2017). Furthermore, Well et al. (2020) write that due to the rapid global nutrition transition, a growing proportion of people are exposed to various types of malnutrition throughout their life-course and are directly or indirectly affected by the multiple burden of malnutrition (Wells, 2020).

Maternal body mass index and home food environment appear to be significant factors in whether pre-schoolers develop overweight or obesity (Kwansa et al., 2022). Thus, the effects of the obesity epidemic have life cycle repercussions that are intertwined.

Consequently, the economic cost of obesity is significant in all countries, irrespective of the economic or geographic settings and will continue to do so in the future if current trends continue (Swinburn et al., 2019; Okunogbe et al., 2021).

At the moment, no country is on track to stop the growing number of obese people. The Global Nutrition Report for 2021 estimates that about 15% of adult women and 11% of adult men around the world are obese (Global Nutrition Report, 2021). As a result, the urgency of the situation justifies global attention.

1.1.2 Regional context

The region of focus is Sub-Saharan Africa (SSA). It refers to all African countries that lie wholly or partially to the south of the Sahara (United Nations, 2022). The World Bank defines the region as comprising 48 out of 54 countries on the African continent (World Bank Group, 2022). According to the World Bank, as of 2020, the total population of SSA was 1.14 billion, with a life expectancy of approximately 62 years and an annual growth rate of 2.6% (World Bank Group, 2022). The GDP of this region also stood at $1.71 trillion in 2020, as outlined by the World Bank (World Bank Group, 2022). The climatic condition of this region is described mainly as tropical.

Although the obesity pandemic has shifted the trends of malnutrition from undernutrition to overnutrition, there is still an unprecedented increase in the number of people affected by undernutrition in the SSA region, which is worrying (Global Nutrition Report, 2021). The FAO estimates that 36.1% of all under-fives who are stunted (those whose height-for-age is more than two standard deviations below the approved WHO Child Growth Standard Median) live in SSA and South Asia (FAO, 2020).

Even though there has been a decrease in undernutrition around the world in the last ten years, the nutrition landscape of SSA remains more complicated (FAO, 2020), with the emergence of obesity and other NR-NCDs coexisting with persistent undernutrition (Steyn et al., 2014; Templin et al., 2019; Popkin, 2022).

According to an ecological framework (ANGELO framework) developed by Swinburn and Raza (Swinburn et al., 1999) to measure and analyse the "obesogenicity" of modern food environments at the micro and macro levels, four broad pathways have been incorporated consisting of physical, political, economic and socio-cultural environmental factors. Similar models have also been proposed by Glanz et al. (2005) and Story et al. (2008) to understand the food environment (Glanz et al., 2005; Story et al., 2008) and as well as monitor and take the necessary action on reducing the obesity pandemic (Swinburn et al., 2013).

Several studies have therefore presented findings based on either the physical, political economic or socio-cultural food environment or a combination of these factors to suggest that the current food environment in SSA is driving unhealthy food and energy consumption which is, in turn, fuelling the obesity pandemic.

The rapid urbanisation taking place in SSA, backed by enormously growing industries (Rakodi, 1997; Tschirley et al., 2015), particularly the so-called "big food and beverage corporations" or “Transnational Food Companies” in African cities, has been cited as one of the key contributors to this obesity problem (Hawkes, 2006; Steyn et al., 2014; Tschirley et al., 2015; Reardon et al., 2019). Although other advantages, like increased development in terms of access to global markets (Hawkes, 2006), transport and employment and many others come with urbanisation. Thus in various urban cities in SSA, the physical food environment has significantly transformed.

This has led to a shift from traditional foods and beverages rich in complex carbohydrates and fibre to the popularisation and increased intake of fast foods, soft drinks and numerous ultra-processed industrialised food brands that may be high in saturated fats, salt and added sugar in the continent (Monteiro et al., 2011; Vorster, 2011; Popkin, 2012, 2022). Evidence supports that most of these kinds of westernised food items have reduced nutrients through processing, causing them to more likely be energy-dense and nutrient-poor (Kant AK, 1994; Vorster, 2011; Chandran et al., 2014; Mbogori et al., 2019), although some nutrients may be added back due to reformulation with the intention of improving health (Gressier et al., 2021).

Some of these industrialised food items are also exorbitantly priced in relation to normal earnings and are frequently regarded as desirable status symbols. Cockx et al. (2016) found that the increase in unhealthy food consumption is largely associated with rising incomes as increased salaries are cited as underlying reasons for higher intake of meat, milk products, vegetable oils and some ultra-processed foods amongst those residing in urban cities compared to rural towns (Cockx, 2016). Although other unhealthy items may also be attractive because they are relatively cheaper and have longer shelf-life than similar perishable food options in the same category.

Various SSA countries or regions in a country may display different stages of the nutrition transition at any point in time (Abrahams et al., 2011). Examining various nutrition-related parameters on a six-point scale, Abraham et al. (2011) established a typical model to quantify the level of nutrition transition in SSA countries. The countries with the highest nutrition transition had higher scores. The results of their research revealed that among 40 SSA countries evaluated, South Africa received the highest score of six, followed by Ghana, Cape Verde and Gabon with a score of five and then Senegal with a score of four (Abrahams et al., 2011). These high-scoring SSA countries were distinguished by the following factors:

i. Low infant mortality rates (between 24-57 fatalities for every 1,000 live births).
ii. High rates of overweight/obesity (more than 29%) in women.
iii. Women exhibit low levels of underweight rates (between 6% and 9%).
iv. High energy (more than 2500 kcals per day) and fat (more than 50 grams per day).
v. There is an average NCD mortality rate of 591-867 deaths per 100,000 people (Abrahams et al., 2011).

These patterns are said to be indicative of the NR-NCDs phase of the nutrition transition (Abrahams et al., 2011). These results demonstrate that SSA countries are going through a nutritional shift despite the fact that more than half of these African countries are still in the initial stages. Nevertheless, a few countries like South Africa and Ghana have revealed dietary pattern changes that have been observed to significantly influence health outcomes (Abrahams et al., 2011).

For instance, the major shifts in the way people eat and drink, previously indicated in 1997 by Drewnowski and Popkin (Drewnowski et al., 1997), in nutrition transition have been highlighted in the “Transition and Health during Urbanisation of South Africans” study that evaluated urban and rural diets in Africa (MacIntyre et al., 2002). This study highlighted the decrease in consumption of starchy staples rich in dietary fibre to an increased consumption of foods high in saturated and total fats, with a decrease in plant-protein sources, like legumes, to an increased intake of snacks and drinks that are energy-dense with added sugars during processing

For example, in this study, the variations in corn meal intake from rural to urban areas in a three-year time frame were 136 grams to 85 grams for males and 122 grams to 55 grams for females, according to MacIntyre and colleagues (MacIntyre et al., 2002). This implied that fewer staples were consumed in urban areas.

On the other hand, the consumption of red meat amongst urban men grew by 34 grams per day from 48 grams to 82 grams, whereas energy-dense snacks, sugar-sweetened drinks and fruits were listed among the most commonly consumed foods by urban women (MacIntyre et al., 2002; Vorster, 2011).

These dietary pattern changes to fast, convenient energy-dense foods, alongside increased consumption of red-meat and fruits, could proportionally be translated into macronutrient patterns dominated by total energy, total fat, carbohydrates, dietary fibre and animal-based protein, which could readily be linked to increased risk of overweight or obesity and related NR-NCDs (MacIntyre et al., 2002; Vorster, 2011; Mbogori et al., 2019). Despite an improvement in urban participants' micronutrients/fruit consumption, these did not reach acceptable levels (Vorster, 2011).

However, according to another study involving a comprehensive systematic review and meta-analysis of population-level diets in two SSA countries (i.e. Kenya and Ghana), the authors concluded that the diets of these populations met the WHO macronutrient requirements and were somewhat diverse, with predetermined meal patterns (Rousham et al., 2020). Notwithstanding, the consumption of fruit and vegetables in these two countries was low in comparison to healthy eating recommendations, while sugar-sweetened drinks were found to be widely consumed (Rousham et al., 2020). Although the systematic review and meta-analysis of these two SSA countries between 1971 and 2010 did not produce sufficient evidence for a nutrition transition, due to the lack of previously documented evidence in these countries (Rousham et al., 2020). The findings suggest that certain characteristics of dietary habits, such as the low proportion of the population eating fruit and vegetables and extensively consuming sugar-sweetened drinks (Rousham et al., 2020), may be contributing to the rise in overweight or obesity in these countries, as has been suggested by other studies (Mbogori et al., 2019; Booth et al., 2021; Popkin, 2022).

Another cross-sectional study looking at foods and drinks available and advertised in underprivileged urban areas of these two SSA countries (Kenya and Ghana) discovered that there was a high exposure to sugar-sweetened drinks and alcohol, indicating a changing urban food environment (Green et al., 2020). Similarly, the widespread consumption of unhealthy foods and drinks in Kenya and Ghana was also noted by Holdsworth and colleagues in 2020. Sugar-sweetened drinks were found to be consumed in 78.5% of eating episodes in Kenya and 36.3% in Ghana. The likelihood of consuming unhealthy foods and drinks was found to be higher in the lower socioeconomic classes (Holdsworth et al., 2020).

Thus, countries in SSA are steadily undergoing their share of the epidemiological and nutrition transition, with an increase in obesity and NR-NCDs (Popkin, 1994; Vorster, 2011; World Health Organization, 2017a; Batal et al., 2018; Pradeilles et al., 2019; Popkin, 2022). This is especially evident in urban areas (Mendez, 2005; Ziraba et al., 2009; Adeboye et al., 2012; Mamun, 2014; Holdsworth et al., 2019; Green et al., 2020; Holdsworth et al., 2020), reflected by changing dietary habits and food environments (Green et al., 2020), resulting in increased consumption of foods high in saturated fat, refined carbohydrates, sugar and salt, whilst low in dietary fibre and accompanied by a decrease in physical activity and increased sedentary behaviour (Popkin, 2002, 2003; Adeboye et al., 2012; Scott et al., 2013; Popkin, 2022).

1.1.3 The local Ghanaian context

Ghana, a LMIC located in SSA, is experiencing its share of the nutritional evolution with changing dietary patterns and a food environment attributable to urbanisation (Imamura et al., 2015; Agyemang et al., 2016; Holdsworth et al., 2019; Holdsworth et al., 2020; Laar et al., 2020; Osei-Kwasi et al., 2020; Laar, 2021b).

The rising prevalence of obesity and NR-NCDs, accompanied by persistent micronutrient deficiencies, needs urgent attention (Dake, 2010; Ministry of Health Ghana, 2012; Bosu, 2015; Agyemang et al., 2016; Dake, 2016; Ofori-Asenso et al., 2016; Osei-Kwasi et al., 2020).

In Ghana, these dietary inadequacies represent a major public health challenge, compounded by poor sanitation, lack of clean water (Awuah et al., 2009) and inadequate access to healthcare (Ghana Statistical Service, 2015).

As suggested by research evidence over the decades (Popkin, 2002), a key driver of obesity and NR-NCDs in Ghana also points to the increased marketing and consumption of unhealthy foods that may be high in sugar, salt and fat, with decreased consumption of staples, fruits, vegetables and pulses (Mogre et al., 2015; Dake, 2016; Green et al., 2020; Holdsworth et al., 2020; Rousham et al., 2020).

Traditionally, the main foods consumed in Ghana according to the FAO nutrition country profiles report include starch-based roots, plantain and cereals (Food and Agriculture Organization, 2010). Across the country, the major staples include cassava, millet, yam, maize, rice, sorghum and cocoyam. These staples are typically served with thick spiced sauces. Palm nut soup, groundnut soup, okra soup, green leafy soup and legumes like "agushi" are some of the most popular dishes. A variety of meals are derived from cassava including: fufu, tapioca and gaari. Also, the most popular maize dishes include: kenkey, banku, akple and Tuo-zaafi (TZ). Traditional Ghanaian dishes vary from one region to another and between the urban and rural areas. In the northern part of Ghana, millet, maize, sorghum and yam are the main staples, while in the southern part, cassava, plantain and cocoyam are the main foods. This could be attributable to climatic variations (Food and Agriculture Organization, 2010).

The relative simplicity of preparing rice combined with its long shelf life undoubtedly explains its widespread consumption and acceptance throughout the country (Anang et al., 2011), especially in urbanised areas (Dake, 2016).

Given the current fast urbanisation, there is a rise in the need for imported foods, which has changed people's dietary preferences and food consumption habits, especially among urban residents (Dake, 2016). In contrast to rural areas, where wholegrains, starchy roots and legumes are consumed (Galbete et al., 2017), urban populations have seen an increase in consumption of meat, poultry products, sugar-sweetened drinks and ultra-processed foods.

In a study of urban individuals (15-59 years) residing in impoverished parts of Accra, Ghana, Dake et al. (2016) found that there was a correlation between the presence of neighbourhood convenience stores (i.e. local shops where processed foods like refined rice, oil and carbonated drinks are sold) and increased BMI after correcting for confounding variables. Their study revealed that BMI increased by 0.2 kg/m^2 for every extra convenience store and a 0.1 kg/m^2 reduction in BMI for ready-to-eat cooked food available in the study area (Dake, 2016). The findings of this study show that the urban deprived areas of Accra, Ghana have an obesogenic local food environment, characterised by an abundance of convenience food outlets and a dearth of fresh fruit and vegetable options (Dake, 2016). While this study provides evidence on the nature of the food environment in urban underprivileged areas in Ghana, it does not incorporate other retail food sources such as local markets or tabletop vendors from whom these inhabitants may also purchase food.

According to findings from a study by Mogre et al. (2015), Ghanaian university students ate animal products more frequently than fruits and vegetables (Mogre et al., 2015). As compared to male students (5.9%), female students were more likely to be overweight or obese (25.8%)

(Mogre et al., 2015). These eating patterns and outcomes are indicative of the Ghanaian nutrition transition.

Furthermore, Galbate et al. (2017) discovered that differences in food preference varied between their study sites when they investigated dietary patterns amongst adult Ghanaians residing in Europe, rural and urban Ghana. For example, in rural Ghana, the diet was dominated by starchy roots and tubers, whereas animal-based food products predominated in urban Ghana, and diets in Europe appeared to be somewhat diverse (Galbete et al., 2017).

A cross-sectional study looking into the unhealthy eating behaviour of urban dwellers living in deprived communities found unhealthy food categories in Ghana to include sugar-sweetened drinks, fried foods and sweet foods. These foods were shown to be consumed more by participants in the lowest socio-economic groups (Holdsworth et al., 2020). Traditional nutrient-rich dishes (related to customs) were also found by the authors to be energy-dense and consumed by more than 84% of study participants. Similar dietary patterns were identified previously by Frank et al. (2014) describing the associations between dietary trends in Urban Ghana and their contributions to diet-related type 2 (Frank et al., 2014). Likewise, Green and colleagues found through their geospatial exploration (i.e., GIS analysis) of the urban food environment in Ghana, notability Jamestown and Ho, that there was a significant exposure of the populace to the advertisement of sugar-sweetened drinks. However, it was surprising to learn that the informal food outlets provided healthier food items than the formal vendors (Green et al., 2020), and thus according to the authors, this could be a target point for policy and intervention.

Furthermore, a school-based cross-sectional study conducted by Hormenu (2022) also revealed comparable trends in the consumption of unhealthy foods by study participants in Ghana. Among a total of 1,311 adolescents that participated in the research, an increased frequency in the consumption of soft drinks (93%; n=1220) and sweets (90%; n=1183) was found amongst the participants (Hormenu, 2022). However, the prevalence of “healthy dietary practices was (49.9%; n=654) among adolescents in the region (Hormenu, 2022). Geographical locations amongst other socio-demographic determinants were found to play a significant role with regard to their dietary practices. Students from the middle and central locations were found to consume more fruit and vegetables as compared to those from the northern and coastal zones, perhaps due to the abundance of fruit and vegetables in the middle and central belts of that region (Hormenu, 2022). More so, seasonality has also been proven to influence dietary diversity in Ghana, especially in rural areas (Abizari et al., 2017).

Ghana is therefore experiencing what Popkin (1994) described as a stage in the nutrition transition called the “*receding famine and increasing degenerative disease patterns*” (Popkin, 1994). This stage is marked by the increased availability of energy-dense nutrient-poor foods and NR-NCDs of lifestyle caused by the emergence of unhealthy food environments (Green et al., 2020; Holdsworth et al., 2020; Rousham et al., 2020; Booth et al., 2021; Laar, 2021b). Correspondingly, the increased consumption of unhealthy foods in Ghana contributes to a high burden of both acute and chronic malnutrition with diverse geographic correlations (Ghana Statistical Service, 2015). The 2014 Ghana Demographic and Health Survey (GDHS) reported that 40% of all adult Ghanaian women (15-49 years) were overweight or obese (BMI $\geq$ 25 kg/m^2). The high prevalence of overweight or obesity in Ghana (see Figure 1.1) is paralleled by increasing incidences of NR-NCDs, including cardiovascular diseases, type 2 diabetes (Amoah et al., 2002) and some forms of cancer (de-Graft Aikins, 2012). Also, micronutrient deficiencies, particularly vitamin A, Iron (Wegmüller et al., 2020) and iodine (Menyanu et al., 2021) are a major concern, which continues to undermine health and development across all age groups in Ghana (Ghana Statistical Service, 2015; University of Ghana, 2017; Wegmüller et al., 2020).

The coexistence of this seemingly contrasting form of malnutrition has engulfed Ghana, and therefore, the double burden of malnutrition currently presents a serious public health challenge in the country, which needs urgent attention.

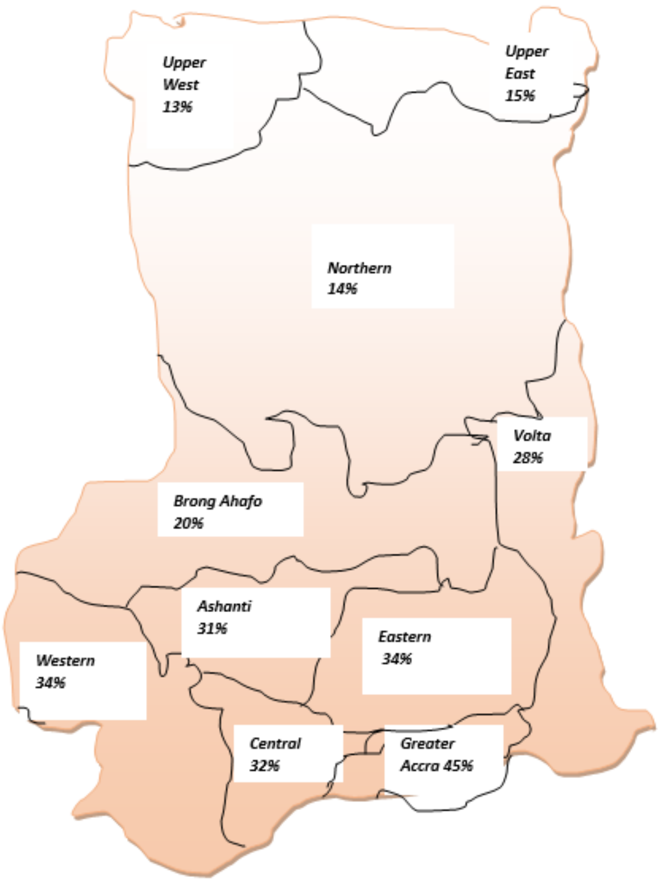

Figure 0.1: Prevalence of overweight or obesity among women (15-64 years)

(Source: GSS, 2015)*

A national strategy framework to prevent NCDs was supported by Ghana's Ministry of Health in 2012 with the goal of reducing the impact of "unhealthy diets" on public health (Ministry of Health Ghana, 2012). In accordance with this policy, the government of Ghana committed to taking the following actions by the year 2025: i) strive to reduce daily salt consumption from an average of 9 grams daily to the WHO daily target level of 5 grams a day or less; ii)

* The regions of Ghana as of 2021 are now 16 and not 10 as indicated in this 2015 reference

collaborate with industry through negotiations and legislation to lower the use of unhealthy fats and oils in food production; and iii) phase out the sale of sugar-sweetened and carbonated drinks with fruits such as bananas, pineapples and oranges, particularly in schools.

More recently, there has been a call on the government by researchers and academics pushing for the implementation of recommended policies to create a healthy food environment in Ghana (Laar et al., 2020). A review by Rousham et al. (2020) clearly identified that the population consumption of recommended intake for healthy eating to be sub-optimal in Ghana (Rousham et al., 2020). These evidence and policy actions, amongst others, reflect the concern of the government and researchers regarding the country's nutritional situation. The rising threat of NR-NCDs and the modifiable dietary risk factors all require early attention and timely interventions. This, therefore, warrants the development of a reliable and validated model and policy instrument for categorising commonly consumed Ghanaian food and beverages as healthy or unhealthy, geared towards addressing the escalating obesity and NR-NCD pandemic.

1.2 **Healthy and unhealthy foods**

Over the past decade, epidemiological and experimental research (Peto et al., 1981; Grunberg et al., 1988) has produced convincing scientific evidence connecting dietary intake to health outcomes (Foltran et al., 2010; World Health Organization, 2017a). Depending on individual needs, such as lifestyle, gender, age, physical activity, cultural background, regional availability/accessibility to food and dietary practices, a diversified, balanced diet can take on many different forms (FAO and FHI 360, 2016). "A healthy diet should contain a variety of naturally fresh foods from all food groups to help attain the right amounts of essential nutrients" (World Health Organization, 2003; World Health Organization., 2020). The recommended ways to meet energy needs in areas of persistent undernutrition is from nutrient-rich foods, which are those that contain complex carbohydrates, proteins, healthy fats and micronutrients in the right amounts rather than from energy-dense, nutrient-poor foods that supply energy needs but fail to provide essential nutrients in a healthy way (Kant, 2000; World Health Organization, 2003; World Health Organization., 2020). Existing evidence generally concur that, high-quality diets lower the risk of malnutrition in all its manifestations by fostering growth, development and immunity as well as preventing obesity and NR-NCDs at all stages of the lifecycle. This is more so in regions where multiple burdens of malnutrition persist (Pradeilles et al., 2019; Hawkes et al., 2020; World Health Organization., 2020).

It has consistently been reported by the WHO, that variety of fruits and vegetables, whole grains, less processed foods with limited levels of saturated and trans fats, sugars and salt, foods high in dietary fibre, nuts and seeds are all part of a healthy diet (World Health Organization., 2017). Conversely, diets that are deficient in fruit and vegetables and fall below the recommended intake puts people at risk for micronutrient deficiencies as well as NR-NCDs (World Health Organization, 2003). Correspondingly, healthy dietary patterns are currently a global, national and regional priority to curb the NR-NCDs (Imamura et al., 2015).Thus, an intake of 400 grams of fruit and vegetables at a minimum per day i.e., exclusive of starchy roots and potatoes is recommended by the World Health Organization for the prevention of NR-NCDs and reduction of various micronutrient deficiencies, especially in LMICs (World Health Organization, 2004; Bosu, 2015). Nonetheless, the high consumption of the so-called "unhealthy foods" linked to the obesity and NR-NCDs epidermic seems to be a much more complex interaction. No single nutrient or food appears to be adequate for preventing the individuals from the obesity/NR-NCDs epidermic but a combination of a diverse amount of food and beverages in their right and recommended proportions.

1.3 **Why define and categorise food as “healthy” or “unhealthy”?**

The global rise in the overconsumption of unhealthy foods and obesity, concurrently raises the urgent need to address the concept of “healthy” and “unhealthy” foods to assist the general population in making informed food choices to prevent nutrition-related diseases (Caballero, 2007; Holdsworth et al., 2019; Holdsworth et al., 2020; Laar et al., 2020; World Health Organization., 2020). Thus, one of the highly contentious issues concerning the development of policies to promote a healthy food environment for healthy eating and address the obesity and NR-NCD epidemic over the past decade has been how best to define healthy and unhealthy food (Lackey et al., 2004; Lobstein, 2009; Laar et al., 2020). Some stakeholders support the total diet approach, arguing that an individual food should not be described as healthy or unhealthy as *“no single food necessarily ensures good health”*, just as *“no single type of food is particularly detrimental to health”* (Nitzke et al., 2007; Freeland-Graves et al., 2013). At the same time, others maintain that some individual foods are indeed less healthful than others, and it is possible to identify these foods as such (Drewnowski et al., 2008). More so, as attempts are made to develop a quantitative statement for healthy or unhealthy foods acceptable to both professionals and the public, the problems inherent in such a task and the reasons for the lack of progress become apparent (Hawkes, 2009).

A research report by Hawkes (2009) suggests that some policy makers and stakeholders are hesitant to label foods as “healthy” or “unhealthy”, instead advising that the focus should be on identifying the “*location*, *time and person”* for whom foods are *“healthy” or “unhealthy”* (Hawkes, 2009). However, in this scenario, the difficulty is that bad diets are inevitably a combination of a variety of unhealthy foods and beverages. Increased consumption of this ostensibly unhealthy food and beverages leads to poor diets and dietary patterns. As diet constitutes the major risk factor for NR-NCDs, death and disability (World Health Organization, 2003; World Health Organization., 2020), it is imperative to assess the cumulative risks or additive value of key nutrients for the evaluation of risks posed by individual/single foods. The numerous factors of i) rapidly expanding research and increased knowledge about nutrient requirements; ii) interrelationships among dietary variables; iii) continuing identification of additional essential nutrients; and iv) the need to consider the potential hazards of excessive intakes many continue to render the task increasingly complicated as various parameters must be considered.

Notwithstanding, the concept of healthy and nutritious food is not new, as in 1977 (Guthrie, 1977). review of the nutrition literature revealed efforts spanning the past four decades to define the concept of a nutritious food and its application to nutrition labelling and in nutrition education (Guthrie, 1977). Early definitions of *"nutrient density"* agreed nutritious or healthy food should provide a significant amount of essential nutrients, but no standards have been provided (Drewnowski, 2005; Drewnowski et al., 2008; Lobstein, 2009). However, in several cases, instead of taking into consideration the presence of beneficial nutrients, the definition of healthy foods has traditionally been the absence of "problematic ingredients" such as saturated fat, sugar, and sodium (Guthrie, 1977; World Health Organization, 2015; Food Standards Agency, 2007). For example, an earlier policy definition of healthy food related to school food services may be open to a wide range of interpretations with no attempt at quantification, stating that: *"food should be considered healthy if it provides significant amounts of vitamins, minerals or proteins in relation to caloric contribution and not reduced in value by excessive amounts of sugar or fat or potential harmful food additives"* (Guthrie, 1977). Such a definition is commendable, but its application may be subjective (Lobstein, 2009).

A more quantitative, earlier definition stresses primarily the absence of what it considers negative qualities rather than the presence of positive qualities (Guthrie, 1977). It proposes a healthy or wholesome food should contain: i) no more than 10% of calories from added sugar, 20% from added fats and oils, less than 0.5% added salt; ii) no artificial colouring or sodium nitrate, and iii) products containing any grain should be made from whole grain. Nutrient-to-nutrient ratios, calories-to-nutrient scores and nutrients-per-calorie indices have all been used in attempts to quantify the nutrient density of food (Guthrie, 1977). Additionally, it has been proposed that a food's geometry defines its nutritional content, thus defining food through the application of mathematical theory (Moon et al., 1974). Although this may allow for the visualisation of the nutritional relationship among foods, it is of little value in conveying the actual concept of healthy food to consumers.

In the 1980s, several other proposals for defining and classifying foods were developed according to Lobstein (2009). These included the UK's Food Commission's recommendations on nutrition labelling which urged policy makers to at least declare the fat content of food for consumer information (Food Commission, 2005) and the Coronary Prevention Group in the UK, which also banned the nutrient levels in packaged foods (Black et al., 1992; Lobstein, 2009). Despite all these efforts, no conclusive definition was reached and a lack of consensus still exists on the definition of healthy or unhealthy food or beverages (Guthrie, 1977; Lackey, 2004; Drewnowski, 2005; Lobstein, 2009). There have been generalised statements suggesting that healthy foods should ought to have significant amounts of essential nutrients, but seldom has any criterion of significance been specified (Lackey et al., 2004).

Currently, the importance of distinguishing between foods as healthy or unhealthy is receiving much greater attention. Unhealthy foods are perceived as a controllable risk factor for the onset of NR-NCDs; therefore, in order to promote healthy eating, policy makers are increasingly looking for novel ways to promote foods for good health (World Health Organization, 2003; Rosenheck, 2008; Lobstein, 2009; World Health Organization, 2015; O'Halloran et al., 2017). Nonetheless, a diverse range of terms are used to describe "*unhealthy foods*" concurrent with a lack of consensus for categorising "*unhealthy foods*" globally. As there is no precise definition of healthy or unhealthy foods, there is a clear research gap regarding the categorisation of individual foods as such. It is therefore crucial to explore the terms and methods used to assess the healthiness of individual foods in a systematized review. This will help identify a context-specific reliable and validated nutrition model suitable for the classification of food as healthy or unhealthy, which is a required precursor of several public health nutrition interventions and policies in Ghana that require food categorisation.

1.4 Identification of research gaps.

In Ghana, although the call for the implementation of government initiatives and programmes to improve the healthiness of food and food environments in other to prevent NR-NCDs has recently gained ground, a reliable and validated context-specific nutrient profiling model is yet to be developed. Following an initial scoping of the literature, previous studies have not yet explored nutrient profiling models for use in Ghana and neither have their validity and reliability been assessed. The following research gaps/ questions were identified:

- How are healthy and unhealthy foods defined and categorised?
- What reliable and validated criteria can be used to categorise foods as healthy or unhealthy with relevance to the Ghanaian context?

1.5 Overall aim

The primary aim of this PhD research is to develop a validated and reliable nutrient profiling model for categorising the healthiness of foods and beverages in Ghana.

1.6 Research objectives

The research objectives include:

1. Study One: Systematized review

Key objectives

1a. To identify terms used in defining and categorising foods and beverages as healthy or unhealthy.

1b. To critically appraise the methods used in defining and categorising foods as healthy or unhealthy including their validity and public health applications.

2. Study Two: Cross-sectional study to develop the Ghanaian NRF11.3 index and determine its reliability, optimal cut-off point, sensitivity and specificity.

Key Objectives

Study 2 Phase 1

2a. To develop a context-specific nutrient profiling model for categorising foods and beverages in Ghana

2b. To determine the optimal combination of nutrients required in the Ghanaian NRF index for classifying Ghanaian foods.

Study 2 Phase 2

2c. To obtain an estimate of the reliability of the Ghanaian nutrient profiling index (i.e., internal consistency and inter-rater reliability)

2d. To determine the sensitivity, specificity and optimal cut-off point for the Ghanaian nutrient profiling index in order to identify the performance

3. Study Three: Cross-sectional online study to determine the convergent validity of a context-specific nutrient profiling model.

Key objective

3. To determine the convergent validity of the Ghana nutrient profiling model by assessing how Ghanaian expert nutrition professionals classify the healthiness/ unhealthiness of commonly consumed Ghanaian foods and beverages.

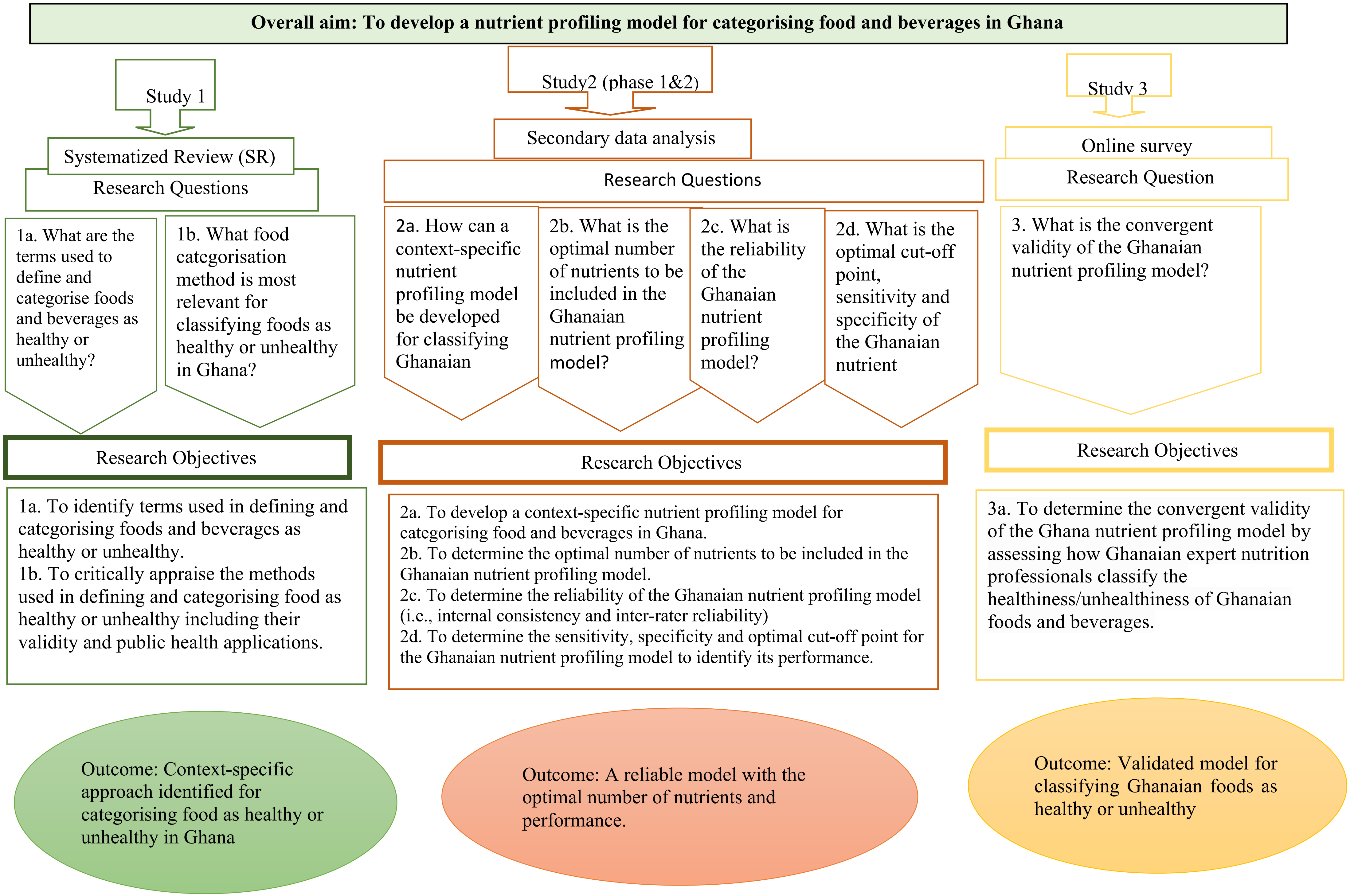

Figure 0.0.2: PhD Research Framework

2 CHAPTER TWO: SYSTEMATIZED REVIEW (STUDY ONE)

The first study of this research is given in this chapter, which is a systematized review (SR). The research question the SR sought to address was "*How are healthy and unhealthy foods defined and categorised and how validated are the approaches used?"*.First of all, the SR begins with a background and need for the research. The methods elaborating details of how the search strategy was developed, the criteria used for the exclusion and inclusion of articles in the SR and the quality assessment process follows-on from the background to the SR.

The second part of the SR summarises the results and compares these findings to the existing literature in the form of a discussion. The last part of the chapter discusses the conclusions and implications of the findings for public health.

2.1 **Background to review**

Given that "unhealthy food" is an important modifiable risk factor in the current NR-NCD epidemic (Development Initiatives, 2017; World Health Organization., 2017), there is an apparent lack of consensus on defining and categorising foods globally (Drewnowski, 2005). Nevertheless, providing consumers with accurate information in the form of nutrition information and labels, are effective strategies to tackle the NR-NCDS (World Health Organization, 2003). A clear understanding of the definition of "healthy" versus "unhealthy" food is warranted in order to classify food as such and to develop effective public health interventions to curb the growing NR-NCD epidemic. While individual foods remain undefined, consumers may not be sufficiently guided in the substitution of less healthy foods in diets with healthier and more nutrient-dense alternatives. Given the importance of having to define food for dietary guidance and public health, it is pertinent to explore how "healthy" and "unhealthy" foods are defined, categorised, and validated. This SR, therefore, goes to the core of this problem. It identifies the range of terms and methods used to define and categorise food and beverages; critically appraises these methods, including their validity and examines the application of each method in developing public health interventions.

Review questions

- What terms are used to define food as "healthy" and "unhealthy"?
- How are "healthy" and "unhealthy" foods defined and categorised?
- How validated are the methods used to define and categorise food?
- How is the definition/categorisation of food as "healthy" or "unhealthy" applied in public health (i.e., as used in policy, intervention and research)?

Review aim

The aim of this SR is to critically appraise the range of terms and methods used to define and categorise food as "healthy" or "unhealthy" with a focus on their validity and public health application.

Review objectives

- To identify the range of terms used to define "healthy" and "unhealthy" foods.
- To summarise the emerging methods identified in categorising food.
- To critically appraise the reliability and validity of the different categorisation methods identified.
- To summarise the range of public health applications of these different categorisation methods that have been used (i.e., in policy, intervention and research).

2.2 Methods

2.2.1 Review typology

A systematized review (SR) was deemed appropriate for the present review because it attempts to incorporate all aspects of a systematic review process while excluding some of the outputs such as the quality assessment of the review papers (Grant, 2009). It is normally done as a postgraduate assignment due to the lack of available resources needed for a thorough evaluation in a full systematic review such as two reviewers (Grant, 2009). Adhering to guidelines for conducting reviews (Grant, 2009) a systematized search, models a systematic review process and resultant outcomes. Thus a systematized review may serve as the starting point for a future funded research project with a larger scope (Grant, 2009). Therefore, a systematic search, appraisal and synthesis of research evidence on defining and categorising food as "healthy" or "unhealthy" was undertaken. The protocol for the review was also registered with PROSPERO (http://www.crd.york.ac.uk/PROSPERO/; registration number CRD42016052124).

Figure 2.1 shows the essential process steps of the SR: definition of the review questions, conducting the search strategy for relevant papers, screening of papers, keywords using titles/abstracts, data extraction and then data synthesis (Petersen et al., 2008). Each step in the process has an outcome and the ultimate outcome of the process is the systematized review (Petersen et al., 2008; Booth et al., 2016).

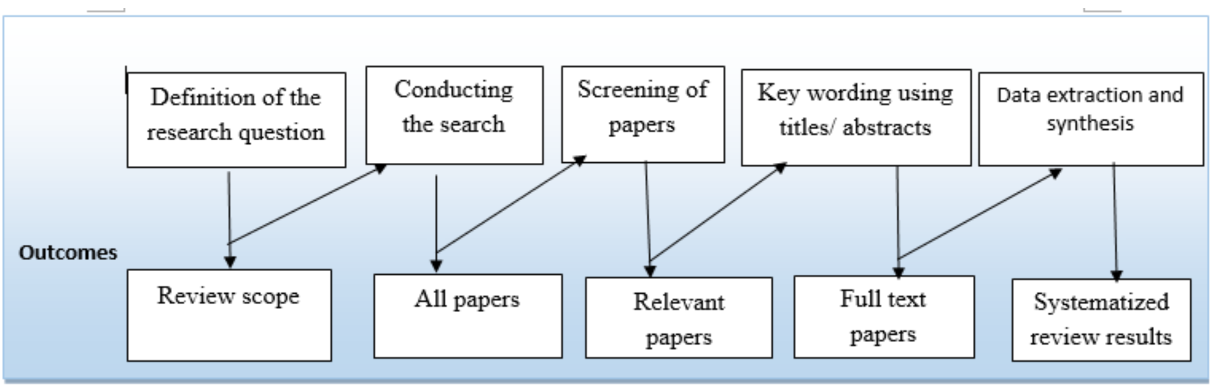

Figure 2.1: Process steps for the systematized review (Petersen et al., 2008)

2.2.2 Search strategy

A preliminary scoping search through MEDLINE was conducted with the goal of estimating the amount of literature available and to determine the most appropriate key terms to use in the main electronic databases. After consulting an information specialist from the University of Sheffield, a search strategy was developed. Multiple iterations and permutations of all search terms were tested to achieve the best level of precision. A computerised search of the following five electronic databases: Web of Science, MEDLINE, Cochrane Library, Scopus and CINAHL, was conducted from the earliest dates available to the 9th of November 2018. Papers were identified using key terms such as unhealth* food*, 'health* food*, defin*, classif*, categori*, and nutrient profile*, in the title, keywords and abstracts. The key terms were combined using Boolean logic terms "AND" and "OR" when the above databases were searched. Medical Subject Headings also known as "MeSH" terms and truncates were used in addition to the key terms. These were "exploded" to incorporate all "MeSH" subheadings. Each database required a slight modification in "MeSH" terms. Furthermore, the limits applied to the search strategy restricted included articles to only human participants and the English language.

In addition, hand searching was undertaken through citation follow-up techniques. For instance, the reference lists of included articles were used to identify additional articles that met the inclusion criteria. Experts in the subject area were contacted for support in identifying relevant sources of data that may have been omitted from the search of the electronic databases by the primary researcher. An Endnote library was used as a means to store and profile all downloaded citations. The duplicates found in the Endnote library were all removed. A complete MEDLINE search strategy is given in **Appendix 1.**

2.2.3 Inclusion and exclusion criteria

To establish the appropriate criterion for the inclusion and exclusion of articles for this review, the SPIDER tool which is an abbreviation for: “Sample”, “Phenomenon of Interest”, “Design”, “Evaluation”, and “Research type” (Cooke et al., 2012), was used as shown in Table 2.1 below. The search was not limited to date, as both past and current efforts to define and categorise food as “healthy” and “unhealthy” were found to be relevant to this topic. Spot checks on the dates of some key papers showed that establishing the criteria for defining and categorising “healthy/unhealthy” foods is an ongoing process.

Table 2.1: An illustration of the inclusion and exclusion criteria

	Inclusion	Exclusion	Justification
Sample	Global human population: Subgroups of adult men and women, adolescent girls and boys and children above 2years	Animal studies or animal species Children less than 2years	Definitions and categorisation of healthy and unhealthy foods are investigated for all human populations in this review
Phenomenon of **I**nterest	Definitions and categorisation of healthy and unhealthy foods globally	Food habits, fortification, and supplementations	The phenomenon allows for mapping out specific studies relevant for addressing the study's aim
Design	All study designs that define and categorise healthy and unhealthy foods: cross-sectional studies, cohort, case-control /case study and ecological/ observational studies Government documents also known to be grey literature were included	Studies that do not define healthy and unhealthy foods or the criteria for categorising them will be excluded	To effectively map out appropriate studies while keeping in view the study aims
Evaluation (The outcome of the study)	Studies that defined healthy and unhealthy foods and their methods used in categorisation and studies that compared different nutrient profiling models	Studies focused on other aspects of food such as food beliefs,	The aim of the review is to map out the criteria for categorising food as healthy and unhealthy and the terms used to define food

Search terms evaluated: unhealth* food*, health* food*, defin*, classif*, categori*, and nutrient profile*		functional foods and feeding practices will also be excluded	
Research type	All research types: both qualitative and qualitative	None	Representation of available research on the topic

2.2.4 Screening

The review was conducted by the lead researcher (ZAH) and was supported by four reviewers (MH, VH, AL, RP)* who were independently involved in the screening and appraisal of the articles included in this review. The titles and abstracts of the 1,456 articles identified were initially imported into Endnote bibliographic software, and all duplicate references were removed. The remaining 1,303 articles were screened at the title and abstract stage by ZAH against the inclusion criteria. Two reviewers (MH and VH) then independently spot-checked 10% of the excluded articles at both the title and abstract stages for adherence to the protocol, leaving 98 articles for full-text screening. ZAH screened all 98 articles for inclusion and reviewers (MH, VH and AL) spot-checked 10% of excluded articles at the full-text screening stage. The main reason for exclusion at the full-text stage pertained to the lack of definition and categorisation of "healthy" and "unhealthy" foods. There was good concordance during the spot checks, however on two papers, the screening results were different. These discrepancies were resolved by discussion and consensus. Figure 2.2 presents the PRISMA statement for reporting systematized reviews of studies. A total of 56 articles were included for data extraction, quality assessment and synthesis.

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* Project supervisors in 2018: Michelle Holdsworth (MH)
Vanessa Halliday (VH)
Amos Laar (AL)
Rebecca Pradeilles (RP)

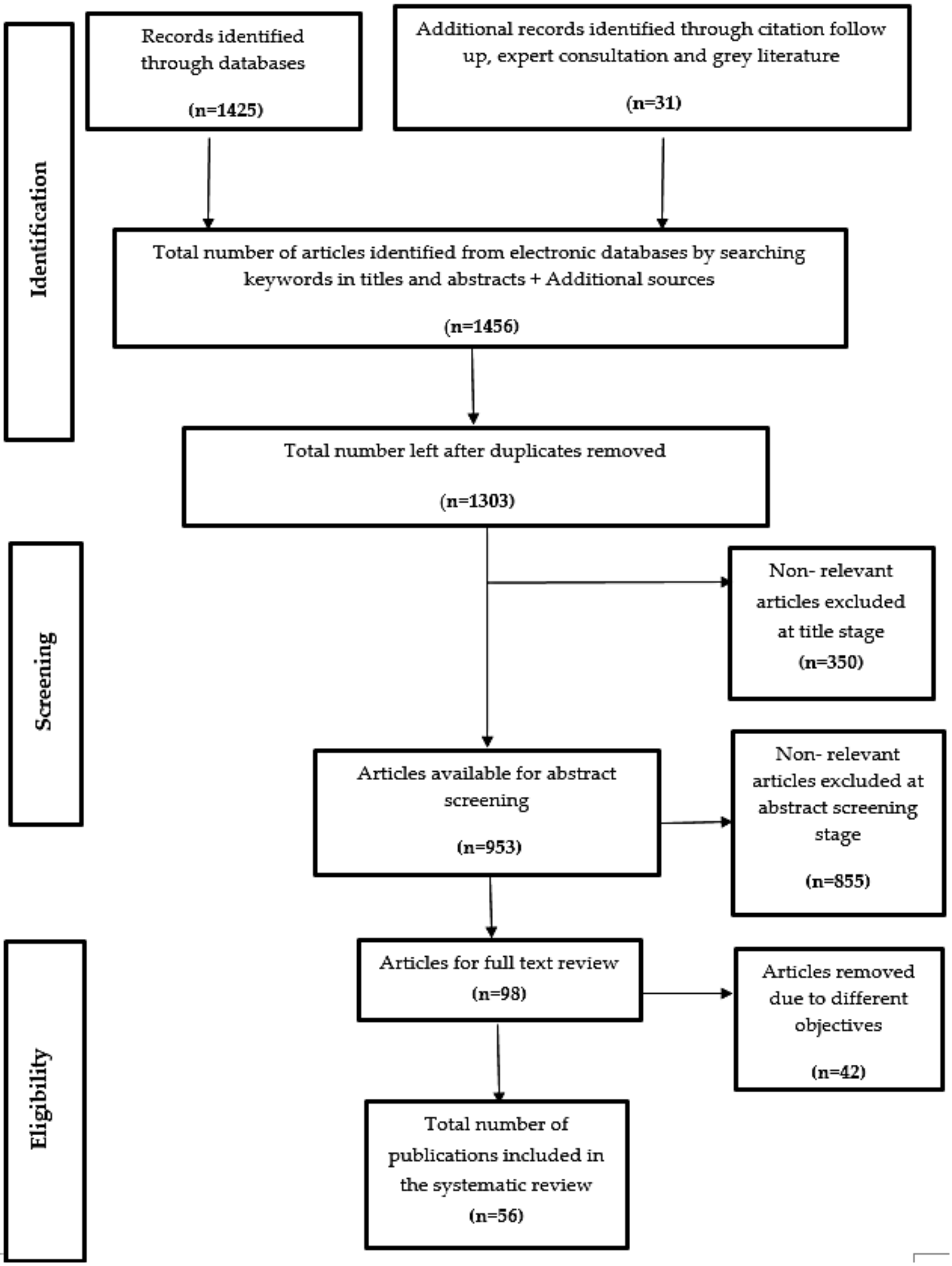

Figure 2.2: "PRISMA (Preferred Reporting of Systematic Reviews and Meta-Analyses) flow-chart of included studies was generated to illustrate this process" (Moher, 2009)

As shown above, the search strategy generated 1,425 study titles from the various databases and 31 from other sources. A final number of 56 studies were included in this SR.

2.2.5 Data extraction and synthesis

A standardised data extraction form was initially piloted on five papers and modified appropriately before the data extraction commenced. ZAH extracted the data from the articles included, and data were appraised and assessed by four reviewers (MH, VH, AL and RP) for accuracy and quality checks (Buscemi et al., 2006), according to the following study characteristics:

- Study characteristics: title, author (s), year, country/location.
- Sample: population type, number of participants, sample characteristics.
- The phenomenon of interest: terms for defining "healthy" and "unhealthy" foods, approach to the categorisation of food, cut-off points applied, reference units used, nutrients included, nutrient profile scores /thresholds, outcomes, validity and reliability and public health application.
- Design: quantitative or qualitative, method of data collection

The data extracted informed the narrative synthesis of evidence gathered from included articles to assess the definition, categorisation, validity and public health application of "healthy" and "unhealthy" foods. A framework was developed based on the nature and extent of literature retrieved on the topic.

2.2.6 Data synthesis

A two-stage largely iterative process was used in the data synthesis. Initially, developing familiarity with the results of included studies was key. This was achieved by tabulating the results in an Excel spreadsheet to identify patterns across the included studies. Each study was comprehensively assessed to highlight the important characteristics of the study in relation to the review objectives. Through this preliminary synthesis, similarities and differences between studies were explored in a systematic sequence.

The second stage involved descriptive summary statistics to describe search results. The definitions and methods used for categorising food were identified into similar groups or clusters according to how they related to each other. For instance, the categorisation methods used in studies were initially extracted according to how the methods related to each other across studies, then clustered, counted, and analysed in groups to determine the three different approaches to food categorisation described in this review.

2.3 **Results**

2.3.1 Description of studies

The studies included were geographically broad Table 2.3, with the majority (n=49) originating from Europe, North /Latin America and the Pacific [UK n=11, USA n=11, Australia n=9, New Zealand n=6, Netherlands n=5, France n=3, Spain n=2, Italy n=1 and Brazil n=1], while only a few (n=3) were conducted in East Asia (the Philippines n=1), the Middle East (Saudi Arabia n=1) and West Africa (Burkina Faso n=1). Four studies had multiple locations. Overall, 53 studies were included from high-income countries (HICs) and three from LMICs. All studies were quantitative in design.

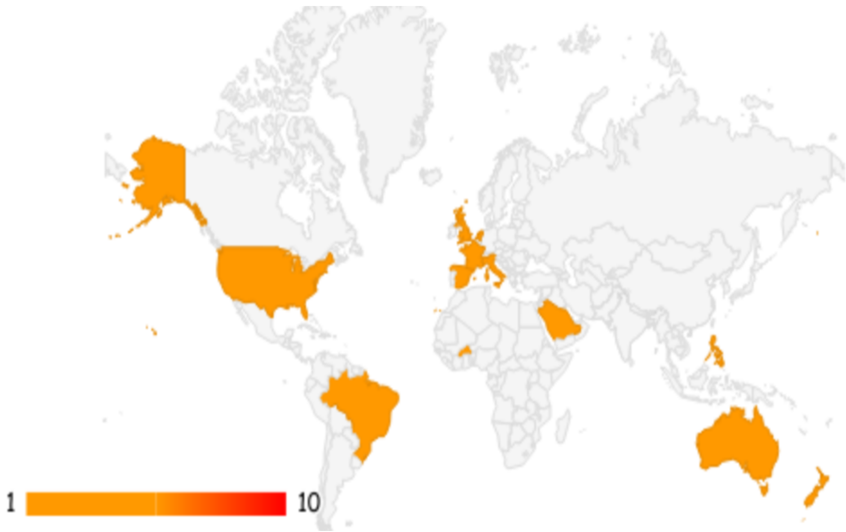

Figure 2.3: A map illustrating the study settings

2.3.2 Range of terms used to define "healthy" and "unhealthy" foods

Thirty-eight different "terms" were identified from the analysis for defining food as "healthy" (n=16 terms) or "unhealthy" (n=22 terms). The most common terms used to define "healthy foods" in the included studies were "core foods", "healthier", "nutrient-dense" and "nutrient-rich" foods. On the other hand, "non-core foods", "less healthy" and "energy-dense nutrient-poor foods" were also common terms used to describe "unhealthy" foods (Table 2.2).

Table 2.2: Range of terms used to define food as 'healthy' or 'unhealthy'

Terms for "healthy" foods	Terms for "unhealthy" foods	Reference
Core foods	Non-core foods, Extra foods	(Kelly et al., 2007; Rangan et al., 2008; Rangan et al., 2009; Kelly et al., 2010; Kelly et al., 2015)
Everyday foods	Occasional foods	(Ministry of Health, 2007; Mhurchu et al., 2016; Vandevijvere et al., 2017; Vandevijvere et al., 2018)
Minimally processed foods, Unprocessed foods	Ultra-processed foods Processed foods	(Monteiro et al., 2011; Adams et al., 2015; Pan American Health Organization, 2016; O'Halloran et al., 2017)
Essential foods	Non-essential foods	(Monroy-Parada et al., 2016)
Traditional dishes	Junk food*, Snack foods	(Guidetti et al., 2014; Vandevijvere et al., 2017)
	Fast foods	(Scully et al., 2014)
	Superfluous items, Empty calorie foods	(Dabone et al., 2013)
Healthy	Unhealthy	(Carels et al., 2006; Dabone et al., 2013; Caparosa et al., 2014; Gosadi et al., 2016)
Most healthy	Least healthy	(Scarborough, 2007b)

Terms for "healthy" foods	Terms for "unhealthy" foods	Reference
Healthier	Less healthy	(Rayner M, 2005a, b; Arambepola et al., 2008; Eyles et al., 2010; Pechey et al., 2013; Romero-Fernandez et al., 2013; Rosentreter et al., 2013; Masset et al., 2015; Food Standards Australia New Zealand, 2016; Mytton et al., 2018; American Heart Association, 2019; Australian Heart Foundation, 2019)
Non-discretionary	Discretionary	(Charlton et al., 2015; Crino et al., 2018)
Nutrient-dense foods, Nutrient-rich foods	Energy-dense, nutrient-poor foods	(Kant, 2000; Drewnowski, 2005; Darmon et al., 2009; Drewnowski et al., 2009b; Fulgoni et al., 2009; Drewnowski, 2010; Streppel et al., 2012; Streppel et al., 2014; Maillot et al., 2018)
Permitted	Not Permitted	(World Health Organization, 2015; Vandevijvere et al., 2017; Vandevijvere et al., 2018)
Preference products	Rare product, Exceptional (use)	(Netherlands Nutrition Centre, 2005; Quinio et al., 2007; Ravensbergen et al., 2015)
OK	Not OK	(Quinio et al., 2007; U.S. Food and Drug Administration, 2019)
Healthful foods	Worst food items, Poor foods	(Scheidt DM, 2004)

There were similarities but also important differences in the range of terms used to describe food as "healthy" or "unhealthy". For instance, terms generated based on food-based dietary guidelines as the reference points were descriptive and qualitative in nature ("everyday foods", "occasional foods", "core foods", "non-core foods" and "extra foods"). Alternatively, terms implying quantitative measures were found to be generated using nutrient profile models to define the nutritional quality of individual food relative to other foods ("healthier foods", "nutrient-dense foods", "less healthy foods").

The terminologies used to define food generally fall under a number of major categories as follows:

- Timing, spacing and regularity of food consumption ("everyday foods", "occasional foods" and "snack foods").
- The context in which food was eaten, such as food eaten at home or away from home ("fast foods", "traditional dishes"); and
- The nutrient composition of food established on nutrient profile scores or its physical characteristics ("ultra-processed foods", "worst foods", "energy-dense nutrient-poor").

There was a varied range of terms identified to define food as "healthy" or "unhealthy". While terms such as "nutrient-dense foods", "energy-dense nutrient-poor foods" were clear-cut, other terms such as "snack foods", "ultra-processed foods" or "fast foods" were ambiguous and sometimes not clear enough for describing a food item as either "healthy" or "unhealthy".

2.3.3 Categorisation methods of "healthy" or "unhealthy" foods

Three major categorisation methods from the 56 studies were identified as follows:

(i) Food-based (using dietary guidelines n=18 studies representing 32%)

(ii) Nutrient-based (using nutrient profiling systems, algorithms, models n=35 studies representing 63%)

(iii) Food processing (using the extent of food processing n=3 studies representing 5%)

Figure 2.4 presents a map out of the emerging categorisation methods identified in this review.

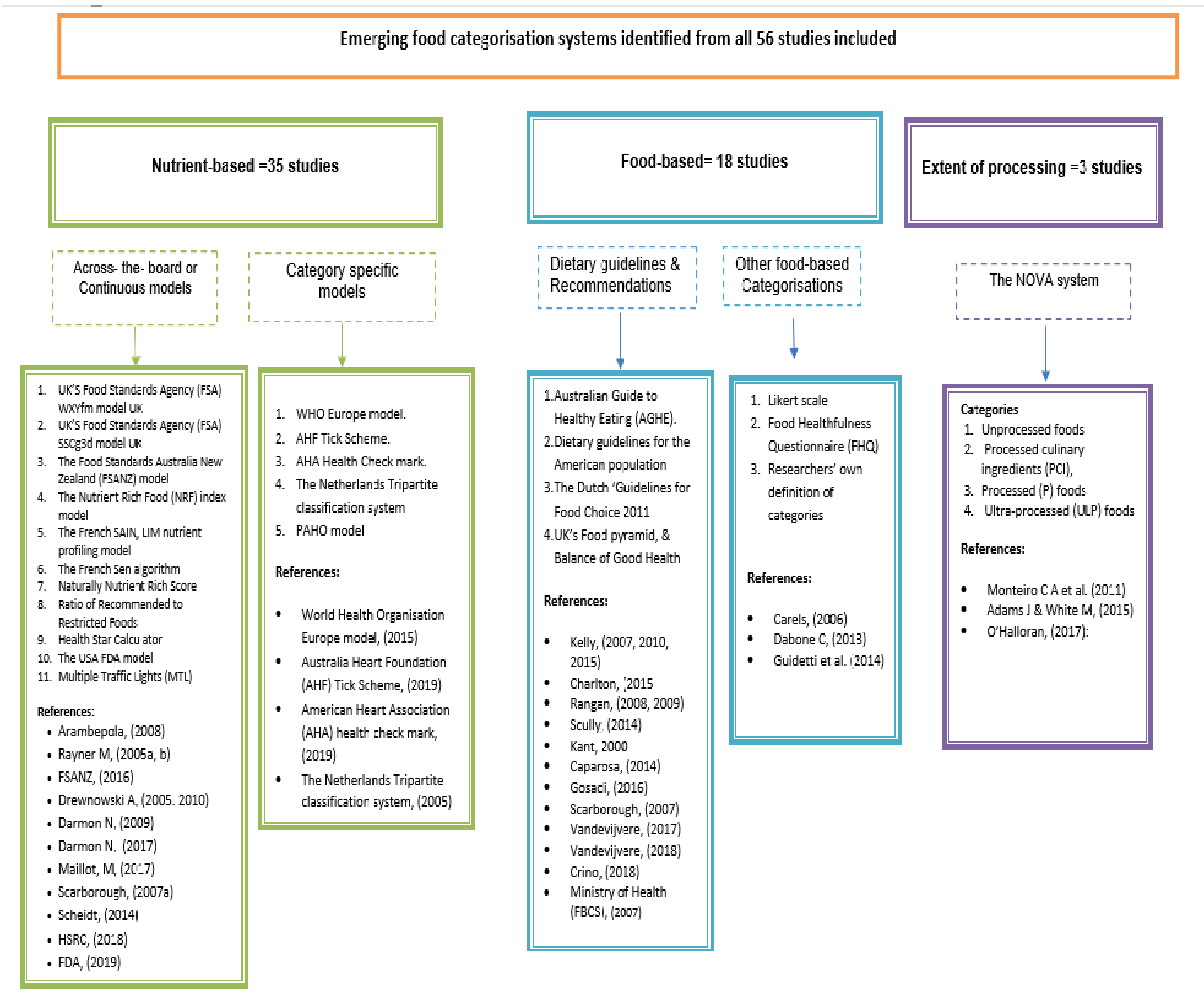

Figure 2.4: A map of emerging food categorisation methods

2.3.4 Food-based categorisation

Essentially, the food-based approach identified in this review was based on national food-based dietary guidelines (FBDGs), which are designed to provide a structural framework around which a range of foods can be used to meet a variety of needs.

Eighteen studies applied the food-based approach to categorise food as “healthy” or “unhealthy”, with a focus on specific food group categories rather than the nutrient composition of individual foods. The number of food groups identified from studies that used this approach ranged from a least of two to forty-three food groups, while the total number of food items categorised into food groups ranged from 102 (Guidetti et al., 2014) to 12,618 food items (Kelly et al., 2010). Although this approach did not demonstrate the capacity to discriminate between the healthiness of individual foods within subcategories, it provided a comparative assessment of the nutritional quality of food in different food groups and took into account other aspects of food culturally specific to populations.

Of the eighteen studies, seven (Kelly et al., 2007; Rangan et al., 2008; Rangan et al., 2009; Kelly et al., 2010; Charlton et al., 2015; Kelly et al., 2015) used the Australian Guide to Healthy Eating (AGHE) tool for categorising food as “healthy” or “unhealthy” (Table 2.3). “Healthy” foods were categorised into a core food group (grains, vegetables and legumes/beans, fruits, lean meat and poultry, fish, nuts and seeds and dairy); and “extra” or “non-core” foods group (mostly high-fat foods, sugary products and miscellaneous foods) considered to be “unhealthy”.

From another perspective, the food-based approach was used to describe the perceived “healthiness” of 102 food items presented three times to participants. The respondents then judged the healthiness of the food items based on their opinion. Food items associated with family were considered “healthy” whereas food items associated with friends were considered “unhealthy”(Guidetti et al., 2014)

Similarly, for all the studies that used the food-based categorisation, “healthy” or “positive” food groups included: grains, meats, dairy, fruit, vegetables, fish legumes and nuts; whilst “unhealthy” or negative foods included convenience meals, pastries, savoury snacks, sweets, ice cream and candy. Overall, whilst food-based approaches classified food into different groups, there was no clear distinction between the nutritional composition of individual food items as “healthy” or “unhealthy”. This approach presented a broad definition of food, which may be subjective. Hence, food-based categorisations may not fit as a standalone tool for discriminating between single foods as “healthy” or “unhealthy”. A more comprehensive system may be to include other measures alongside this approach.

Table 2.3: Studies that applied the food-based categorisation method

Study characteristics			Emerging food-based categorisation methods	Range of public health applications
First author, year	**Study design**	**Country**	**Categorisation guidelines/system identified**	**Specific applications**
Kant, 2000 (Kant, 2000)	Cross-Sectional	USA	Dietary guidelines for the American population	Nutrition surveillance
Carels, 2006 (Carels et al., 2006)	Cross-Sectional	USA	Food Healthfulness Questionnaire	Nutrition education
Caparosa, 2014 (Caparosa et al., 2014)	Cross-Sectional	USA	US Department of Agriculture's Healthier US School Challenge guidelines	Food advertising and marketing controls
Debone, 2013 (Dabone et al., 2013)	Cross-Sectional	Burkina Faso	Food Consumption Questionnaire	Nutrition surveillance
Guidetti, 2014 (Guidetti et al., 2014)	Cross-Sectional	Italy	Perceived healthiness by participants (7-point scale)	Nutrition education
Scully, 2014 (Scully et al., 2014)	Cross-Sectional	UK and Ireland	The Healthy Eating Guidelines and Food pyramid	Food advertising and marketing controls
Scarborough, 2007(Scarborough, 2007b)	Cross-Sectional	UK	Perceptions of the healthiness by experts (Likert scale)	Food labelling (ranking)
Gosadi, 2016 (Gosadi et al., 2016)	Cross-Sectional	Saudi Arabia	Food Healthfulness Assumptions	Nutrition education
Kelly, 2007 (Kelly et al., 2007); Rangan, 2008 (Rangan et al., 2008); Rangan, 2009 (Rangan et al., 2009); Crino, 2018 (Crino et al., 2018)	Cross-Sectional	Australia	Australian Dietary Guidelines for Healthy Eating	Food advertising and marketing controls Nutrition surveillance
Kelly, 2010 (Kelly et al., 2010)	Cross-Sectional	11 countries*		
Kelly, 2015 (Kelly et al., 2015)	Cross-Sectional	Mongolia and The Philippines		
Charlton, 2015 (Charlton et al., 2015)	Cross-Sectional	12 countries *		
Ministry of Health (FBCS), 2007 (Ministry of Health, 2007); Vandevijvere, 2017 (Vandevijvere et al., 2017); Vandevijvere, 2018 (Vandevijvere et al., 2018)	Cross-Sectional	New Zealand	Ministry of Health (FBCS) guidelines for healthy children and adolescents	Nutrition surveillance Food advertising and marketing controls

* **11 countries: Greece, Germany, China, Spain, Sweden, USA, Australia, UK, Canada, Italy and Brazil**

* **12 countries: Australia, Canada, Hong Kong, India, Malaysia, New Zealand, Philippines, Singapore, South Africa, Sweden, UK and USA**

2.3.5 Nutrient-based approach

In contrast to the food-based approach, nutrient-based approaches adopt quantitative food classification measures that rank food according to their nutritional composition, also known as nutrient profiling. This approach provides a means for distinguishing between foods that are more likely to be included in a healthy diet and those that are less likely, according to scientific and pragmatic principles. In this review, 35 studies employed nutrient profiling models for ranking and categorising foods as "healthy" or "unhealthy" (Table 2.4). The various nutrient profiling models (n=21) used to categorise food were based on specific parameters (Table 2.5) The two main methodological approaches evident in the design of the nutrient profiling models included: **"across-the-board"** models where all foods are assessed according to the same nutrition criteria and **"category-specific"** models where specific thresholds are defined for several food groups. Most models (n=16) applied the across-the-board approach whilst only a few applied (n= 5) the category-specific approach.

The "across-the-board" approach is practical and simple to establish and does not require judgments for food categories as compared to the category-specific approach. However, the "across-the-board" approach uses the same measure for all foods, which may be intrinsically different. Conversely, although the category-specific approach may well address the intrinsic differences between foods, defining food categories may be culture-dependent and variable across countries. In this review, the number of category-specific groups used ranges from two (American Heart Association criteria) to 17 (WHO-Europe model)

Other features of the nutrient profiling models identified were based on a) the choice of nutrients; b) the selection of reference values for the chosen nutrients; c) the type of cut-off methods; d) the algorithm to combine the content information; e) validation of the model. With regards to the choice of nutrients, models included positive nutrients (desirable or recommended nutrients known to promote good health, particularly vitamins and minerals);

negative nutrients (disqualifying nutrients: sugars, fats and sodium); or a combination of the two. The contents of fruit and vegetables including nuts and legumes were also taken into account in some models (Rayner M, 2005a; Food Standards Australia New Zealand, 2016). The positive nutrients included a minimum of selected macronutrients (proteins, fibre); vitamins A and vitamin C, including minerals like calcium and Iron. In a few instances, the list was extended to include essential fatty acids, folate, B vitamins and minerals, typically magnesium, zinc and potassium. In total, the number of positive nutrients varied from a minimum of two to a maximum of 23 (Table 2.5). In addition, the standard negative nutrients were saturated fat (SFA), total fat, trans fat, total, sugar and sodium. The Food Standards Australian New Zealand models adapted from the UK FSA models (Rayner M, 2005a) defined negative nutrients similarly to include energy, SFA, total sugar and sodium (Food Standards Australia New Zealand, 2016) , whilst models originating from the US FDA definition included total fat, saturated fat, cholesterol and sodium (Scheidt DM, 2004; Drewnowski, 2005; American Heart Association, 2019; U.S. Food and Drug Administration, 2019). Other definitions distinguished total, free and added sugars (World Health Organization, 2015; Pan American Health Organization, 2016) Consequently, as nutrient composition databases pose limitations some nutrients like trans fats were included by only a few models (Pan American Health Organization, 2016; American Heart Association, 2019). Table 2.5 provides a summary of nutrient profile models and parameters on which they are based.

Table 2.4:Studies that applied the nutrient-based categorisation methods

Study characteristics			Emerging types of nutrient-based profiling models used	Validation	Public health applications
First author, year	Study Design	Country	Categorisation guidelines/models used	Type of validity or reliability tested	Specific application
Rayner, 2005 (Rayner M, 2005b)	Cross-Sectional	UK	FSA SSCg3d model (earlier version)	Construct validity	Food labelling and regulations
Rayner, 2005 (Rayner M, 2005a)	Cross-Sectional	UK	FSA WXYfm model	Construct validity	Food advertising and marketing controls
NNC, 2005 (Netherlands Nutrition Centre, 2005)	Cross-Sectional	Netherlands	Netherlands Tripartite system	None identified	Nutrition education
Drewnowski, 2005 (Drewnowski, 2005)	Cross-Sectional	USA	NQI; CFN; NNR; RRR models	Construct validity	Not applicable
Quinio, 2007 (Quinio et al., 2007)	Cross-Sectional	5 countries**[1]	Netherlands Tripartite system, FDA criteria for health claims, FSA WXYfm model	Construct validity	Not applicable
Scarborough, 2007a (Scarborough, 2007a)	Cross-Sectional	UK	FSA WXYfm; FSA SSCg3d; Netherlands Tripartite System; NFI; AHF; AHA; RRR; NNR;	Construct validity	Not applicable
FSA, 2007 (Food Standards Agency, 2007)	Cross-Sectional	UK	MTL scheme	None identified	Food labelling and regulations
Arambepola, 2008 (Arambepola et al., 2008)	Cross-Sectional	UK	FSA WXYfm model	Construct validity, Convergent validity, Discriminant validity	Food advertising and marketing controls
Drewnowski, 2009 (Drewnowski et al., 2009b)	Cross-Sectional	USA	NAS; NDS; NNR; NR; LIM; LIM $_{tot}$; FSA WXYfm	Construct validity	Nutrition education
Jenkin, 2009 (Jenkin et al., 2009)	Cross-Sectional	New Zealand	FSA WXYfm model	None identified	Food advertising and marketing controls
Darmon, 2009 (Darmon et al., 2009)	Cross-Sectional	France	SAIN, LIM systems	Construct validity	Nutrition education
Fulgoni, 2009 (Fulgoni et al., 2009)	Cross-Sectional	USA	NRF $_{n.3\ (6.3,\ 9.3,11.3,15.3)}$ models	Construct validity	Nutrition education
Eyles, 2010 (Eyles et al., 2010)	Cross-Sectional	Australia	MHFT; MFSANZ models	Construct validity	Food Labelling
Drewnowski, 2010 (Drewnowski, 2010)	Cross-Sectional	USA	NRF 9.3 model	Construct validity	Nutrition education
Streppel, 2012 (Streppel et al., 2012)	Cross-Sectional	Netherlands	NRF 9.3 model	Criterion validity	Nutrition education
Rosentreter, 2013 (Rosentreter et al., 2013)	Cross-Sectional	New Zealand	MTL scheme; FSANZ model	Construct validity, Inter-rater reliability	Food advertising and marketing controls
Pechey, 2013 (Pechey et al., 2013)	Cross-Sectional	UK	FSA WXYfm model	None identified	Nutrition surveillance
Romero-Fernandez, 2013 (Romero-Fernandez et al., 2013)	Cross-Sectional	Spain	FSA WXYfm model	None identified	Food advertising and marketing controls
Scheidt, 2014 (Scheidt DM, 2004)	Cross-Sectional	USA	RRR model	None identified	Nutrition education

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5 countries:** Belgium, Denmark, France, Ireland and Italy.

Study characteristics			Emerging types of nutrient-based profiling models used	Validation	Public health applications
First author, year	**Study Design**	**Country**	**Categorisation guidelines/models used**	**Type of validity or reliability tested**	**Specific application**
Streppel, 2014 (Streppel et al., 2014)	Cohort	Netherlands	NRF 9.3	Predictive validity	Nutrition education
Sluik, 2015 (Sluik et al., 2015)	Cross-Sectional	Netherlands	NR (9,11,15,18,19,20); NRF (9.3,11.3,15.3,18.3, 19.3, 20.3); LIM	Criterion validity	Not applicable
Ravensbergen, 2015 (Ravensbergen et al., 2015)	Cross-Sectional	Netherlands	Netherlands Tripartite System	None identified	Food advertising and marketing controls
WHO, 2015 (World Health Organization, 2015)	Cross-Sectional	WHO-Europe	WHO–Europe model	None identified	Food advertising and marketing controls
Masset, 2015 (Masset et al., 2015)	Cohort	UK	FSA WXYfm; SAIN, LIM models	Predictive validity	Not applicable
Monroy-Parada, 2016 (Monroy-Parada et al., 2016)	Cross-Sectional	Spain	FSA WXYfm model	None identified	Food advertising and marketing controls
PAHO, 2016 (Pan American Health Organization, 2016)	Cross-Sectional	USA	PAHO model	Construct validity	Food advertising and marketing controls
Mhurchu, 2016 (Mhurchu et al., 2016)	Cross-Sectional	New Zealand	HSRC; Ministry of Health (FBCS); WHO–Europe model	Inter-rater reliability	Food advertising and marketing controls
FSANZ, 2016 (Food Standards Australia New Zealand, 2016)	Cross-Sectional	Australia	FSANZ model	None identified	Food labelling and regulations
HSRC, 2018 (Food Standards Australia New Zealand, 2018)	Cross-Sectional	Australia	HSRC model	None identified	Food labelling and regulations
Mytton, 2018 (Mytton et al., 2018)	Cohort	UK	FSA WXYfm model	Predictive Validity	Food advertising and marketing controls
Maillot, 2018 (Maillot et al., 2018)	Cross-Sectional	France	The SEN algorithm	Construct validity	Food labelling and regulations
Darmon, 2018 (Maillot et al., 2018)	Cross-Sectional	France	The SEN algorithm	Construct validity	Food labelling and regulations
FDA, 2019 (Food and Drug Administration, 2019)	Cross-Sectional	USA	FDA criteria for health claims	None identified	Food labelling and regulations
AHA, 2019 (American Heart Association, 2019)	Cross-Sectional	USA	AHA heart check criteria	None identified	Nutrition education
AHF, 2019 (Australian Heart Foundation, 2019)	Cross-Sectional	Australian	AHF tick system	None identified	Food labelling and regulations

Abbreviation used in Table 2.4-American Heart Association's heart-check mark (AHA); Australian Heart Foundation's Tick scheme (AHF); Calories-for-nutrient (CFN); Food and Drug Administration (FDA); Food Standard Agency (FSA); Food Standards Australia New Zealand (FSANZ); Health Star Rating Calculator (HSRC); Limited Nutrient Score (LIM); Limited Nutrient Score tot (LIMtot); Ministry of Health Food and Beverage Classification System (FBCS); Modified Food Standards Australia New Zealand Health Claims Nutrient Profiling Calculator (MFSANZ); Modified Heart Foundation Tick Model (MHFT); Multiple Traffic Lights (MTL); Naturally Nutrient Rich (NNR); Netherlands Nutrition Centre (NNC); Nutrient Adequacy Score (NAS); Nutrient Density Score (NDS); Nutrient Rich (NR); Nutrient Rich Food Index (NRF); Nutritional quality index system (NQI); Nutritious Food Index (NFI); Pan American Health Organization Model (PAHO); Ratio of recommended to restricted (RRR); United Kingdom (UK); United States of America (USA);World Health Organization (WHO).

Table 2.5: Summary of selected nutrient-based profiling models identified in studies

Nutrient profiling model used	Design	Cut-off method	Reference Unit	Positive /negative nutrients	Positive nutrients (macronutrients, vitamins, minerals)	Positive food groups	Negative nutrients
FSA SSCg3d Model (earlier version) (Rayner M, 2005b; Scarborough, 2007a)	AC	Scoring	100 g / 200 ml	+Ve and -Ve	n-3 fatty acids, Ca, Fe	Fruit and vegetable	Energy, SFA, Na, added sugar
FSA WXYfm model (Rayner M, 2005a; Quinio et al., 2007; Scarborough, 2007a; Arambepola et al., 2008; Drewnowski et al., 2009b; Jenkin et al., 2009; Pechey et al., 2013; Romero-Fernandez et al., 2013; Masset et al., 2015; Monroy-Parada et al., 2016; Mytton et al., 2018)	AC	Scoring	100 g / 100 ml	+Ve and -Ve	Protein, fibre	Fruit, vegetable, nut	Energy, SFA, Na, total sugar
Netherlands Tripartite system (Netherlands Nutrition Centre, 2005; Scarborough, 2007a; Ravensbergen et al., 2015)	CS (n=14)	Threshold	100 g	+Ve and -Ve	Fibre, omega-3 fatty acids, vitamin C, folate	Not applicable	Energy, SFA, total sugars
WHO–Europe model (World Health Organization, 2015; Mhurchu et al., 2016)	CS (n=17)	Threshold	100 g	-Ve	Not applicable	Not applicable	Energy, SFA, total fat, Na, sugar (total, added)
PAHO model (Pan American Health Organization, 2016)	CS (n=5)	Threshold	% of energy in food	-Ve	Not applicable	Not applicable	SFA, total fat, trans fat, Na, free sugars, and other sweeteners
MTL Scheme (Rosentreter et al., 2013; Food Standards Agency, 2007)	AC	Threshold	100 g / 100 ml	-Ve	Not applicable	Not applicable	SFA, total fat, Na, total sugars
FSANZ Calculator (Eyles et al., 2010; Rosentreter et al., 2013; Food Standards Australia New Zealand, 2016)	AC	Scoring	100 g / 100 ml	+Ve and -Ve	Protein, fibre	Fruit, vegetables, nut, legume	Energy, SFA, Na, total sugars
HSRC model (Mhurchu et al., 2016; Food Standards Australia New Zealand, 2018)	AC	Scoring	100 g /100 ml	+Ve and -Ve	Protein, fibre	Fruit, vegetables, nut, legume	Energy, SFA, Na total sugars
SEN algorithm (Maillot et al., 2018)	AC	Scoring	100 kcal & 100 g	+Ve and -Ve	Protein, fibre, MUFA, a-linolenic acid, vitamin C, Ca	Not applicable	Energy, SFA, Na, free sugar
SAIN, LIM system (Darmon et al., 2009; Masset et al., 2015)	AC	Scoring	100 kcal & 100 g	+Ve and -Ve	Protein, fibre, MUFA, a-linolenic acid, calcium, iron, vitamin C, E, optional vitamin D	Not applicable	SFA, Na, added sugar
FDA criteria (Quinio et al., 2007; U.S. Food and Drug Administration, 2019)	AC	Threshold	Serving size	+Ve and -Ve	Protein, fibre, iron, calcium, vitamin A, C	Not applicable	SFA, total fat, Na, cholesterol
AHA heart check criteria (Scarborough, 2007a; Australian Heart Foundation, 2019)	CS (n=2)	Threshold	Serving size	+Ve and -Ve	Protein, fibre, iron, calcium, vitamins A, C	Not applicable	SFA, total fat, Na, cholesterol, trans fat
AHF tick system(Scarborough, 2007a; American Heart Association, 2019)	CS (n=10)	Threshold	Serving size	+Ve and -Ve	Protein, fibre	Not applicable	Energy, SFA, total fat, Na, total sugars
RRR model (Scheidt DM, 2004; Drewnowski, 2005; Scarborough, 2007a)	AC	Scoring	Serving size	+Ve and -Ve	Protein, fibre, vitamins A, C, Ca, Fe	Not applicable	Energy, SFA, total sugar, Na, cholesterol
NQI model (Drewnowski, 2005)	AC	Scoring	2000 kcal	+Ve and -Ve	Protein, fibre, MUFA, CHO, vitamins A , C, B1, B2, B3, B6, B12, Ca, Fe	Not applicable	SFA, total fat, Na, cholesterol
CFN model (Drewnowski, 2005)	AC	Scoring	1000 kcal	+Ve	Protein, vitamins A,C, B1, B3, B6, B12, folate, Ca, Fe, Zn, Mg	Not applicable	Not applicable

Nutrient profiling model used	Design	Cut-off method	Reference Unit	Positive /negative nutrients	Positive nutrients (macronutrients, vitamins, minerals)	Positive food groups	Negative nutrients
NFI model (Scarborough, 2007a)	AC	Scoring	Serving size	+Ve and -Ve	Fibre, vitamins A, C, B1, B2, B3, folate, Ca, Fe, Zn, Mg, K, P	Not applicable	SFA, total fat, Na, cholesterol
NNR model (Drewnowski, 2005; Scarborough, 2007a)	AC	Scoring	2000 kcal	+Ve	Protein, MUFA, vitamins A, C, D, E, B1, B6, B12, folate, Ca, Fe, Zn, K	Not applicable	Not applicable
NDS ($_{n=-5-23}$) model	AC	Scoring	100 kcal	+Ve	Protein, fibre, linoleic/linolenic acid, DHA, vitamin A, C, D, E, B1, B2, B3, B6, B12, folate, Ca, Fe, Zn, Mg, K, Cu, I, Se	Not applicable	Not applicable
NAS	AC	Scoring	100 kcal	+Ve	Protein, fibre, vitamins A, C, D, E, B1, B2, B3, B6, B12, folate, Ca, Fe, Mg	Not applicable	Not applicable
NRF n.3 (Fulgoni et al., 2009; Drewnowski, 2010; Streppel et al., 2012; Streppel et al., 2014; Sluik et al., 2015)	AC	Scoring	100 kcal	+Ve and -Ve	Protein, fibre, MUFA, vitamins A, C, D, E, B1, B2, B12, folate, Ca. Fe, Mg, Zn, K	Not applicable	SFA, Na, sugar (total, added)

Abbreviation used in

Table 2.5: Across-the-board (AC); American Heart Association's heart-check mark (AHA); Australian Heart Foundation's Tick scheme(AHF); Calcium(Ca); Calories-for-nutrient (CFN); Category Specific (CS); Cobalamin (B12); Copper (Cu); Docosahexaenoic acid (DHA); Food and Drug Administration (FDA); Food Standard Agency (FSA); Food Standards Australia New Zealand (FSANZ); Health Star Rating Calculator (HSRC); Iodine (I); Iron (Fe); Magnesium (Mg); Monounsaturated fatty acid (MUFA); Multiple Traffic Lights (MTL); Naturally nutrient rich (NNR); Negative (-Ve); Niacin (B3); Nutrient Adequacy Score (NAS); Nutrient Density Score (NDS); Nutrient Rich Food Index (NRF); Nutritional quality index system(NQI); Nutritious Food Index (NFI); Pan American Health Organization Model (PAHO); Phosphorus (P); Positive (+Ve); Potassium (K); Pyridoxine (B6); Ratio of recommended to restricted (RRR); Riboflavin (B2); Saturated Fatty Acids (SFA); Selenium (Se); Sodium (Na);Thiamine (B1); World Health Organization (WHO); Zinc (Zn).

Three different reference bases for calculating nutrient profiling scores became apparent. These included 100 grams, 100 kcals and serving size. Two models uniquely combined the 100 g and 100 kcals in their algorithm to define nutrient density scores (Darmon et al., 2009; Maillot et al., 2018).

The cut-off method adapted by nutrient profiling models was either a scoring approach or one based on thresholds. The criteria and algorithms used to define "healthy" and "unhealthy" foods were not uniform. For instance, the UK FSA nutrient profile model WXYfm, from which other models like the FSANZ and HSRC originated, defined food using four negative and three positive nutrients, calculated per 100 grams of food or 100 milligrams of drink. Using a sophisticated formula, the food's content of fruits, vegetables, nuts and legumes is taken into account. The sum of positive nutrients is then subtracted from the negative nutrients to generate a final score. On those bases, a food scoring 4 points or more is then categorised as less healthy or healthier if it scores zero points or less (Rayner M, 2005a, c).

Similar but less sophisticated, NRF scoring, also based on both positive and negative nutrients, determines the nutrient density (NRFn.3) of food using a variable number of nutrients to encourage, where n represents the number of positive nutrients selected. A minimum of three nutrients make up the negative component, these include: total fat or saturated fat, added sugar or total sugar and sodium. The NRF scores are calculated per 100 kcals using the simplest algorithm, which subtracts the sum of the three nutrients from the nutrient density component.

2.3.6 Categorisation based on food processing.

In this review, three studies (Monteiro et al., 2011; Adams et al., 2015; O'Halloran et al., 2017) based the categorisation of food as "healthy" or "unhealthy" on the level and purpose of food processing. This method of food categorisation aligns with a system also known as the "NOVA system" (a name, not an acronym), that was developed in response to the increasing dominance of industrially processed foodstuffs in the global food chain. The "NOVA system" has been used in countries such as Brazil (Monteiro et al., 2011), the United Kingdom (Adams et al., 2015), and Australia (O'Halloran et al., 2017) to classify food as "healthy" or "unhealthy". This approach is used to distinguish homecooked or freshly cooked dishes from industrially manufactured foodstuffs and thereby to categorise food into 3-4 groups according to the level and purpose of industrial processing: 1) Minimally processed food (MP), 2) Processed culinary ingredients (PCI), 3) Processed food (P) and 4) Ultra-processed foods (ULP) (Table 2.6). The emphasis in the studies that used this approach was that classifying foods items by the extent of processing gave prominence to variations in nutritional quality among foods within the same food category. For instance, bread is classed as either (MP) or (P) whereas cereal bars and biscuits fall into (P) or (ULP) food groups. O'Halloran and colleagues (2017), in their study using the Australian food composition database, reported that some types of bread and pasta recommended as good sources of grains by the Australian Dietary Guidelines were classified as ULP, despite having considerably better nutrient profiles in comparison to many other highly processed foods items such as sugar-sweetened drinks.

Table 2.6: Studies based on food processing

Study Characteristics			Emerging types of categorisation methods
First author, year	**Study Design**	**Country**	**Categorisation method**
Public health application: Nutrition surveillance			
Monteiro, 2011 (Monteiro et al., 2011); Adams, 2015 (Adams et al., 2015)	Cross-Sectional	Brazil; UK	Extent and purpose of processing Three groups: Group 1- “Unprocessed foods, Group 2- “Processed culinary ingredients”, Group 3- “Ultra-processed”
O'Halloran, 2017 (O'Halloran et al., 2017)	Cross-Sectional	Australia	The NOVA system Four groups as: Group 1- “Unprocessed”, Group 2- “Processed culinary ingredients” Group 3- “Processed foods” Group 4- “Ultra processed foods”

2.3.7 Validity and reliability of methods identified

Validity is described as an estimate of the accuracy of an instrument or measure (Streiner, 2015; Cooper et al., 2016). It shows how well a measurement tool performs its intended function (Streiner,2015), whereas reliability refers to the extent to which a measure produces consistent results (Streiner, 2015). It is worth pointing out that a valid instrument is mostly reliable; however, a reliable instrument does not necessarily mean a valid instrument. Hence, validity relates to accuracy, whilst reliability is a measure of precision.

The nutrient-based models were identified to be subjected to validity and reliability testing (Table 2.7). There are various types of validity studies identified for establishing the accuracy of food categorisation methods depending on how the system is to be used. A valid instrument is mostly reliable; however, a reliable instrument does not necessarily mean or imply a valid instrument. Validity was assessed more in the studies included in this review (n=17)

(Drewnowski, 2005; Rayner M, 2005b, a; Quinio et al., 2007; Scarborough, 2007a; Arambepola et al., 2008; Darmon et al., 2009; Drewnowski et al., 2009b; Fulgoni et al., 2009; Drewnowski, 2010; Streppel et al., 2012; Rosentreter et al., 2013; Streppel et al., 2014; Masset et al., 2015; Sluik et al., 2015; Pan American Health Organization, 2016; Maillot et al., 2018; Mytton et al., 2018) than reliability (n=2) (Eyles et al., 2010; Mhurchu et al., 2016) (Table 2.7). More so, the nutrient-based model was observed to be extensively validated in comparison to the other methods. Validity was the term mostly used in nutrient profiling to describe the robustness of the method used rather than reliability.

The recommended approaches for measuring validity include content, face, and construct (convergent, discriminant criterion, predictive) validity. The main type of validity revealed in this analysis was construct validity, which ranged from the ranking of a defined set of foods and linear programming to the associations with potential health outcomes in cohort studies. Some methods were simpler, requiring the least collection of data (Quinio et al., 2007; Scarborough, 2007a; Arambepola et al., 2008; Rosentreter et al., 2013), whereas more complex ones required individual-based data or more advanced modelling (Darmon et al., 2009; Fulgoni et al., 2009; Drewnowski, 2010; Streppel et al., 2012; Streppel et al., 2014; Sluik et al., 2015; Maillot et al., 2018; Mytton et al., 2018). Thus, validity testing consisted of testing for construct validity, which included criterion validity, predictive validity, convergent validity and discriminant validity (Table 2.7).

Table 2.7: Studies that tested the validity and reliability of nutrient profiling models

Title of Publication	Nutrient profile model tested	Type of validity	Type of reliability	Results from statistical analysis
Scarborough, 2007	UK's model (FSA models SSCg3d and WXYfm); Nutritious Food Index (NFI); Ratio of Recommended to Restricted (RRR); Naturally Nutrient Rich (NNR); Netherlands Tripartite System; Australian Heart Foundation Tick; American Heart Association heart-check mark	Construct (Criterion-related)	None identified	"The models defined as continuous showed a good correlation with the standard rating (Spearman's rank correlation = 0.6–0.8). UK's models WXYfm and SSCg3d attained higher scores compared to the other models, suggesting a better agreement with the standard food rankings."
Quinio, 2007	UK's FSA WXY model The Dutch Tripartite system US FDA model.	Construct (convergent)	None identified	"Indicator food items associated with healthy diets were classified using each nutrient profiling model." The sensitivity and specificity of the three models were fairly good. Differences in performance between the models were small. No statistically significant difference in sensitivity ratio was identified for foods consumed in the "healthy diets." The "Wilcoxon Mann–Whitney" test was applied with three levels of statistical significance of p-values of (0.05, 0.01, and 0.001). The FSA WXY model achieved a score of 100 % (p=0.001) with the "reference standard" for food consumed in a healthy Italian diet.
Scarborough, 2007	Experts' standard ranking of indicator foods'	None identified	Internal consistency	The experts classified "raw green peppers" with a score of 5.91 as the healthiest. They also classified "clotted cream," with a score of 1.21 as least healthy. The energy was found to correlate with fat (r=0.86; p=0.05) and thus was removed from the regression analysis. Carbohydrates were removed because it was found to correlate with total sugars (r=0.69; p=0.05). Results suggest that experts tended to categorise food with larger serving sizes as less healthy. The Cronbach's alpha for internal reliability of the questionnaire was calculated.

Title of Publication	Nutrient profile model tested	Type of validity	Type of reliability	Results from statistical analysis
Arambepola, 2008	UK's WXY fm model	Construct (convergent and discriminant)	None identified	The results showed that the level of agreement between the way the WXYfm model classifies food and how the Balance of Good Health (BGH) classifies food was good (kappa = 0.69).
Darmon, 2009	The SAIN, LIM system	Construct	None identified	Mathematical modelling of theoretical diets was performed using sensitivity analysis. Four classes of food groups were determined. Class 1: contained (80%) of fruit and vegetables, including (50%) of food from the eggs/meat and poultry category and (40%) of food from the starches and grains category. Class 2: contained most refined cereals and cereal products containing reasonable amounts of SFAs, salt and sugar. Class 3: contained (66%) most cheeses, some dele meat, smoked or salted meats, with medium fat and also vegetable oils. Class 4: mostly contained foods from the salt and sweets category, soft drinks, fatty meats and dairy food high in fat. Both "healthy" and "unhealthy" diets can be modelled from the middle classes.
Fulgoni, 2009	Nutrient-Rich Food Index family (NRF 6.3, NRF 9.3, NRF 11.3, NRF 15.3)	Construct	None identified	The percentage of the variation (R^2) and the p-value of models were used to validate the algorithms. All NRF indices evaluated had a strong correction ($p<0.001$) with the Healthy Eating Index (HEI). NRF9.3 explained the highest variation ($R^2=0.453$) for 100 kcals. NRF11.3 and NRF15.3 exhibited lower percentage variations calculated per 100 kcals respectively ($R^2=0.397$ and 0.340) When total sugars were used instead of added sugars, it resulted in a slightly lower R^2 for all NRF algorithms per 100 kcals and per RACC.
Drewnowski, 2009	Nutrient Adequacy (NAS23, NAS16) Nutrient Density (NDS23, NDS16) Nutrient-Rich (NR 5–7; 10–12, and 15) LIM scores and a modified WXYfm model.	Construct	None identified	When the number of nutrients in the model was decreased from 23 to 10, the NDS and NR scores still has a strong correlation ($r= 0.93$). As the number of beneficial nutrients was decreased to five, correlations were reduced to ($r=0.78$).
Drewnowski, 2010	The Nutrient-Rich Food Index (NRF 9.3)	Construct	None identified	The "analyses of variance", "regression models", and "univariate comparisons" of means across quintiles were the primary analyses performed to identify affordable foods using the NRF9.3 index

Title of Publication	Nutrient profile model tested	Type of validity	Type of reliability	Results from statistical analysis
				Results show that the cheapest sources of protein were dried beans, lentils, eggs, meat and dairy products. The cheapest sources of "calcium" were milk and milk products, while the cheapest sources of "vitamin C" were fruits and vegetables. The majority of calories were delivered by energy-dense grains, fats and sweets, but there were fewer nutrients per dollar.
Eyles, 2010	Modified Heart Foundation Tick Model (MHFT) Modified Food Standards Australia New Zealand Nutrient Profiling Calculator (MFSANZ)	Construct	Inter-rater reliability	An inter-rater reliability analysis applying the kappa statistic was carried out to determine the agreement and consistency across the two systems. The percentage agreement between the two nutrient profiling systems was 72% and a kappa = 0.46 (p=0.00). The products labelled "healthier" were on average lower in saturated fat, sugar, sodium, protein and energy as compared to the "less healthy" products.
Streppel, 2012.	Nutrient-Rich Food Index (NR9.3)	Criterion validity	None identified	Linear regression was used to examine the association between the NRF index scores and waist circumference, waist-to-height ratio, waist-to-hip ratio and body mass index (BMI). Participants with high NRF9.3 index scores had lower energy intake, whereas those with lower NRF 9.3 index scores comparatively exhibited higher energy intakes.
Rosentreter, 2013.	The Multiple Traffic Light (MTL) Food Standards Australia New Zealand (FSANZ)	Construct	Inter-rater reliability	Kappa statistic estimated the inter-rater agreement between the models: "Multiple Traffic Light -MTL" and the "Food Standard Australia New Zealand Nutrient Profiling Standard Calculator (FSANZ-NPSC)". The agreement between the FSANZ-NPSC and the MTL model scores was 73% but altered by the food group. The agreement was high ranking for "sausages" (99%) and low ranking for "breakfast cereals." (59%). As a result, Kappa statistics revealed that the two models had a "fair level" of agreement using an MTL aggregate score of <7 (k=0.35) and a "moderate level" (k=0.52) of agreement using a higher threshold.
Streppel, 2014	Nutrient-Rich Food Index (NR9.3)	Criterion validity (predictive validity)	None identified	A high NRF9.3 index score was inversely correlated with all-cause mortality. Participants with higher scores were more likely to have hypertension, diabetes and on a diet. The mean NRF9.3 index scores were greater in females than in males. Fruit and vegetables, milk and dairy products, and bread and potatoes were the primary food group contributors to the NRF9.3 index.

Title of Publication	Nutrient profile model tested	Type of validity	Type of reliability	Results from statistical analysis
Masset, 2015	The UK's model The SAIN, LIM model	Criterion (predictive)	Not specified	"Multi-adjusted Cox regressions" were fitted with an incident of coronary heart disease (CHD), diabetes, cardiovascular disease (CVD), and cancer and all-cause mortality. Food variety score (FVS) was linked to a lower risk of prospective CHD and all-cause mortality risk. A variety of recommended food from the UK's Ofcom model in the (third versus the first quartile) was correlated with a reduction in all-cause mortality (27%) and cancer mortality risk (35%). Similar relationships were hypothesised for the variety of selected recommended foods from the SAIN, LIM model, but they were not statistically significant.
Sluik D, 2015	Fifteen NRF index scores were tested against the Dutch Healthy Diet Index (DHD index)	Construct (convergent validity)	None identified	"The index score that better predicted the Diet Healthy Diet-index (DHD-index) included 9 qualifying nutrients and three disqualifying nutrients on a 100 kcal bases"- NRF9.3 with R^2=0.34. Energy density and NRF index score were associated, although nutrient density more accurately predicted the DHD-index than did energy density. Cereals, vegetables and dairy products were the main contributors to each participant's NRF9.3 score.
Mhurchu, 2016	Health Star Rating system (HSR) Ministry of Health (FBCS) WHO Europe Model	Construct	inter-rater reliability	Percentages and proportions of food classified as healthy or unhealthy were identified. According to the WHO model, 29% of products would be permitted for marketing, 36% under the HSR system and 39% under the FBCS system would be regarded as healthy and permitted for marketing. The WHO model limits the marketing of unhealthy foods more efficiently compared to the HSR and FBCS systems.
Pan American Nutrient Profiling model, 2016	Pan American Nutrient Profiling Model WHO's European Regional Office (WHO-EURO) WHO's Eastern Mediterranean Regional Office (WHO-EMRO) United Kingdom's Food Standard Agency (FSA)/Ofcom model	Construct validity	Not specified	The PAHO Model was compared with three other nutrient profile models: WHO- EURO (68%), WHO-EMRO (76%), and UK FSA/Ofcom (53%) and the PAHO (78%) show the highest percentage performance in classifying foods with excessive amounts of critical nutrients.
Darmon, 2018	The SENS algorithm	Construct	None identified	The "Kruskal–Wallis" test was used to statistically compare distributions across SENS classes. The categorisations were in line with the advice to eat large amounts of whole grains, fruits and vegetables whilst consuming fats, salt, sugar, meat and sugar-sweetened drinks in moderation.

Title of Publication	Nutrient profile model tested	Type of validity	Type of reliability	Results from statistical analysis
Maillot, 2018	The SENS algorithm	Construct	None identified	The "Kruskal–Wallis" test was used to compare allocations of food items across SENS four classes. Daily frequency for Class-1 group foods increased for 98.4% of participants on observed diets and decreased for Class-4 group foods for 94.2% of people on optimised diets. Food in classes 2 and 3 likewise exhibited patterns consistent with their expected ranking.
Mytton, 2018	The UK's profile model	Criterion (predictive)	None Identified	The consumption of less-healthy foods was linked to an event of cardiovascular disease (CVD) in the unadjusted analyses (tested for linear trend over quintiles, $p<0.01$). However, no relationship between eating of less healthy food and incident of CVD ($p=0.84$) or cardiovascular mortality ($p=9.0$) was found after adjusting for covariates however there was a relationship between intake of less healthy food and all-cause mortality ($p=0.006$; quintile group 5, highest consumption of less healthy foods, versus quintile group 1, Hazard Ratio=1.11, 95% CI 1.02-1.20) Similar findings from sensitivity analysis were obtained. Cox proportional hazards regression was used to approximate the hazard ratio and confidence interval (95%) for the association between exposure and outcome.

The 19 studies (Table 2.7) above examined and tested the validity and reliability of one or more nutrient profiling models. The validation approaches identified varied from the comparisons of ranking of a predetermined set of food items to associations with potential health outcomes within longitudinal studies.

A summary of the validation approaches identified (Table 2.7) above is provided as follows:

a. Evaluation of food rankings based on several nutrient profiling models.
b. Rankings from nutrition professionals compared to those from nutrient profiling models
c. The use of nutrition survey data to compare nutrient profile rankings and the healthiness of diets and dietary goals.
d. The use of linear modelling to create hypothetical diets with healthy food options to determine the construct validity of the models
e. The use of prospective associations with health outcomes determines the predictive validity of the nutrient profile models. The most common type of validity used in studies to validate nutrient profile models was construct validity.

2.3.8 Range of public health application

The main applications of definitions for “healthy” or “unhealthy” foods can be categorised into four major groups as follows: food advertising and marketing controls (n=22); food labelling and regulation (n=8); nutrition education (n=12); and nutrient surveillance (n=8). The nutrient profiling models that emphasised positive nutrients or beneficial nutrients mainly were designed for nutrition education, whereas those focusing on negative nutrients were more concerned with food labelling regulations, food advertising and marketing controls.

Though the public health applications differed, categorically, models originating from the European Union (EU) identified foods for food labelling, advertising, market purposes and regulatory purposes. In the UK, the traffic light labelling system ranks Food-based on negative nutrients by assigning the colours green, amber and red according to the nutrient content levels. In addition, the WHO-Europe model, like the UK FSA WXYfm model, is designed to regulate the broadcasting to children of foods that may be high in fats, SFA, sugar and sodium (Rayner M, 2005b, a; World Health Organization, 2015; Monroy-Parada et al., 2016). Conversely, other models are mainly used for nutrition education and surveillance, such as the NRF index.

2.4 Discussion

2.4.1 Summary of the main results

This systematized review presents the results of the range of terms and methods used to define and categorise food as “healthy” or “unhealthy”. Further, it discusses the validity of categorisation methods and their public health applications.

The findings of this investigation suggest that the terms for defining healthy or unhealthy foods were expressed in either quantitative or qualitative terms in relation to the timing of food consumption, the context in which food was eaten and the nutritional quality of food.

Terms such as “healthier” or “less healthy” and “nutrient-dense” or “energy-dense nutrient-poor food” were backed by firm standards using nutrient profile models that were subjected to validity testing. On the other hand, qualitative terms such as “snack foods”, “ultra-processed foods” and “fast foods” exhibited a less transparent basis, without evidence of validity found. A term such as “snack foods” may divert the attention of consumers from the quality of food by restricting the definition to time of consumption, whilst “fast foods” may apply only to a subset of takeaway foods and moreover not all “ultra-processed” foods have poor nutritional composition. The concern in using such qualitative terms to define food is that they may be imprecise and some foods may be misclassified. This implies that clearer definitions of terms for defining healthy and unhealthy foods need to be included in any intervention aimed at curbing today’s high consumption of unhealthy foods.

These findings are in corroboration with previous studies in relation to defining “healthy and unhealthy foods” (Guthrie, 1977; Lackey, 2004; Drewnowski, 2005; Lobstein, 2009). Guthrie, in a review conducted in 1977, concluded that there is a lack of a common definition for the concept of “healthy” food (Guthrie, 1977) and over the past four decades no conclusive agreement has been reached on the definition of “healthy or nutritious" food.

The methods used in categorising food were identified as “food-based”, “nutrient-based” and “food processing” (Figure 2.4). The food-based and food processing approaches provided a comparative assessment to the more rigorous nutrient-based approach. Though the former were simpler and feasible in settings with limited nutritional composition data and resources they may not fit as standalone tools for discriminating between individual foods as “healthy” or “unhealthy”. More so, reviewed studies that used the food-based and food processing approaches were not subjected to any validity testing, unlike the nutrient-based approach.

This corroborates suggestions by studies on ultra-processed foods, that food items not considered ultra-processed (meat, milk, flour, cheese) were often misclassified by consumers based on this approach to food categorisation (Ares et al., 2016; Aguirre et al., 2019).

By contrast, the nutrient-based approach categorised food using nutrient profiling models. Despite having diverse goals, nutrient profiling models exhibited, rigorous and science-driven rules and were mostly validated (Drewnowski, 2005; Rayner M, 2005a; Scarborough, 2007c, a; Darmon et al., 2009; Fulgoni et al., 2009; Drewnowski, 2010; World Health Organization, 2015; Food Standards Australia New Zealand, 2016; American Heart Association, 2019; Australian Heart Foundation, 2019; U.S. Food and Drug Administration, 2019). While it was observed that nutrient-based models demonstrated the capacity to discriminate between nutrient levels in foods (energy-dense, nutrient-poor) and their direct effects on a person’s health (healthier or less healthy), it can be argued that there are some methodological considerations during the design of nutrient profile models that may pose as limitations or strengths in the use of a specific model over another. This includes but is not limited to the design and purpose of the model, as these determine the ease of implementation and adaptability of a nutrient profiling model for public health interventions and policy.

Of the 21 nutrient profiling models identified in this review, the NRF index model (Fulgoni et al., 2009; Drewnowski, 2010) has demonstrably been applied and extensively validated in other settings, such as the Netherlands, different from the US setting where it was developed and initially tested (Drewnowski, 2010; Drewnowski et al., 2014). Unlike category-specific models or similar across-the-board models, the NRF index is relatively easy to use and allows for the choice of a range of nutrients (positive nutrients n=5 to 23 and negative nutrients n=3) depending on the context for which it is adapted and the population's public health nutrition concerns as well as available nutrient composition data (Fulgoni et al., 2009; Drewnowski, 2010). Distinctly the aim or purpose for the development of the NRF index was found to be educational and consumer-focused, unlike the other models that were inclined toward food marketing advertisement and the food industry. Such models were exclusively based on nutrient to limit and were more associated with energy density than the nutrient density of foods. This close relation to energy density meant that these models provided only a few other details besides calories, unlike the NRF index that focused on nutrient density and provided an option for a balance of nutrients (Table 2.5)

In addition, the NRF index presents the flexibility for calculations to be based on either 100 grams, 100 kcal or portion size, unlike other models. Typically, calculations based on 100 kcals, in relation to energy can easily compare to daily recommendations and suggestions normally presented in terms of 2000 kcals. This is also congruent with the public health problem of the excessive intake of high energy dense nutrient-poor foods and allows for easier comparison of foods with variable energy and nutrient densities, like solid foods and beverages. Food items with low energy content, on the other hand, will be given abnormally high scores because of this. In particular, the 100 kcal bases for fruit and vegetables, may be higher than the usual serving size typically consumed and this may be challenging for some consumers to comprehend (European Food Safety, 2008). The method based on portion-size provides the most accurate presentation of how food is consumed and may serve as a motivator to lower the energy content. Nonetheless, it can still be a challenge to define the appropriate serving size for the certain foods (European Food Safety, 2008; Drewnowski et al., 2021). It necessitates a definition of a serving size, which differs depending on the person, eating occasion, cultural views or dietary customs (European Food Safety, 2008). Conversely, models that use 100 grams do not account for the energy content of food but tend to penalise foods that are nutrient-rich per 100 grams and eaten in smaller portions, and also beverages due to the influence of water content (Drewnowski et al., 2008).Thus, the NRF (9.3) model has been found to be an adaptable and user-friendly nutrient-based model that has been objectively validated against measures of healthy eating indices in other populations and can readily be adapted to other context-specific populations, especially where the availability of nutrient composition data remains a problem. A crucial phase in the development of nutrient profiling models is validation. The approaches to testing the validity and reliability of nutrient profiling models varied across nutrient profiling models (Table 2.7). Construct validity was found to be frequently tested and reported as compared to reliability. This may be because validity testing is embedded as a module to be reported on in the last stage of the nutrient profiling development process (World Health Organization, 2011b). More so, only a few reliability studies may have been published at the time frame of this review. The review suggests the different ways for testing the validity of nutrient profiling models included simpler (i.e., less data-intensive) and complex (i.e., more data-intensive) methods. The simpler approach in this review included two main methods. First, the comparison of food item rankings by several nutrient profiling models. This approach to testing nutrient profile models included the ranking of a selected list of foods representative of a target population and generated from two or more nutrient profiling models (Scarborough, 2007a). This was identified to have been used in the development process of nutrient profiling models allowing earlier versions of the same nutrient profiling model to be modified (Scarborough, 2007a). For instance, the UK Food Standards Agency (FSA)/Ofcom (WXYfm model), the Nutrient Rich Food (NRF index) and the French SAIN, LIM models identified from this review were developed through numerous stages; such as content validation methods to improve and enhance the models from a selecting a reference amount, choice of nutrients, algorithms and other decision points (Rayner M, 2005a, b; Darmon et al., 2009; Fulgoni et al., 2009). The use of food indicator panels to evaluate, review and redefine whether a model categorises food according to dietary recommendations is considered a particular aspect of face validity though this was rarely reported in this review.

Second, the comparison of the rankings by nutrient profile models with the ranking from nutrition professionals. This method of validation is similar to the first, with the exception that rankings produced from nutrient profiling models and rankings derived from nutrition professionals are statistically compared (construct/convergent validity).

In this review, the FSA/Ofcom model was validated in a study comprising nutrition professionals from the British Dietetic Association and the Nutrition Society (Scarborough, 2007a). Each participant was sent an email with 40 random foods chosen from a master list of 120 items and the participants had to give each food a score on a six-item Likert scale from less healthy to healthier. To help facilitate the categorisation of foods, the protein, carbohydrate, total sugar, fat, saturated fat, fibre, sodium, iron, calcium and energy contents per 100 grams of food were provided. These "standard scores provided by the nutrition professionals were subsequently compared with rankings generated by the following nutrient profiling models[*]: "WXYfm", "SSCg3d", "NFI", "NNR", "RRR", "Dutch Tripartite Scheme", "AHF" and "AHA" models with the focus on the UK models WXYfm, SSCg3d (Scarborough,

[*] 1.These two models (WXYfm and SSCg3d) were algorithms developed for the FSA with the aim of identifying less healthy foods for OFCOM (the broadcast regulator in the United Kingdom)
2.NFI- Nutritious Food Index with three variants a, b and c
3.NNR-Naturally Nutrient Rich score
4.Netherlands Tripartite Classification Scheme for food
5. AHF-Australian Heart Foundation Tick Scheme
6.AHA-American Heart Association heart-check mark

2007a). In their article, Scarborough et al. (2007) write that the Ofcom models "WXYfm" and "SSCg3d" were the most correlated models to the "standard rankings" by the UK nutrition experts in relation to all the other models considered (Scarborough, 2007a). This may be expected because of the country-specific nature incorporated in the design of nutrient profiling models. More so, the "standard rankings" generated by the nutritionist could not be regarded as a "gold standard". Thus, the standard list used for testing all the models in their study may not be appropriate for testing nutrient profile models in countries with different consumption patterns. The main limitation was the cultural bias observed therein. Nonetheless, using the judgement of professionals might be the most straightforward and closest approach to criterion-related validity to apply during the early developmental stages of a nutrient profiling model, as its procedures tend to be transparent and replicable. It was typically observed that the less data-intensive or simpler methods were applied mostly during the initial development stages of a nutrient profiling model to first establish a robust classification of foods.

The advanced and complex methods in the validation process included three approaches: i) The use of dietary survey data to compare nutrient profile rankings and the healthiness of diets and dietary goals ii) The application of statistical modelling to design hypothetical diets and iii) The use of prospective associations with health outcomes to test the predictive accuracy of the nutrient profile models. These more data-intensive approaches to validation were primarily used to strengthen the model's evidence base after the developmental phase of the nutrient profiling model and therefore to boost up confidence in the use of the model. For example, the SAIN, LIM French model, the USA's Nutrient Rich Food index model and the UK's Ofcom nutrient profiling model were found to have been validated using the rarely conducted predictive validity in this review.

In addition, this study identified advertisement and marketing controls of unhealthy foods on television and in public places such as schools, vending machines and supermarkets as the most popular application of food categorisation methods. The current trend that associates obesity and NR-NCDs with unhealthy food has created an urgent need for regulators and policy makers to determine which foods need to be promoted, especially on television and in outdoor places and those foods that have to be either reformulated or restricted in the interests of public health (Kelly et al., 2010; Kelly et al., 2015; Crino et al., 2018).

In summary, the nutrient-based approach was identified to be robust and largely validated for defining "healthy" and "unhealthy" foods compared to both the food-based approaches and the extent of food processing. Nutrient-based models categorise foods according to their nutrient makeup and this information can be applied to help achieve dietary recommendations. As a result, nutrient-based profiling models are required to complement dietary guidelines. Although nutrient-based profiling models do not cover every aspect of nutrition, diet and health, can be useful tools when combined with other interventions aimed at enhancing diets. Nutrient-based models have been used to develop a range of policies and interventions, including food advertising and marketing controls and food labelling schemes targeting the prevention of NR-NCDs.

A holistic model, the NRF scoring system, an example of a nutrient-based approach comes across as the most flexible and highly validated nutrient scoring system that could be applied to determine the nutritional density of foods in varied contexts, be it that of overnutrition or undernutrition or the double burden of malnutrition.

2.4.2 Strengths and limitations of this study

This review has identified evidence in the literature for defining and categorising food as "healthy" or "unhealthy", notable from a global perspective as there were no limits set for study context. There was no restriction to the publication date for eligible studies, which is a strength of the current review. Thus, this review is novel and benefits from the inclusion of both current and earlier evidence of definitions and categorisation of "healthy" and "unhealthy foods" and indicates that the early findings are supported by more recent research. The main limitation of this literature review is that only a few studies included were conducted in low-and middle-income countries.

2.4.3 Conclusion

The findings of this review acknowledge the heterogeneity of definitions and categorisation widely available for defining and categorising foods as unhealthy or healthy. The nutrient-based approach was shown to have been more validated, using transparent quantitative criteria for defining and categorising "healthy" and "unhealthy" food compared to food-based and food processing approaches. Beyond this, the nutrient-based approach can easily be adapted to complement interventions and inform policy. The evidence from this review may contribute toward discussions in the development of food categorisation methods for public health interventions.

3 CHAPTER THREE: METHODOLOGY

Chapter overview

This chapter explains the methodological approach for conducting this multimethods study. The two study components are a secondary analysis of data (Study 2 of the PhD) and a primary quantitative survey (Study 3 of the PhD). The first section of this chapter discusses the epistemological stance of the research, as well as the theoretical underpinning of the methods, i.e., the justification for employing a particular method. This is then followed by a detailed description of the sequence of the research design, and instruments employed in the collection and analysis of data. It concludes with a discussion of the ethical considerations of the study.

3.1 Theory of research methodologies

3.1.1 Ontological and epistemological considerations

Two distinct theoretical or philosophical perspectives on viewing the nature of inquiry are known as Ontology and epistemology (Bryman, 2016; Byrne, 2017). Ontology (“ontos”, Greek: being) deals with the study of “being” and the perception of reality, while the epistemology, (“episteme”, Greek: knowledge) relates to what is regarded as acceptable knowledge and its validity (Crotty, 1998; Bryman, 2016; Byrne, 2017). In health and social research, similar ontological and epistemological principles are organised into paradigms, which along with methodology form the domain in which research is conducted (Sarantakos, 2013; Bryman, 2016).

Table 3.1: Theoretical constructs of research, adapted from Sarantakos (2013)

Research Approach One	Research Approach Two
Objectivist ontology	Constructionist ontology
Empiricist epistemology	Interpretivist epistemology
Quantitative methodology	Qualitative methodology
Positivist paradigm	Phenomenologist paradigm
Fixed-designed research	Flexible research design

Table 3.1 outlines the theoretical constructs of the research. The first approach encompasses "the objectivist ontology, empiricist epistemology, quantitative methods, a positivist worldview and a fixed research strategy"(Sarantakos, 2013). Researchers who employ an approach consisting of the positivist paradigm believe that a single reality involving a cause-and-effect relationship and the researcher's beliefs and values do not influence the process (Tashakkori, 1998; Fadhel K., 2002; Majeed, 2020). Surveys are commonly regarded as the preferred data collection tools within this paradigm because they can be better suited to such concerns (Bryman, 1984; Fadhel K., 2002; Bryman et al., 2008). Through survey questionnaires the distance between the observer and the observed allows concepts to be operationalised whilst maintaining objectivity (Bryman, 1984; Kivunja et al., 2017; Majeed, 2020). Replication can be done by using the same research tool in a different setting and regression techniques are frequently employed (Bryman, 1984; Majeed, 2020). Bryman (1984) adds that research that uses secondary analysis of previously collected data is also often recognised as exhibiting similar fundamental philosophical precepts (Bryman, 1984). The results of a positivist approach include concepts, such as reliability, validity and statistical significance, which are used for describing some parts of reality with confidence (Brewer, 2006; Bryman, 2016). Thus, positivist knowledge is viewed as being unbiased, objective,

generalisable and repeatable (Al-Saadi, 2014; Wellington, 2015). Therefore, positivism is often perceived as synonymous to scientific methods (Al-Saadi, 2014; Majeed, 2020).

However, since the early 20th century, the positivist paradigm has been the subject of debate due to the claim the observer's values may influence the outcomes (Ritchie et al., 2014). This brought about the second iteration of positivism known as post-positivism. The postpositivist approach is similar to the positivist approach in continuing to apply mainly quantitative approaches and deductive reasoning.

Meanwhile, the second research approach as shown in Table 3.1 comprising the constructionist ontology is in sharp contrast with the positivist/post-positivist paradigm, where an "interpretivist epistemology, a qualitative methodology, including phenomenology and a flexible design are used to induce reasoning" (Sarantakos, 2013). The constructivist focuses on a qualitative methodology that directly opposes the quantitative methodology of the positivist (Lincoln et al., 1989). Constructivism postulates that there is no single truth and that there are numerous realities out there depending on people's subjective perceptions, cultural beliefs and values (Guba et al., 1994). Consequently, it is challenging to accurately distinguish between cause and effect in this worldview (Guba et al., 1994).

These two distinct worldviews resulted in a third paradigm known as pragmatism. This world view falls perfectly neither within a positivist nor a constructivist paradigm but adopts the mixing of both paradigms (Tashakkori et al., 1998; Johnson et al., 2004; Yvonne Feilzer, 2010). The pragmatic approach, therefore, entails both qualitative and quantitative research methodologies and asserts that nature may be interpreted in terms of its utility and what is most effective (Creswell, 2003; O'Cathain et al., 2010). This pragmatic paradigm is popularly described by the phrase "mixed methods" (Tashakkori et al., 1998; Denscombe, 2008; Tashakkori et al., 2010; Creswell, 2015; Johnson and Onwuegbuzie, 2016; JohnsonOnwuegbuzie et al., 2016) and it continues to attract increasing attention (Archibald, 2016; Archibald et al., 2017). Since its inception, the categorisation of mixed methods research design has grown increasingly complex, with numerous terminologies in literature (Hunter, 2003; Morse, 2003; Thomas, 2003; Johnson, 2004). The term "mixed methods" and "multimethod" are sometimes used interchangeably by some authors. For example, according to Stange et al. (2006), mixed methods (also known as multimethod) integrate qualitative and quantitative approaches to provide new information (Stange et al., 2006). Furthermore, Johnson et al. (2007), in their work, identified and analysed 19 definitions of mixed methods and offered a general definition (Johnson et al., 2007) as follows: "mixed methods research combines components from quantitative and qualitative research methodologies for purposes of breadth and depth in understanding a research question". Due to the lack of precision in the definition of mixed methods, a typology has been created by numerous authors (Tashakkori et al., 1998, 2010; Johnson and Onwuegbuzie, 2016; Anguera et al., 2018). Tashakkori and Teddlie (2010) write that mixed methods research design employs qualitative and quantitative approaches in terms of the kind of questions, research methods, data collecting and analysis procedure. This resonates with the description of mixed methods by Plano Clark and Ivankova (2016), who view mixed methods as a process of combining quantitative and qualitative data collecting and processing in order to understand a research question (Vicki et al., 2016). On the other hand, the author distinguishes mixed methods from multimethod research; by stating that "multimethod research implies the combination of multiple quantitative approaches or a combination of multiple qualitative approaches or multiple quantitative and qualitative approaches" (Vicki et al., 2016).

Mixed methods and multimethod are therefore two different research approaches but quite often used interchangeably by some researchers (Stange et al., 2006) Thus, it is important to distinguish these terms.

In this PhD research, these philosophical positions are largely informed by what best fits and addresses my research questions, with reference to the strengths and limitations of each approach. The research design employed in this PhD adopts a positivist/postpositivist paradigm using a multimethod approach to address the research inquiry.

The emerging consensus towards answering research questions has advocated the use of an array of conceptual and methodological approaches involving multimethods, which enable research questions to be answered coherently (Morse, 2003; Brewer, 2006; Teddlie et al., 2012; Creswell, 2018).

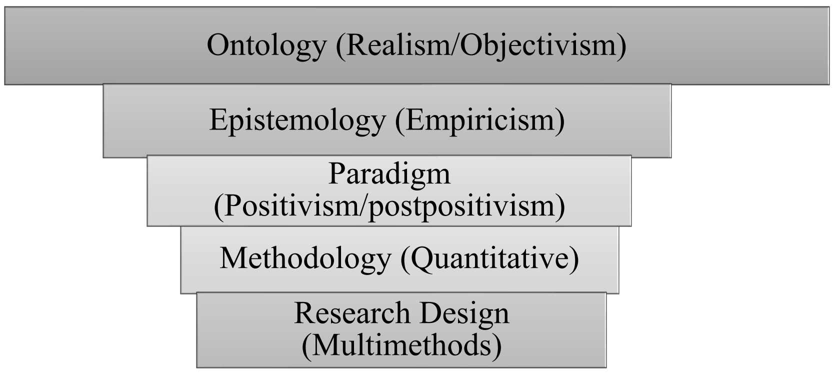

Figure 3.1: Theoretical construction of the PhD research

The subsequent section features the multimethod approach used in this study.

3.2 **Research Methodology: Multimethod**

Multimethod research has its origins in the landmark work of Campbell and Fliske (1959), which is possibly considered the earliest multimethods publication in the scientific literature (Campbell et al., 1959; Centra, 1969; Anguera et al., 2018). The concept of "multimethod" was linked to measurement validity, with a justification that if different methods were applied to measure a phenomenon these had to be converged (Campbell et al., 1959). This led to the concept of triangulation credited to Denzin (1978), which is similar to the approach applied in this study.

Multimethod research triangulates elements of several study designs from the same research paradigm that occurs in distinct strands to address specific research questions to increase validity (Campbell et al., 1959; Centra, 1969; Bryman, 2016). These study designs have non-overlapping weaknesses and complement each other in their methodological strength (Bryman, 2016).

In this research, the multimethods design commenced with the secondary analysis of 24-hour recall dietary data, with the priority to address the reliability of an adapted nutrient profiling model (Study 2-secondary data analysis). This phase was then followed by a subsequent primary quantitative survey involving nutrition experts (Study 3-survey of nutrition experts). Individual food scores generated from Study 2 of this PhD are compared to the same foods scored by experts in Study 3 for validity testing. However, both quantitative strands were distinct, and the data collection and analysis were separate. During the overall analysis, the two strands were interpreted to draw conclusions at the end of the study (Figure 3.2).

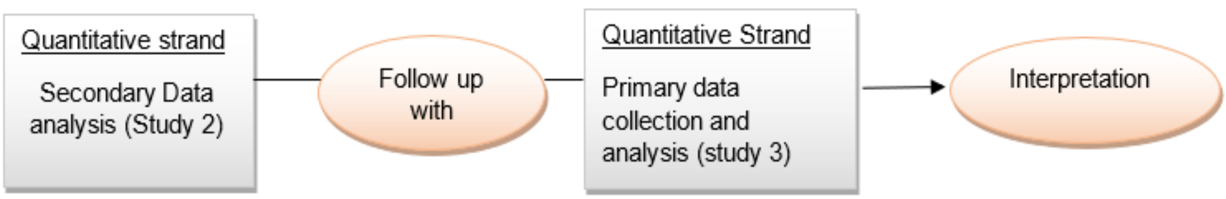

Figure 3.2: Diagram illustrating the multimethod design used in the research

The advantages of the multimethods approach include rich opportunities for cross-validation of research procedures, findings, and theories (Brewer, 2006a). Hesse-Biber et al. (2015) discusses how a multimethod approach using study designs from a similar paradigm can serve a supplementary function in supporting the core aim of measuring the same phenomenon in-depth (Hesse-Biber, 2015). The main reason for using multiple methods in this research is for outcome triangulation -seeing the social phenomenon in its multiple dimensions (Morse, 2003; Brewer, 2006a). Thus, multiple sets of information or findings addressing the same research question from different study designs are required for triangulation (Brewer, 2006). The researcher derives validity from the data set's agreement and invalidity from their disagreement (Brewer, 2006). Divergent findings, however, are equally important in multimethods research design (Bryman et al., 2008). This signals the necessity of additional analysis of the research problem as well as caution in interpreting the significance of the results (Brewer, 2006; Bryman et al., 2008; Bryman, 2016) During the overall analysis of this research, the results from two study designs (secondary data analysis and primary quantitative survey) were triangulated to draw a conclusion at the end of the study (Figure 3.2).

3.2.1 The quantitative approach: A brief description of the methodology

According to Aliaga and Gunderson (2002), the quantitative methodology is simply described as a phenomenon by which numerical data are collected and analysed using mathematically based methods. These methods emphasise objectivity and the statistical analysis of data gathered through primary surveys and secondary data using computational statistical techniques (Aliaga, 2002). Other authors add that quantitative methodology perceives reality as objective and is fundamentally different from speculation and reason(Muijs, 2011; Cohen, 2018). It is an approach that is interested in discovering the variance and regularity in the effects of one or more independent variables on an outcome. The questions "what" and "how much" typically drive the research and are determined from the outset (Muijs, 2011; Cohen, 2018).

The central criteria of the quantitative methodology used in this study encompass but are not limited to the following recommendations proposed for quantitative research (Campbell et al., 1959; Aliaga, 2002; Muijs, 2011; Sarantakos, 2013; Cohen, 2018) (Table 3.2).

Table 3.2: The fundamental standards for quantitative research

▪ Employ empirical methods	▪ Validity and reliability
▪ Objective	▪ Repeatability
▪ Clear in design and procedure	▪ Generalisability and representativeness
▪ Distance between participants and researcher	▪ Rigorous systematic procedure
▪ Precision and accuracy	▪ Ethical considerations

3.2.2 Methodological justification: Testing the reliability and validity of a nutrient profiling model for use in Ghana.

Previous studies have not sufficiently explored nutrient profiling models for use in Ghana and neither have their validity and reliability for scoring the healthiness of individual Ghanaian foods and beverages been assessed (Drewnowski et al., 2021) In line with the multimethod approach, the validity and reliability of the Ghanaian NRF 11.3 index as described in this thesis were determined based on two studies. Study 2 (i.e., secondary analysis of current and robust dietary data from Ghana) and Study 3 (i.e., primary data collected from an online survey) were conducted sequentially using quantitative methods to determine the construct validity and reliability of the Ghanaian NRF 11.3. According to Brewer (2006), such a multimethod design is deemed to generate a complete account that allows a comprehensive analysis of the research question while maximising the strengths of each approach towards validity and reliability (Morse, 2003; Brewer, 2006; Bryman, 2016). No studies have explored the validity and reliability of a nutrient profile model adapted for classifying Ghanaian foods using a multimethod approach based on secondary data analysis and a survey of nutrition experts in

Ghana. Moreover, in the literature, most of the validity and reliability studies using this quantitative approach have been conducted in high-income countries and there are none in Ghana. Brewer (2006) notes that the most compelling reason for using a multimethod design is the investigator's need to assess the same phenomena towards triangulation or increased validity of results.

The justification is therefore to first establish the validity and reliability of a nutrient profiling model adapted for classifying Ghanaian foods. Furthermore, converging the two methods to establish validity and reliability increases confidence in the findings. In addition, combining the results of the two quantitative methods produces contextually relevant knowledge and more rigorous conclusions about the nutrient profiling model. This is the first time a multimethod study has been done on the validity and reliability of a nutrient profiling model in Ghana. The outcome will ultimately provide a multi-layered perspective of contextual relevance. For example, practical outcomes such as which foods are considered unhealthy and should not be marketed to children will be established.

3.3 Quantitative research methods

Study 2 and Study 3 involved testing the validity and reliability of a nutrient profiling model named the Ghanaian NRF11.3 index. To address the main objectives listed below a quantitative approach was taken.

Key objectives of Study 2

Study 2 Phase 1

2a. To develop a context-specific nutrient profiling model for categorising foods and beverages in Ghana.

2b. To determine the optimal combination of nutrients required in the Ghanaian NRF index for classifying Ghanaian foods.

Study 2 Phase 2

2c. To obtain an estimate of the reliability of the Ghanaian nutrient profiling index (i.e., internal consistency.

2d. To determine the sensitivity, specificity and optimal cut-off point for the Ghanaian nutrient profiling index in order to identify the performance.

Key objectives of Study 3

3a. To assess how expert nutrition professionals in Ghana classify the healthiness/unhealthiness of commonly consumed Ghanaian foods and beverages.

3b. To determine the convergent validity of the Ghanaian NRF11.3 index

Before describing the method followed for Study 2 and Study 3 in chapters four, five and six, it is important to consider some of the theories and justification behind testing measurement scales for their reliability and validity.

3.4 Theory and justification for adapting an existing nutrient profiling model.

A multitude of nutrient profiling models has been developed to measure and evaluate the healthfulness of foods (Labonté et al., 2017; Poon et al., 2018). Although many nutrient profiling models exist, only a small number have been examined for their predictive validity and several have been validated for construct validity using the most basic approaches (Cooper et al., 2016; Poon et al., 2018). A complex validation procedure is caused by the subjectivity of the phenomena (i.e., what constitutes healthy or unhealthy food) that these models are attempting to measure. In view of this, an initial step in this PhD research was to systematically review and critically evaluate all existing nutrient profiling models that have been designed with the aim of measuring the same concept. The development of a new model from the scratch is only considered after all other options, including the use of an existing reliable and validated model, have been excluded. Therefore, after an appraisal of existing nutrient profiling models, the Nutrient Rich Food (NRF) index was deemed adaptable as a starting point for the development of a new nutrient profiling model for classifying the healthiness of Ghanaian foods. This is because the NRF index was identified as highly validated and robust (Drewnowski and Fulgoni, 2008) to use in classifying food and beverages in the Ghanaian context where NR-NCDs co-exist with undernutrition.

3.4.1 The developmental approach of the adapted model

By drawing on the concept of "traditional assessment" in psychology and education, Streiner and Norman (2015), in their renowned book *Health Measurement Scales: A practical guide for their development and use*, described two measurement models: the categorical versus the dimensional model (Streiner, 2015). In the categorical approach there is a clear distinction between cases and non-cases (i.e., healthy and unhealthy foods), but not with the dimensional model. In the former, a food item either meets the criteria and is counted as healthy food or else the criteria are not satisfied, and the item is counted as unhealthy. With the latter, "healthiness" is a matter of degree and there is no clear dividing line (Streiner, 2015)

The foundation for the dimensional model theory is based on the writings of Smith Stevens (1951) who highlighted the concept of "level measurements" which categorises variables as nominal, ordinal, interval or ratio (Streiner, 2004; Streiner, 2015). The basic idea is that the more precisely we can measure a characteristic, the better. Thus, making use of attributes as a continuum with items falling along the dimension in accordance with how much of the attribute, they have is the ideology it proposes (Streiner, 2015). Therefore, the model adapted for use in classifying Ghanaian foods and beverages in this study is one built upon this theory. In order to classify the healthiness of a particular food item several responses from "very healthy", "slightly healthy" and "slightly unhealthy" to "very unhealthy" could be elicited. A simple "healthy' or 'unhealthy" would be difficult for some respondents as answers are likely to fall along a continuum (Streiner, 2015). In addition, a more extensive range of response options for each item may likely produce a more accurate instrument (Streiner, 2015). The explanation here is that, for example, if the categories are limited to only two responses there will be greater extremes between potential responses will exist and the introduction of error is greater. The measuring instrument may not be able to pick up on slight changes in state and conversely, the respondents might struggle to give responses that most accurately reflect their current state.

Contrary to categorical models, the tools created with the dimensional model do not categorise items into, for example, "healthy" or "unhealthy". To use this kind of tool for diagnostic purposes, attention needs to be given to the optimal cut-off point. This have to be decided based on statistical analysis that evaluates the tool (Streiner, 2004) . However, the dimensional model permits for comparisons between items and evaluation of change over time.

3.5 Testing reliability and validity of measurement scales

In choosing an appropriate scale (i.e., a nutrient profiling model) there are two characteristics that are usually of concern: reliability and validity (Streiner, 2015). Both elements can influence the quality and outcome of the results (Streiner, 2015). Reliability without validity is of little use. Therefore for measuring instruments, it is useful to interpret reliability results in combination with validity scores (Pallant, 2010; Sarantakos, 2013).

3.5.1 Reliability testing

A scale's reliability reveals how free it is from random error (Streiner, 2004). It also describes the scale's ability to produce consistent results (Bryman, 2016). The objective of reliability testing in this study is to make sure that the instrument is robust and not susceptible to changes of the researcher, the respondent and research conditions (Bryman,2016). Reliability encompasses both external and internal reliability. External reliability relates to the consistency and reproducibility of data across different contexts, whereas internal reliability refers to the consistency of results within the dataset (Bryman, 2016). There are numerous methods for testing the reliability of an instrument; the most commonly used indicators include internal consistency and alternate-form reliability. For this study, a measure of internal consistency and alternate-form reliability of the Ghanaian NRF11.3 index was made because these are sufficient to assess the reliability of a model. Details of these techniques are discussed below.

3.5.1.1 Internal consistency reliability

This is the degree to which each component of the scale measures the same underlying attribute. Internal consistency is commonly assessed statistically by Cronbach's coefficient alpha (Pallant, 2010). This shows the scale's overall average correlation across all of its components. Greater reliability is indicated by higher values, which range from 0 to 1(Streiner, 2015; Bryman, 2016). Even though different levels of reliability may occur, it is recommended that a minimum cut-off level of 0.7 is acceptable (Nunnally, 1978). Nonetheless, the number of elements on the scales has an impact on Cronbach alpha values (Nunnally, 1978). Fewer items or elements on the scale (e.g. <10), can produce quite small Cronbach alpha values. Berthoud (2000) suggests that a minimum value of 0.60 is considered "good" (Berthoud, 2000).to account for this.

3.5.1.2 Alternate-form reliability.

This type of reliability is determined by testing two comparable instruments at the same time and is measured by the degree of correlation between the scores of the groups (Pallant, 2010). In this study, the Ghanaian NRF11.3 index was compared to a reference model (WHO model) as a measure of reliability.

3.5.2 Validity testing

Validity describes the adequacy with which a measurement reflects what is intended to measure (Pallant, 2010). There are no clear-cut indicators of a scale's validity and it is also distinct from related concepts including accuracy, precision and reliability.

There are two major methods for determining if an instrument is valid in quantitative research: empirical validation and theoretical validation. In both cases, tests of internal and external validity are used (Sarantakos, 2013; Streiner, 2015). Internal validity is the adequacy of the measurement for the specific population being studied, whereas external validity (also referred to as generalisability) is the adequacy of the measurement when applied to wider populations, not under study (Streiner, 2015). Empirical validation (also called "criterion validity") is the degree to which the accuracy of a test can be demonstrated through experimentation and systematic observations. Its findings are backed by existing empirical evidence or by new discoveries that support the predictions of the measure in question (Brewer, 2006). On the other hand, when empirical confirmation of validity is challenging or impossible, theoretical or conceptual validation is used (Brewer, 2006). An instrument is taken to have theoretical validation if its results conform to the theoretical principles of the disciplines to which it is aligned. The forms of theoretical validity include face, content and construct validity (Streiner, 2015). Theoretical validity was employed in this study.

Considering this, Brewer (2006) writes that the comparisons between measures and measurements that constitute steps in the validation process are of several kinds. Each supplies a different type of information about a scale's performance, and all are necessary for determining accurate measurements. First, measures are compared to determine their relative face and content validity with respect to the concept being measured (i.e., the focal concept, in this case, is the healthiness of food items). Second, measurements of other focal concepts are compared to test the measures' reliability and convergent validity. Finally, multiple measurements of one focal concept are compared to multiple measurements of other concepts to test the measures' criterion validity (Brewer, 2006).

In alignment with the definition of nutrient profiling as proposed by the WHO, the validity of a nutrient profile model refers to the adequacy with which the model classifies the healthiness of foods in order to promote health and prevent illness. The different types of validity vary with respect to their robustness in contributing to the validation of a model. It is therefore recommended in the WHO nutrient profiling manual that "simpler (i.e. less dependent on data) validation approaches be employed during the development and adaptation of profiling tools to first ensure the robust classification of foods" (World Health Organization, 2011b). Then, more complex strategies can then be used later to increase the evidence-based supporting the model and hence improve confidence in the model (World Health Organization, 2011b).

As shown in Figure 3.2Figure 3.3 and Table 3.3 these approaches include content validity, face validity, construct (convergent & discriminant) validity and criterion (concurrent and predictive) validity (Streiner, 2004). However, within the scope of this study, face, content and construct (convergent) validity of the Ghanaian nutrient profiling model were tested and discussed.

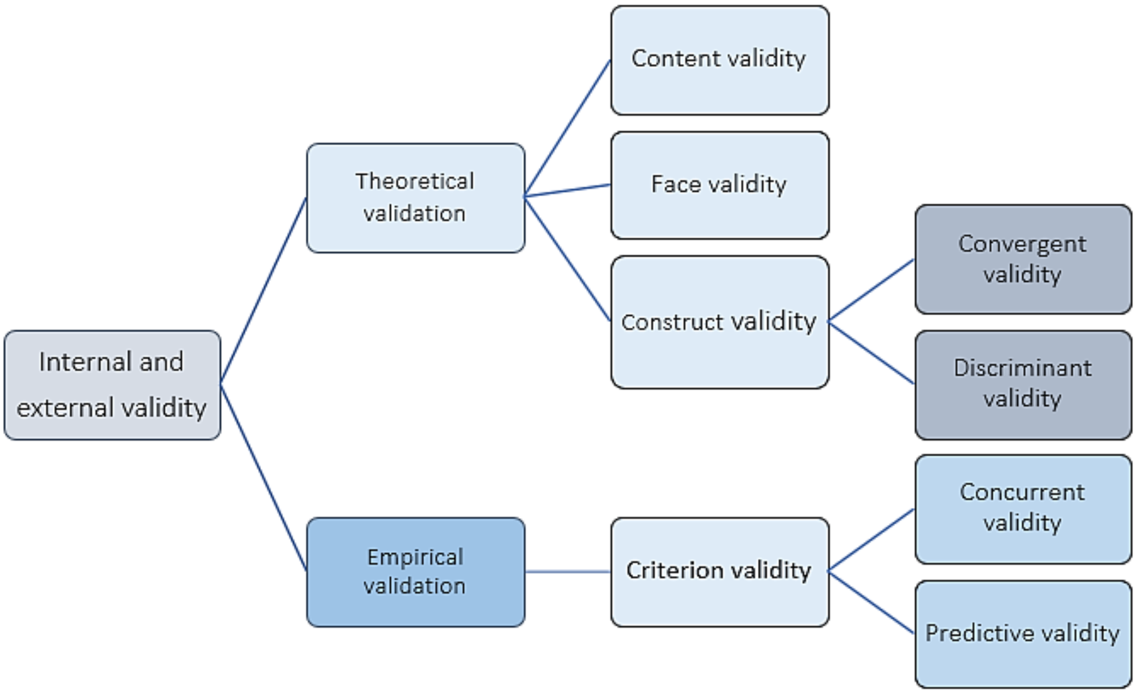

Figure 3.3: The various validation approaches(Sarantakos, 2013)

Table 3.3: Validation methods used in nutrient profiling (NP).

Simpler validation methods	Type of Validity	Reference
i)The degree to which a measure appears logical upon superficial examination as determined by the end users of the system	Face validity	(Cooper et al., 2016)
ii)The degree to which the measure takes the phenomenon under examination into account	Content validity	(World Health Organization, 2011b; Cooper et al., 2016)
III) Comparing food ranking results from several nutrient profile models	Construct/convergent validity	(Eyles et al., 2010)
IV) Comparison of food rankings based on nutrient profiles with rankings provided by nutritionists or dietary guidelines	Construct/convergent validity	(Scarborough, 2007a; World Health Organization, 2011b)
Complex, data-intensive methods		
III) Dietary survey data used to compare nutrient profiles with the healthiness of diets and attainment of dietary targets.	Construct validity	(Fulgoni et al., 2009; Maillot et al., 2018)
IV) Theoretical modelling of diets	Construct validity	(Maillot et al., 2018)
V) Use of prospective associations with health adverse outcomes	Criterion validity, Predictive validity	(Streppel et al., 2014)

3.5.2.1 Content and face validity

The degree to which a tool captures all possible interpretations of the concept being measured is considered content validity (Bland, 2002; Streiner, 2015). It is arguably the first test or fundamental step in validity assessment because it is concerned with ensuring that the correct "concept" is measured. Townsend (2010) adds that content validity measures the science underlying the algorithms (Townsend, 2010).

A measure is said to be having face validity if it is obviously more pertinent to the meaning of the focal concept than it is to the meaning of other concepts. It includes what we believe it ought to cover. This is contrary to content validity which measures the extent to which adequate sampling of the various items is subsumed by the focal concept (Brewer 2006). To many researchers, the techniques applied to determine the content and face validity of a tool are similar (Streiner, 2008; Townsend, 2010). Both entail experts giving their subjective judgements as to whether items within a scale are appropriate and relevant. Assessment of content validity including face validity is not generally associated with statistical analyses. Only once a tool has been approved as appearing to contain the correct contents for a given construct can it be statistically and comparatively assessed to see how well it works in practice.

3.5.2.1.1 Content and face validity of the Ghanaian NRF11.3 index.

The content and face validity of the Ghanaian NRF11.3 index were tested through a series of supervision meetings with project supervisors (MH, VH and AL) who are experts in the field of nutrition. A presentation was also made by the researcher to the wider Drivers of Food Choice project team of about 12 researchers, Ghanaian academics and government members as part of a nutrient profiling workshop in Ghana. This was operationalised by assessing the congruence between the nutrients included in the model versus those considered important in disease prevention and promotion within the public health nutrition context of Ghana, where a double burden of malnutrition exists.

The methodological steps and decision points of nutrient profiling were thoroughly discussed in these meetings. Chapter 4 gives a detailed account of the decision points and development process. As described by Brewer (2006), careful face and content validation serve to eliminate the measurement errors that would result from using irrelevant measures (Brewer, 2006). But while high face and content validity are no guarantee of highly convergent, discriminant and predictive validity, they are nonetheless prerequisites.

3.5.2.2 Construct validity

This refers to how well a measurement resembles theoretical concepts (constructs) about the phenomenon being researched (Streiner, 2008, 2015). It tests the degree to which a test agrees with other measures in a way that is expected, and it is measured in situations when a "gold standard" is not available (Peat, 2002). A measure can claim to have construct validity if its theoretical construct is valid. There are two different but complementary multimethods to construct validation: i) verification studies that do multimethods testing of a hypothesis involving the construct in question, and ii) validation studies that focus more on convergent and discriminant validation. Validation concentrates here on the validity of the theoretical construct (Brewer, 2006; Sarantakos, 2013).

3.5.2.2.1 Convergent Validity examines whether the model correlates in a predicted manner with variables with which, theoretically, it should correlate (Streiner, 2008); for instance, nutrient profiling scores of foods most consumed by a specific cultural group compared with classification of the same foods by nutrition professionals using a food list. This approach to validity was used to assess the convergent validity of the Ghanaian NRF11.3 index in Study 3 of this PhD. This method is considered relatively simple and cheap compared with other forms of construct validity.

3.5.2.2.2 Discriminant Validity, on the other hand, measures variables that are not closely related, to establish whether groups expected to be different, are in fact unrelated. This type of construct validity was not explored in this current study because of limited data and time.

3.5.2.3 Criterion validity

This approach to validity is concerned with the correlation between scale scores and a specified quantifiable criterion (Streiner, 2015). A correlation between a new measurable scale and a validated "gold standard" measure is used to determine criterion validity (Bland, 2002). Predictive and concurrent validity are both divisions of criterion validity (Bryman, 2016). Whereas concurrent validity measures the degree to which an instrument relates to an external criterion established as the "gold standard", at the same moment or within a short period from each other, predictive validity measures the phenomenon which it has been developed to predict and which may not become evident until sometime later (Streiner, 2008). According to Bryman (2016), in the case of predictive validity, a future criteria measure is employed, rather than a contemporary one as in concurrent validity. For instance, predictive validity may measure the degree to which a nutrient profile model reflects the nutritional and health status of an individual over time. However, this method may be relatively more expensive and time-consuming as compared to the former methods and beyond the scope of the current study due to the lack of data, time and resources.

In nutrient profiling, there is a lack of a "gold standard" for defining a healthy food. Thus, the most common type of validity test is construct validity whilst, criterion validity is the least approach employed. However, the assessment of criterion validity is sometimes considered to have greater public relevance, this is because medical records and biomarkers are sometimes used as external indicators which are generally considered to be more accurate measures.

Nonetheless, these external sources of data although considered gold standard measures are not also devoid of systematic error.

3.5.2.4 Distinguishing reliability testing from convergent validity

According to Brewer (2006), when two or more measures appear to provide the definition of a concept, the next stage in the validation process is to test the reliability of the measures. However, if the measures employ different enough research techniques then convergent validity is determined (Brewer, 2006). In order to test that the consistency between the measurements is not attributable to constant or systematic error, convergent validity is used to establish that the agreement between the different sets of measurements is in fact attributable to the measured phenomenon and not due to bias coming from research procedures. Therefore, convergent validity is determined by comparing measurements made with dissimilar methodological measures. In other words, when there is convergent validity, reliability is also achievable. In this study, reliability was estimated to ensure that the Ghanaian NRF11.3 index produces the same results every time, and validity is assessed to ensure the model is measuring the concept it is supposed to measure accurately.

3.5.2.5 Optimal performance of the Ghanaian NRF11.3 index (sensitivity, specificity, and cut-off point)

Receiver operating characteristics curves provides a way of assessing the sensitivity and specificity and cut-off point of the Ghanaian NRF11.3 index. These were assessed as a part of the reliability and validity testing to determine the optimal performance of the Ghanaian NRF11.3 index.

In summary for this study, the reliability of the Ghanaian NRF 11.3 index was tested through internal consistency and alternate-form reliability; whilst validity was tested in the form of construct validity (i.e., convergent validity). The performance of the model was also tested by assessing the specificity and sensitivity and optimal cut-off point of the model.

3.6 Ethical considerations and information governance (Studies 2 and 3)

The ethical clearance procedures and information governance for the studies in this research are presented in this section. Given that this was a multimethods PhD, involving secondary analysis of data and primary survey, ethical approval was sought and obtained independently for both studies. The ethical approval and clearance documents are included in Appendix 3.

3.6.1 Ethical considerations: Secondary data analysis – Study 2

Ethical clearance for secondary analysis of the Drivers of Food Choice (DFC) and Leveraging Evidence for Interventions and Policy (TACLED) projects dataset used in Study 2 was obtained from the University of Sheffield Ethics Committee (016387-reference number).

3.6.2 Ethical considerations: Primary survey of nutrition experts– Study 3

Study 3 received ethical approval from the University of Sheffield Ethics Committee (reference number 032486) as well as from the Ghana Health Service Ethics Review Committee (Protocol ID: GHS-ERC001/04/20) (See Appendix 2-4).

3.6.3 Information governance

3.6.3.1 Participant informed consent form, privacy and confidentiality – Study 2

Ethical approval and consent from participants to collect the primary data were received for the Drivers of Food Choice (DFC) and TACLED projects from which the secondary data used for this PhD research originated. Ethical clearance for secondary analysis of the data was then sought from the University of Sheffield Ethics Committee. In addition, permission to use this data was granted by the project leads in Ghana and the University of Sheffield. The secondary data set was stored on the University's X-Drive on an encrypted file as recommended in the ScHARR Research Governance Policy; however, backup copies of the data set were stored on two separate encrypted portable storage devices (which were used ONLY for that purpose) to which unauthorised persons (persons not part of the research team) had no access. In the event of data analysis taking place away from the main work site (ScHARR West Court), then the work was undertaken on an encrypted personal laptop. Permission was granted by the primary supervisor and ScHARR IT (virtual private network-VPN) for occasions when data analysis was required off-site, as per ScHARR policy. The dataset will be kept until after the researcher has completed the final PhD just in case there is a need to rerun the analyses or make clarifications on issues raised and PhD corrections. However, at the end of the data retention period, the secondary data files (master copy and all backup files) will be safely destroyed with technical assistance from ScHARR IT or Corporate information systems (CIS).

3.6.3.2 Participant informed consent, privacy and confidentiality – Study 3

The research participants who took part in Study 3 (i.e., online survey) had reviewed the study participants' information sheet and agreed to a completed informed consent statement before proceeding to answer the main questionnaire. Thus, before data collection commenced informed consent was attained from all participants. Participants were informed that taking part in the survey was completely voluntary and given details of what taking part in the survey would entail, the kind of data that would be gathered, the purpose of the study and how security and confidentiality would be ensured. Participants were also informed that they could close their browser to exit the survey at any point before submitting their responses. They were told that since participation was voluntary, they could leave without justifying or giving a reason why and with no adverse consequences. Also, they were informed that after completing the survey they would have the opportunity to enter a voluntary draw to win a nutrition textbook. The online survey data were collected using the Qualtrics system and stored in an access-restricted folder on the University of Sheffield Shared Networked Filestore. Data were only made available to the researcher and the supervisory team. Data collected were handled with the utmost duty of confidentiality owed to participants and were not shared with anybody else apart from the PhD research supervision team when required.

4 CHAPTER FOUR: SECONDARY DATA ANALYSIS (STUDY TWO)

Study 2 Phase 1: The development of the Ghanaian NRF11.3 index

Chapter overview

As mentioned in chapter 3, the first phase of Study 2, comprised the secondary analysis of data that was undertaken to develop the Ghanaian NRF11.3 index. This chapter introduces the steps followed and the results attained. First and foremost, a description of the datasets used in the study is presented, i.e., the 2017/2018 Drivers of Food Choice (DFC) and the Leveraging Evidence for Interventions and Policy to Prevent Diet-Related NCDs (TACLED), Ghana. After that, a description of the study settings for DFC /TACLED data and the sampling methods used are comprehensively detailed. Then, an overview is given of the development of the NRF11.3 index, with the principal decisions and considerations in the developing process of the NRF11.3 index recounted. Then the steps involved in the profiling of individual food items using the NRF11.3 index are described.

Key objectives of Study 2

Study 2 Phase 1

2a. To develop a context-specific nutrient profiling model for categorising foods and beverages in Ghana (Study 2).

2b. To determine the optimal combination of nutrients required in the Ghanaian NRF index for classifying Ghanaian foods.

4.1 The 2017/2018 Drivers of Food Choice (DFC) and TACLED datasets: settings, participants and data collection

The 2017/2018 DFC and TACLED survey data analysed in this study was derived from a serial cross-sectional dietary survey. The DFC project was a collaboration between six academic institutions across Ghana, the UK and France (Holdsworth et al., 2020). The TACLED project, which followed on from the DFC, was a sister project whose aim was to map “the factors in the physical and social food surroundings that influence the consumption of EDNP foods and to employ this knowledge in the development interventions to reduce their consumption”(Holdsworth et al., 2020)

4.1.1 Study setting

The 2017/2018 DFC and TACLED survey was conducted in two Ghanaian cities at distinct stages of nutrition transition: the provincial city of Ho (population of 83,715) and the capital city Accra (population of 2,291,352) also see Figure 0.1 (Chapter 1) for a map of Ghana with cities showing the prevalence of obesity amongst women. Collectively they represented rural and urban nutrition transitions. Jamestown and Ho Dome were then selected from an index of deprived neighbourhoods to represent Accra and Ho, respectively (Holdsworth et al., 2020).

4.1.2 Sampling

Participants were sampled using a strategy known as the stratified purposive sampling (quota sampling) method, which is described in more detail elsewhere (Holdsworth et al., 2020). Using this technique, firstly, the regional cities of Ghana were divided into strata. Subsequently, two growing cities of different sizes and transitions were purposively selected to maximise the range of responses relevant to the study, i.e., the provincial city, Ho and the capital city, Accra. Using data from the Accra poverty map and Ho city profile, the most deprived neighbourhoods in the selected cities (Accra and Ho) were then randomly sampled, resulting in one deprived neighbourhood per city, i.e., Jamestown representing Accra and Dome representing Ho. Afterwards, quota sampling was used within each neighbourhood to sample participants for the study. The set sample quotas for selecting women for the dietary 24-hour recall interviews were based on: (i) age, (ii) body mass index (BMI), (iii) women in work and/or in education, (iv) pregnant or lactating and (v) not pregnant or lactating. A target sample size of 294 participants were subsequently sampled from the two cities (Holdsworth et al., 2020). Following this, eligible participants for the study were randomly identified by the research team, as adolescents/adults (female and male) aged 13 years and above resident in the chosen deprived areas of Accra and Ho (Holdsworth et al., 2020).

4.1.3 Data collection: measures and instrumentation

Continuous and non-continuous variables for secondary data analysis

Data collected during the DFC/TACLED surveys included information on various variables including participant's place of residence, age, weight, height, education, socioeconomic status category, pregnant, lactating, marital status, occupation, and dietary intake (via qualitative 24-hour dietary recall). Specific data on the survey participants' socioeconomic and demographic characteristics and 24-hour recall have been detailed elsewhere (Holdsworth et al., 2020). The only data used for secondary analysis in this PhD thesis was the dietary intake data (from the 24-hour recall), which included all food items recalled as consumed by participants the day before the interview (FAO and FHI 360, 2016).

Collection of Dietary intake data using qualitative 24-hour recall data

Prior to data collection, all research assistants that were to be involved in the data collection participated in training workshops organised by both local and international lead researchers. Following this training, pilot interviews were conducted in the two selected cities, Accra and Ho (Holdsworth et al., 2020).

The dietary intake data were gathered from a single qualitative 24-hour recall dietary survey at the individual level: DFC project (n=192) women and adolescent girls at four vital phases of the life span: (i) early adolescence not pregnant or lactating (aged 13 to14 years); (ii) pregnant (aged 15 to 49 years); (iii) lactating (aged 15 to 49 years) and (iv) women not pregnant or lactating (aged 15 to 49 years) (FAO and FHI 360, 2016; Holdsworth et al., 2020). Additional dietary intake data were collected from the TACLED project from men and older adults (n=96). In the first step of the 24-hour recall, participants were prompted to list all the food and beverages (including snacks) that they had eaten within the past 24-hours, i.e., from midnight to midnight the previous day. The second step required participants to provide a qualitative pictorial description of the food and beverage items, they had previously listed, following the prompts of the trained research assistants (Holdsworth et al., 2020). This equally comprised the ingredients and cooking methods of the listed foods (FAO and FHI 360, 2016). Most of these research assistants that collected the 24-hour recall data were graduates of the University of Ghana with a Nutrition or Food Science qualification (Holdsworth et al., 2020).

Data collection instruments (questionnaires) for the 24-hour recall were mainly in English but interpreted into the local languages by the trained research assistants in the region where the survey was conducted. The DFC/TACLED project used an innovative way of collecting field data which was different from the traditional paper-based questionnaires used in collecting data. Herein, Android tablets with an incorporated application known as the CSEntryPro6.3

were used to gather data from participants. This also enabled data to be referred directly to a central secured server for storage. All screening questions, sample quotas and 24-hour recall questions were programmed into the tablets.

Data collected during the pilot phase was downloaded and relevant adjustments were made to the questionnaire and sampling method before the main data collection took place. Data from the qualitative 24-hour recall therefore form the basis for this Study 2.

The next section describes an overview of the development of the nutrient profiling model and the methods involved in classifying commonly consumed food items as identified from the qualitative 24-hour recall dietary intake data.

4.2 **The development of the Ghanaian NRF11.3 index.**

4.2.1 Nutrient profile models

The WHO's recommendation to promote a healthy balanced diet coupled with Ghana's Ministry of Health's concern regarding the nutrition situation in Ghana demands an objective method of categorising foods that are essential components of healthy diets and those that are not likely to constitute a healthy diet (Drewnowski et al., 2021).

Nutrient profiling refers to the scientific process of categorising food and beverages according to their nutritional composition (World Health Organization, 2011b). It provided a process of distinguishing between foods and beverages (i.e. non-alcoholic) that form part of a healthy diet from those that may contribute to excessive consumption of sugar, trans fat, saturated fat, sodium and energy. Nutrient profile models thus vary in intricacy based on the design of the system (Drewnowski et al., 2009a; Drewnowski et al., 2021).

4.2.2 Overview of the decision points in the development of the Ghanaian NRF 11.3 index

The increasing development of multiple nutrient profile models can lead to confusion for both consumers and policy makers, therefore according to the WHO, there is an urgent need to optimise nutrient profiling models for use (World Health Organization, 2011b). With respect to this recommendation by the WHO to optimise existing nutrient profiling models for use, and as identified in chapter two of this thesis, existing nutrient profiling models are currently designed to address dietary excesses in high-income countries which may not be easily transferable to lower-income countries where food inadequacies still exist (see section 2.3.5). In other words, nutrient profiling models created to address a dietary issue in a given setting or population might not directly transferable to another without any modification (Drewnowski et al., 2021). In the Ghanaian context, overweight/obesity prevalence are on the rise (Ghana Statistical Service, 2015). Meanwhile, issues like hunger, undernutrition and micronutrient deficiencies persist and pose a threat to public health, particularly amongst the vulnerable and disadvantaged groups (see section 1.1.3). Secondly, the adaptation and development of a nutrient profiling model have to be transparent using publicly available nutrient composition databases and nutrient standards (Drewnowski et al., 2014), which are inadequate in Ghana. The underlying algorithm must also be made publicized, made freely available, and placed in the public domain (Drewnowski et al., 2021).

As a result, in the development of the Ghanaian nutrient profiling index, some decisions and considerations were made that involved asking the following questions iterative questions:

1. For what purpose, context and population is the model to be used? what is the starting point for development?
2. Are food category-specific or across-the-board standards more appropriate for this context?

3. Which nutrient components should be included?
4. Beneficial nutrients only, nutrients to limit only or both?
5. Which base (i.e., 100 g, serving size and 100 kcal) should be used?
6. What type of nutrient profiling algorithm should be used; one using a threshold for nutrients criteria or one which allocates scores to nutrients?
7. What is the validity and reliability of the nutrient profiling model?

4.2.3 Step 1: Deciding the purpose and starting point for the development of the Ghanaian nutrient profiling model

A systematized review and critical appraisal of nutrient profiling models and their validity (see section 2.4 findings from chapter two of this thesis) identified three models that have been published and are totally transparent and have been validated with respect to objective diet quality measures: the UK Ofcom (Arambepola et al., 2008) model, the French SAIN/LIM model (Darmon et al., 2009) and the NRF 9.3 index (Fulgoni et al., 2009).

However, given the public health focus on reproductive health (i.e., with respect to micronutrient deficiencies) and the double burden of malnutrition in the Ghanaian context, a holistic model that caters for both beneficial nutrients to encourage and nutrients to limit with a consumer focus was deemed appropriate. Thus, a model that addresses imbalances in energy intakes and prevalent (micronutrient and macronutrient) deficiencies was considered fit for purpose in this context (Drewnowski et al., 2021). In addition, the NRF index became a viable option because it allowed nutrients that can easily be sourced in relevant food composition tables.

The NRF9.3 index belongs to the NRFn.3 family of indices developed in the United States (Drewnowski et al., 2008; Drewnowski, 2010) and has been proposed as the most robust index in the family of NRF indices and is easily adaptable for optimisation and use in classifying food and beverages in the Ghanaian context where, NR-NCDs co-exist with undernutrition (see chapter 2, section 2.4.1). More so, because the nutrient-rich approach is an evolution from including only “nutrients to avoid” to including “nutrients to encourage” and considering the whole food and total nutrient package (Drewnowski et al., 2008). Unlike some other nutrient profiling models that are based on the idea of avoiding certain nutrients (Rosentreter et al., 2013; Pan American Health Organization, 2016), the NRF index focuses on nutrient density to help consumers choose foods rich in nutrients first and then the less nutrient-dense foods as calorie needs allow. By incorporating several beneficial nutrients to encourage the index shifts the emphasis from “negative” nutrients to “positive” and “better” foods.

More so, as highlighted in section 2.3.7 and (Table 2.7), the NRF9.3 index was found to have been extensively validated for its construct and predictive validity and was appropriate to use as a platform or starting point for the development of the Ghanaian nutrient profiling model.

4.2.4 Step 2: A choice between “across-the-board” and “category-specific” nutrient profiling models

Nutrient profiling models can be defined as “across-the-board” or “category-specific”. An “across-the-board” nutrient profiling model was chosen because it applies the same parameters or criteria across all food and beverage categories (Drewnowski et al., 2008). Consequently, some food categories may receive low scores even if they are essential to a healthy diet (Fulgoni et al., 2009; Drewnowski et al., 2021). Fruits and vegetables often receive maximum scores, especially in their raw, unprocessed state (i.e., without added salt, sugar, or fat) (Drewnowski et al., 2013). On the other hand, foods that are energy dense usually receive comparatively lower scores (Drewnowski et al., 2014; Hess et al., 2017). For nuts and seeds, their high energy and high-fat content results in a low score using the across-the-board scoring system (Drewnowski et al., 2021). Perhaps a nutrient profiling model should be designed to do more than placing emphasis on the well-known disparities in nutritional content across and between the various food groups.

Category-specific nutrient profiling models, on the other hand, help to discover the "best of category" foods within a given food group by applying various nutrition standards to different food groupings. Although most nutrients are provided by a variety of food groups, the category-specific approach acknowledges that for some nutrients, one food group is the primary source (Hawkes, 2009; Drewnowski et al., 2021). However, classifying food into smaller groups or subcategories presents a challenge and thus a limitation to the use of this approach in the Ghanaian context. The category-specific approach is said to favour the food industry (Scarborough, 2010). This is because using this approach may allow the food industry to innovate several products within a particular food category to promote or market to consumers as healthier options, although in principle, they would not exclude the less healthy options from being promoted.

Therefore, models developed in high-income countries that use the category-specific approach might not correspond to how Ghanaians perceive food categories and it may be difficult to adapt such algorithms in this context. Food classification decisions require specialist knowledge and may be influenced by ethnography. As a result, different categorisation schemes exist depending on the geography and the characteristics of the target population. Categorisation schemes differ by region and by the characteristics of the population of interest. Thus, the across-the-board approach was considered simple and easy to use in this study.

4.2.5 Step 3: Selection of nutrients

This step in the development process is concerned with the selection of qualifying and disqualifying nutrients. These have also been referred to, in accordance with public health goals, as “nutrients to encourage” or “positive nutrients” and “nutrients to limit” or “negative nutrients”, respectively. Particularly in a setting like Ghana, where the double burden of malnutrition exists, the choice of qualifying and disqualifying nutrients must be responsive to particular community health needs. Thus, the selection of nutrients to be included in the Ghanaian model was based on the focus on micronutrient deficiency in concurrence with NR-NCDs. Thus, using the NRF9.3, which is based on six Food and Drug Administration (FDA) nutrients (calcium, fibre, vitamins A and C, iron and protein) and vitamin E, magnesium and potassium, was used as the foundation for the creation of the Ghanaian model, as indicated earlier.

In the African region, diets can be deficient in peculiar micronutrients, including but not limited to: Vitamin A, thiamine, Vitamin B-12, calcium, iron, iodine, and zinc (Harika et al., 2017). Therefore, in the case of Ghana, the NRF9.3 index was expanded to include two more beneficial nutrients (folate and zinc) because of their public health importance. This resulted in a total of 11 beneficial nutrients to be incorporated into the Ghanaian nutrient profiling model (i.e., Ghanaian NRF11.3 index) to be used for categorising Ghanaian food.

The disqualifying or negative nutrients have often included total fat, saturated fat, total sugar, added sugar and sodium. Sugars found in milk (lactose) and fruit (sucrose and fructose) are typically included in total sugars; added sugars are those that are added during the preparation and processing of food (sucrose and high-fructose corn syrup). However, there were technical limitations with regard to data on added sugars as this information was not available in all the food composition tables considered for use in the analysis of Ghanaian foods. Hence all these were taken into account in the development of the Ghanaian model. Although a model based on more nutrients of (up to 23 or more) might seem more comprehensive, many of the nutrients tend to correlate with each other. Nonetheless, the number of nutrients, especially those of public health concern in Ghana, ought to be prioritised in the context in which the model is to be used. The food sources of common nutrients may vary, especially amongst those countries where a conventional diet of starchy staples is consumed (Trijsburg et al., 2019), as in the case of Ghana.

4.2.5.1 Public health importance of Zinc

A strong immune system is largely dependent on maintaining micronutrient balance (Gammoh et al., 2017). Zinc (Zn) is an essential micronutrient crucial for public health (Gupta et al., 2020). Its role is to control both the inherent and adaptive immune response. It is said to support various processes involving wound healing and infant development. However, zinc has been discovered to be a significant contributor to illness in LMICs (de Benoist et al., 2007; Gupta et al., 2020). Regardless of the assessment indicator used zinc deficiency appears to be a public health issue in nearly all LMICs, according to de Benoist et al.(2007). It has been listed as one of the significant leading causes of mortality and morbidity in developing countries (Caulfield et al., 2004; Khalid et al., 2014)

Walker et al. (2009) also demonstrated that the prevalence of zinc deficiency was high amongst people with an increased risk of infectious diseases such as malaria, pneumonia and diarrhoeal disease (Walker, 2009). The lack of zinc usually results primarily from malnutrition. Thus extra zinc is usually recommended for people with extra nutritional needs or compromised immune system, such as pregnant or lactating women (King et al., 2006; Roohani et al., 2013; Kumera et al., 2015). Zinc is present in foods such as shellfish, legumes and animal protein. Beside animal protein being a rich source of zinc, adding small amounts of it to plant-based foods increases their absorption (Gibson, 2007). Thus the bioavailability of zinc differs considerably from one food to another. For instance, the presence of calcium or iron influences the absorption of zinc (Gupta et al., 2020). According to Gupta et al.(2020), zinc deficiency is not only prevalent amongst women and children, but also amongst adolescents and adult males (Gupta et al., 2020).

4.2.5.2 Public health importance of Folate

Folate (also referred to as vitamin B9) is found widely in a range of foods such as green leafy vegetables, eggs, livers, offal and legumes especially black-eye beans (National Institutes of Health, 2021). According to a systematic review by Marchetta et al. (2015) increased intake of unprocessed or natural food rich in folate increases red blood cell concentration and an adequate amount is necessary during pregnancy and childbirth to prevent adverse outcomes (Marchetta et al., 2015). However, the bioavailability of naturally occurring folate in foods is said to be less as compared to synthetic folic acid (Marchetta et al., 2015; National Institutes of Health, 2021). Folate is therefore essential for the formation of blood cells and the proper development of infants. Due to its importance in public health, it is routinely given to pregnant women as a supplement during pregnancy (Kancherla et al., 2022). Insufficient intake of folate below recommended levels is primarily associated with neural tube birth defects such as spina bifida and adverse outcomes during pregnancy and childbirth (Blencowe et al., 2018; Kancherla et al., 2022).

Folate deficiency can also contribute to anaemia, which is one of the leading causes of death and disability worldwide (World Health Organization, 2011a, 2014). In 2019, the global prevalence of anaemia was estimated to be 36.5% in pregnant women and 29.9% in women of reproductive age (World Health Organization, 2019). Anaemia is regarded as a major public health problem in Ghana, affecting 42% of women and approximately 66% of children, according to the Ghana Demographic and Health Survey (Ghana Statistical Service, 2015). Therefore, both zinc and folate are crucial micronutrients of public health importance and thus need urgent attention through government policies and programmes, especially in Ghana.

4.2.6 Step 4: Selection of nutrient standards

The nutrient standard is typically based on local reference dietary amounts. The development of the Ghanaian NRF index closely adhered to the US FDA's regulatory criteria (U.S. Food & Drug Administration, 2013). The FDA classifies food as "healthy" based on its iron, protein, vitamins A and C, calcium and fibre content. Foods that have higher than the allowed levels of fat, saturated fat, trans fat, cholesterol, or sodium are not permitted by the FDA to make nutrition and health claims. However, in Ghana these local standards are scant, and the nutrient standard used for the development of the Ghanaian nutrient profiling was based on the FDA's published US reference daily values that are used on nutrition labels. The daily values (DVs) generally consist of two sets of reference values for reporting nutrient labels: the Daily Reference Values (DRVs) and the Reference Daily Intakes (RDIs). These DVs are used to calculate the percentage daily value that helps consumers understand how the amount of a nutrient present in a serving of food contributes to the daily diet and allows for the comparison of the nutritional value of food products.

The maximum recommended values for the nutrient to limit were 2400 milligrams of sodium and 65 grams of total fat, all based on a daily calorie intake of 2000 kcal/d diet (U.S. Food & Drug Administration, 2013). The reference intake for total sugar was taken as 90 grams, as used in Britain and across the EU. For qualifying nutrients, the daily reference values and reference daily intakes are given in Table 4.1 below. With the NRF index approach, this set of references were converted to per cent daily values per 100 kcals. In order to prevent foods with extremely high concentrations of single nutrients from having an unreasonably high index score, the percentage daily values (%) were capped at 100%.

Table 4.1: Values used to calculate the percentage daily values of beneficial nutrients (U.S. Food & Drug Administration, 2013).[†]

Food Component	Daily Value
Calcium	1000 mg
Dietary Fibre	25 g
Folate	400 µg
Iron	18 mg
Magnesium	400 mg
Potassium	3,500 mg
Protein	50 g
Vitamin A	5,000 IU
Vitamin C	60 mg
Vitamin E	30 IU
Zinc	15 mg

4.2.7 Step 5: Which base or combination of bases (i.e., 100 g, serving size and 100 kcal) should be used

The nutrient density of food is determined based on a reference amount, which can be a serving size, 100 grams or 100 kcals. Local regulatory requirements are typically what determines the calculation base (U.S. Food and Drug Administration, 2019). No regulated, government-approved serving size calculation bases exist in Ghana at this time, therefore the Ghanaian NRF index scores were calculated per 100 kcal. By contrast, 100 grams was not considered the base because models based on 100 grams have trouble handling various serving sizes by food group (Drewnowski et al., 2008). For example, sodium, sugar, and fats calculated per 100 grams of food or beverages and consumed in small amounts tend to be penalised (i.e., nuts, dried fruits),

[†] mg =milligram ; g=gram ; IU=international Unit; µg=micrograms

while favouring sugary drinks with low energy density unless volume adjustments are made. However, in some models, a combination of these bases are used (Maillot et al., 2018). As the focus of the current model was on nutrient density, the NRF nutrient scores were calculated per 100 kcal. Thus, the choice of bases for the Ghanaian model was driven by a focus on the nutrient density of the food.

4.2.8 Step 6: Deciding on the nutrient balance of the nutrient profiling model

Another point that was considered was whether the nutrient profiling model should be compensatory or not. Some nutrient profiling models balance nutrients to encourage against those to limit, whereas other models do not. Existing models have relied solely on qualifying nutrients, disqualifying nutrients or a combination of the two. Non-compensatory models typically rely on the amount of fat, sugar, and sodium present in the food being consumed. For example, if a product is high in total fat or sugar, it cannot claim to be low in salt. On the contrary, a model that calculates the difference between positive and negative nutrients to determine the final score is said to be compensatory. The NRF index is entirely compensatory because it is centred on the difference between two scores (positive and negative, respectively). The consideration is whether the inclusion of fibre, protein and other positive nutrients can make up for the specified levels of sugar, fat and sodium. Thus, the Ghanaian nutrient profiling model takes this compensatory approach.

4.2.9 Step 7: Deciding on the nutrient profiling algorithm

Nutrient profiling systems can incorporate a continuous or a dichotomous score. The NRF index is an example of a continuous score and the final score can be calculated using the sums, ratios or means of the nutrients. In developing the Ghanaian NRF index algorithm, first two sub-scores were created: the nutrient-rich scores (NR_n) and the nutrient-to-limit scores (LIM).

The NR_n sub-scores were based on 11 variable nutrient components to encourage. These 11 beneficial nutrients were presented as unweighted sums of percent daily values (i.e., sums) per reference amount. Whereas the negative nutrients (LIM) sub-score was determined by only three nutrient components (total fat, total sugar, and sodium), which were calculated as the percent daily value per reference amount. The final NRF index algorithm was illustrated as the mathematical difference between the positive (NR_{11}) and the negative (LIM) components. Thus, given as $NRF_{11.3} = NR_{11} - LIM_3$.

4.2.10 Step 8: How to approach the validation of the index

A crucial step in creating nutrient profiling models is validation (Drewnowski et al., 2008; Fulgoni et al., 2009; Drewnowski et al., 2014). Approaches to nutrient profiling model validation have compared scores generated from models to expert opinion or looked for a correlation between several models (Fulgoni et al., 2009). Other approaches to validation have examined the relationships between nutrient density scores and other independent indicators of diet quality such as the Healthy Eating Index (HEI), a determinant of compliance with dietary guidance (Arambepola et al., 2008). For example, the NRF index based on 9 nutrients to encourage (calcium, fibre, vitamin A, C, E, iron, protein, potassium, and magnesium) and three negative nutrients (saturated fat, added sugar, and sodium) was found to have the best correlation between participant HEI scores and individual NRF levels (Fulgoni et al., 2009). Even though some models have up to 23 or more nutrients (Trijsburg et al., 2019), in general, higher correlations with HEI scores were observed with a more constrained number (Fulgoni et al., 2009). However, the HEI is based on US dietary goals and may not be applicable elsewhere, such as in Ghana. Thus, this approach of using HEI for validation was not tested in this study. The subsequent section that follows describes how a regression analysis was undertaken to determine the optimal level of nutrients in the Ghanaian NRF index.

4.3 Steps that were undertaken in the nutrient profiling of individual food items using the Ghanaian NRF11.3 Index

Nutrient profiling for this study was conducted using the Ghanaian NRF11.3 index (see sections 4.2.3 - 4.2.10). The steps taken in the profiling of commonly consumed Ghanaian foods included:

(i) cleaning and managing the secondary data

(ii) generation of a food list of commonly consumed food items from 24-hour recall data

(iii) identification of food composition tables to be used, and

(iv) generation of individual food scores using the nutrient profiling model.

The subsequent section explains how each of the above steps, was conducted in this study.

4.3.1 Data management

As outlined above, the secondary data were collected from qualitative 24-hour recall interviews (n=288) (see sections 3.4.1 and 4.1) (Holdsworth et al., 2020). Dietary data were transferred directly to a statistical software SPSS version 25 (IBM Corp., 2017). To get a better understanding of the data before commencing analysis data were examined for familiarisation with a focus on dietary data only. A codebook was prepared with all foods identified (i.e., all foods in the dataset and those marked as consumed). The 24-hour recall data were then cleaned in SPSS; by looking for any missing values and inconsistencies in the data. All personal data linked to the 24-hour recall data were removed.

4.3.2 Identification of foods items to be analysed

A list containing all foods consumed in the 24-hour dietary recall data were identified and a final food list was created and used for the nutrient profiling of Ghanaian food items. This process generated a total list of (n=138) single foods identified as foods consumed in Ghana (Holdsworth et al., 2020).

4.3.3 Food composition tables used: principal decisions and considerations

In order to generate the nutrient profiles of the food items, the dietary intake data from the 24-hour recall described earlier in section 4.1.3 and the nutrient composition of each food and beverage item were needed to generate the nutrient profiles of food items (Drewnowski, 2010). Nutritional content information for each of the food items identified as consumed in the database was determined by a synthesis of food composition tables (FCTs). This was necessary due to the lack of one comprehensive FCT for generating all the required nutrient information for profiling Ghanaian foods. Thus, six main FCTs were considered for the analysis as follows.

4.3.3.1 Principal food composition table

The main FCT utilised was the published **2012 West Africa Food Composition Table** (WAFCT) (Stadlmayr et al., 2012), as it was the most suitable one available at the time of analysis. The nutrition composition for food and drink in the WAFCT was produced from the average food composition values collected from nine countries ("Ghana, Benin, Gambia, Burkina Faso, Guinea, Senegal, Mali, Nigeria, Niger, and Senegal") (Stadlmayr et al., 2012). The WAFCT was used as the principal FCT to make sure that the nutrient information for the food items were obtained from a source specific to the context. However, this FCT only had information for 13 of the 14 nutrients inputted into the algorithm for nutrient profiling, i.e., calcium, fibre, iron, magnesium, potassium, sodium, zinc, vitamin A, E, C, folate and total fat. For foods recognised as consumed from the 24-hour recall dietary dataset (Holdsworth et al., 2020) that were found in the WAFCT, the nutrient information available for 13 nutrients were obtained. Furthermore, as the nutrient composition information from WAFCT was incomplete and mainly lacked nutrient information for sugar, this information was supplemented from other FCTs when required in order of priority.

4.3.3.2 Supplementary food composition tables

Subsequently, if a food item was not found in the 2012 WAFCT, the updated 2016 WAFCT was employed to either gather the complete nutrition information for the food item or add to that obtained in the 2012 WAFCT (Stadlmayr et al., 2012). In a situation when a food item was not available in either of the two WAFCTs, then the 2008 Tanzania Food Composition Table (TFCT) was used (Lukmanji Z., 2008). This data source was particularly relevant for total sugar values of local foods as the WAFCT contained no nutritional information for total sugar. In cases where the nutrient information was not found in the TFCT, then any details about the particular item was then sourced from the 2018 Kenya Food Composition Table (KFCT)(FAO/Government of Kenya., 2018). The KFCT and TFCT were considered as secondary FCT because these African FCTs contained published food items with some similarities to Ghanaian foods. If the nutrient information of a food or beverage item was not available in the selected four FCTs according to priority, then the seventh Edition of McCance Widdowson UK Food Composition Table (UFCT) was consulted. The Ghana RIING database local to Ghana, was the sixth FCT, sparingly consulted if a food or beverage item's information was not found in any of the five previous FCTs. This was used with caution due to the lack of FAO approval of the local laboratory. This was especially important for Ghana-specific mixed dishes. Since there was virtually any information on sugar in the several African FCTs, with the exception of the TFCT, the nutritional values for total sugar were supplemented from McCance and Widdowson FCTs.

Irrespective of the FCT utilized, when extracting the nutrient composition data, foods or beverages with similar nomenclature to those in the dataset were objectively considered and used. In a case where a food item was absent from any FCTs under its recognised local name or original name, the closest substitute was used in its place. For example, for "kontomire stew," information for *"green leaves relished with oil"* was used as found in TFCT. More so, the full nutrient information of 14 nutrients for "*okra stew"* found in the TFCT as "*Okra relished* with oil". Also, for "*tom brown*" the closest as found in the TFCT was "*mixed flour porridge with sugar*". This process was systematically followed in cases where some ingredients of the original local dish were missing or not the exact name as stated in the food list. Thus, the closest mixed dish with ingredients approximate to the original local mixed dish was used. Out of all the 138 food items profiled, similar judgements were made just for a few items, only one food item ("wele") could not be substituted and was incomplete in all FCTs.

In other cases, nutrient information was available twice for the same description of a food item as named in the food list from the 24-hour recall database. Based on the familiarity with the local foods and context, an assumption made was for the average of the two to be taken. For example, "gaari" appeared in line number 629 and 643 of the WAFCT 2016 food composition table and an average of the two nutrient compositions was taken in this instance. More so, where a particular food item in the dataset was not found in any of the Africa FCTs but found in the seventh edition of the UFCT, the full nutrient information was taken therein. For instance, this was done for example in the case of noodles.

4.4 Steps in nutrient profiling using the Ghanaian NRF11.3 index

To be able to classify Ghanaian foods identified as consumed from the dietary 24-hour recall data applying the Ghanaian NRF11.3 index the following procedure was followed.

First, for every individual food item (n=138), the nutrient values per 100 grams for the 11 beneficial nutrients ("calcium, fibre, folate, iron, magnesium, potassium, protein, vitamin A, C, E and zinc") and three disqualifying nutrients ("total sugar, total fat and sodium") were taken from the food composition tables and entered into an Excel spreadsheet. Then, applying USDA dietary recommendations (U.S. Food & Drug Administration, 2013), the percentage

DV for every one of the 11 beneficial nutrients and the three nutrients to limit was calculated per 100 kcals (see section 4.2.6). The percentage DV shows what percentage a product contributes to reaching the daily value. Using the same Excel spreadsheet, the energy density of each food item was entered as kcal/100 grams. Capping was used to prevent specific food items that scored over 100% daily value from unduly affecting the resultant NRF11.3 index, as recommended by Drewnowski and colleagues (Drewnowski et al., 2014; Drewnowski, 2017). In order to do this, columns that had any values above 100 for the percentage DV for any beneficial nutrient were identified. Subsequently, if a column's percentage DV values were greater than 100, a new column was inserted next to it, and it was renamed as "DV-capped at 100%". Therefore, in this new column, all percentage DV were duplicated from the original column, but then any value greater than 100 was made100 (Drewnowski, 2017). For example, grounded pepper (chilli, capsicum, species) had a percentage DV for vitamin C at 715.18 but capped at 100 to avoid influencing the final score. On this bases, consequently, the percentage DV per 100grams for each one of the 11 beneficial nutrients to encourage resulted in an upper limit value of 100. The negative nutrients, however, were not subjected to this capping process, and their percentage DV per 100 grams remains the same.

The succeeding step was to add all the individual percentage DV's and the newly capped percentage DVs per 100 grams for the 11 beneficial nutrients ("calcium, fibre, folate, iron, magnesium, potassium, protein, vitamin A, C, E and zinc") and three disqualifying nutrients ("sodium, total sugar and total fat") for each food item. This resulted in calculating the Ghanaian NRF11.3 index score per 100 grams ($NRF_{11.3\ 100grams}$) for each of the individual food items (n=137) by subtracting the total of the disqualifying nutrients from the sum of the qualifying nutrients. The algorithm applied was:

$NRF_{11.3\ 100\ grams}$ = [(percentage DV protein + percentage DV fibre + percentage DV calcium + percentage DV iron + percentage DV potassium + percentage DV magnesium

+ percentage DV zinc + percentage DV folate + percentage DV vitamins A + percentage DV vitamin C+ percentage DV vitamin E) - (percentage DV total sugar + percentage DV total fat + percentage DV sodium)] /100grams.

The final step was to convert from NRF11.3 100 grams to NRF11.3 index scores per 100 kcals (NRF$_{11.3\ 100\ \mathrm{kcal}}$) by multiplying 100 by the NRF11.3 index in 100 grams and then dividing the outcome by the energy density of that particular individual food. Thus, in this study, the calculation of the nutrient density of individual food items were based on NRF11.3 $_{100\mathrm{kcal}}$ and not NRF11.3 $_{100\mathrm{grams.}}$ The use of portion size was not considered in this study because there is no standard portion size measure in the Ghanaian context. Though calculations using portion sizes may provide a clearer option of communicating the concept of a food's nutrient density. More so, Drewnowski et al. (2009) writes that calculations based on 100 grams often disregard the usually large variations in portion sizes and may potentially penalise foods that are consumed less frequently and in smaller amounts (Drewnowski et al., 2009a)

On the other hand, calculations established on 100 kcals bases have the effect of giving higher scores to individual food items with the highest content of water and lowest energy density (Drewnowski et al., 2009a). Given that context and focus on nutrient density, which reflects the proportion of nutrients to the total energy content of a food item, 100 kcals bases was used for all calculations. The daily values used were based on an adult's 2,000 kcal energy intake. The US FDA recommended daily allowance served as the bases since that is also used in Ghana. Thus, the nutrient-rich index scores were generated for each individual food and beverage item (n=137) based on NRF $_{11.3\ 100\ \mathrm{kcals}}$.

The next sections describe the reliability and validation of the Ghanaian NRF11.3 index.

4.5 **Optimisation of the Ghanaian Nutrient Rich Food (NRF11.3) index**

One of the objectives of Study 2 was to determine the optimal combination of nutrients required in the Ghanaian NRF index model for classifying commonly consumed Ghanaian foods. The premise or hypothesis for this objective is whether, in the Ghanaian context, a fewer number of nutrients (NRF n.3, where n is the number of beneficial or positive nutrients) can be used to classify food in the same way as the newly developed Ghanaian NRF11.3 classifies food. This would be of particular benefit, considering that in Ghana there is limited nutrient composition data. Furthermore, this is a vital point to consider as regulatory organisations would probably choose a model with the fewest nutrients for ease of enforcement whereas models based on an optimal number of nutrients may perhaps exhibit a higher correlation to a nutrient-dense diet. Hence, regression analyses were performed using the NRF11.3 index score as the dependent variable and with the individual nutrients ("calcium, fibre, folate, iron, potassium, protein, vitamin A, C, E, zinc, magnesium, total fat, sugars and sodium") incorporated into the food scores as independent variables. The proportion of explained variance (R^2), standardised regression coefficients and Bayesian information criterion (BIC) were also assessed to determine the best fit model. The p-values of the models were also assessed. The statistical programme SPSS version 25 was used to conduct the analysis (IBM Corp., 2017).

4.6 **Data Analysis 1: Conducting the regression**

Why Multiple Regression?

Multiple regression was employed because it is based on correlation but permits for a more advanced investigation of the association amongst a group of variables (Pallant, 2010; Mooi, 2011). In this multiple regression analysis, the variable that the researcher aims to predict is the dependent variable also known as the outcome variable (i.e., NRF11.3 index) and the variable that the regression analysis applies to predict the value of this NRF11.3 index, the dependent variable is referred to as the independent variable ("calcium, fibre, folate, iron, magnesium, potassium, protein, vitamin A, C, E, zinc, total fat, total sugars and sodium"). This method provides information about the NRF11.3index in totality and the relative contributions of each independent variable that makes up the index (Pallant, 2010). More so, linear regression analysis provides insights concerning the strength of the relation between the dependent and the independent variables and where there are more than two variables this is called a multiple regression analysis (Peat, 2002; Streiner, 2004), as in the case of this study. More so, the outcome variable is continuous, hence linear regression. This form of statistical analysis was selected as ideal for investigating the current research question of 'what is the optimum amount of nutrients needed to predict the Ghanaian NRF11.3 index model?' rather than similar techniques such as factor analysis which looks at the elements that belong together/similar each other and so would not answer the current query.

The standard multiple regression allowed for statistical testing that would determine: i) whether adding or removing a variable (e.g. an individual nutrient) contributed to the predictive power of the index, up and above the variables already incorporated in the index and ii) how effective a set of variables would be able to determine a certain outcome. How well the regression model fits the observed data is commonly indicated by the R^2. This takes values between 0 to 1 (Pallant, 2010). A higher R^2 indicates a better fit model, however, it does not indicate the correctness of the regression model and therefore conclusions about the models are drawn by analysing the R^2 together with other indicators in the statistical model (Pallant, 2010). In addition, the adjusted R^2 represents a modified version of the R^2 that adjusts for predictors that are not significant in a regression model. The Bayesian information criterion (BIC), another measure of how well a chosen model fits the data, was generated alongside the regression analysis to check for model fit. The smaller the BIC, the better the model regardless of whether the models being compared are nested. In most cases, the BIC is used to identify the optimum model. Thus, the BIC is a useful tool for model fitting and comparing models to each other (Vrieze, 2012). Although other researchers tend to report a similar check for model fit known as the Akaike information criterion (AIC), in this case, the BIC was deemed better than the AIC, because AIC tends to prefer models with more terms (Vrieze, 2012), which is opposite to the objective of the current research question.

4.6.1 Steps used in the regression model

The following steps, as shown in Figure 4.1, were considered sequentially in the regression analysis and included: checking for the regression analysis requirements, specifying and estimating the model, testing the assumptions for validation and use of regression model (Mooi, 2011).

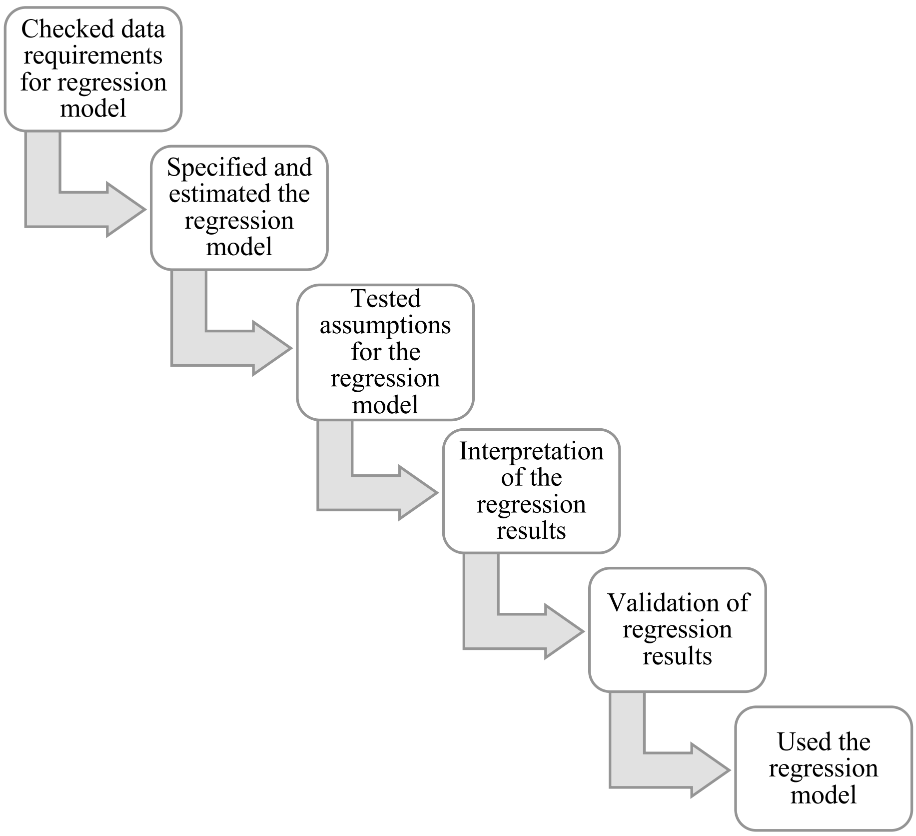

Figure 4.1: Steps followed to conduct regression analysis (Mooi, 2011)

4.6.2 The data requirements for regression analysis

Some requirements had to be taken into consideration before undertaking the regression analysis. These included sample size, variability of variables, normality of residuals and collinearity.

The first and primary data requirement was the need for an adequately large sample size (Kelley et al., 2003). In this study, 14 independent variables were incorporated to predict the outcome variable. Green (1991) proposed a standard or guiding principle for determining the sample size for a regression analysis of 104 + k, whereby k represents the number of independent variables (Green, 1991). When this was calculated in this study, 138 valid observations were evident. This was above the recommended minimum sample as proposed (Green, 1991) (i.e., 104 +14 =114). Nonetheless, Harrel (2001) and Austin et al. (2015) propose 10 observations per every variable (so 10*14=140) as the minimum sample size needed for regression models to guarantee an accurate prediction (Harrell, 2001; Austin et al., 2015). Thus, in alignment with Green's recommendation, this data set fulfils the requirement for the regression analysis. Nonetheless, since other recommendations (Austin et al., 2015) puts this sample on the border, some caution is to be taken in the interpretations.

Second, if there is no variation in the dependent as well as the independent variables, a regression model cannot be accurately specified and estimated (Mooi, 2011).

The last requirement was to check the data to ensure that no or little collinearity was present (Pallant, 2010; Mooi, 2011). This presents as an issue that ensues when two independent variables are found to be highly correlated and therefore this needs to be examined. Collinearity diagnosis in this analysis was checked by considering the tolerance or variance inflation factor (VIF). By definition, "tolerance shows how much of variability of an estimated independent variable is not explained by the other independent variables included in the model" (Pallant, 2010). It is determined using the formula (1-R) squared for each variable (Pallant, 2010). A very small tolerance value (i.e., below 0.10) indicates that multicollinearity with other variables exists (Pallant, 2010). Similarly, the VIF is a reciprocal of the tolerance value. Therefore, VIF values of more than ten indicate that there are collinearity issues (Pallant, 2010). In this study, the tolerance of the independent variables was above the 0.10 cut-off. These values are presented in the table labelled coefficients under the result section.

4.6.3 Specification of the regression model

To conduct the regression analysis, the variables for inclusion were selected and the decisions on a model estimation were made. The following is an explanation of how this was applied in this study. Firstly, data containing all information on the calculations of individual food scores using the NRF11.3 were exported to SPSS, version 25. This data contained all the 14 independent variables (i.e., all nutrients incorporated into the model) and the dependent variable (i.e., NRF11.3 index score for the individual foods). Following from this the linear regression was conducted after specifying those variables that were needed for the analysis accordingly. The analysis procedure was then set with respect to the study objective. Two general options under the methods were available for selection (i.e., the enter and stepwise). In this study, the enter method was selected because it would allow the researcher to be in full control to add or remove variables that are truly significant and useful to the purpose of the research rather than handing it over to the computer system that does not understand the context. Thus, regression analysis was conducted using NRF11.3 index score as the dependent variable, the percentage daily value/100kcal of each of the 11 nutrients beneficial nutrients to encourage capped at 100% DV, and the three negative nutrients as the independent variable. As the goal was to identify an optimal model, all the possible models that could be made by combining the 11 positive nutrients and three negative nutrients in the regression analysis were explored. An iterative process was followed whereby one nutrient was removed or taken from the regression model one at a time but with replacements (i.e., the nutrient is then put back in and the next one taken out) to identify whether removing a variable (e.g. an individual nutrient) contributed to the predictive ability of the regression model. This process resulted in 14 different models for analysis, a model with each respective nutrient removed, plus one with all nutrients. The proportion of explained variance, standardised regression coefficients and the BIC were estimated. The variation (R^2) and adjusted (R^2) of the models were used to assess the various algorithms.

4.7 **Results**

The findings of the statistical regression analysis are presented in this section.

4.7.1 Findings from testing the assumptions of the regression model

Scatterplots were used to explore the relationships between the variables and an indication of whether variables are correlated in a linear fashion (see Appendix 6). One way the assumption for the regression model was checked was by observing the shape of the histogram, the regression standardised residual and scatter plots that were presented as part of the analysis (Hair, 2010; Pallant, 2010). The histogram provided in this study illustrated a belled shape appearance, with maximum distribution at the middle and minimum at the edges. This showed some outlined data points. The majority of the scores were concentrated in the centre, along the 0 point. The output for the scatter plots and histogram are attached as Appendix 6.

4.7.2 Results of the optimal model from multiple regression

The overall fit of the model was assessed by considering the R^2, the adjusted R^2 and the BIC information (see Table 4.1 below). The R^2 shows how much of the variation in the dependent NRF11.3 index is accounted for by independent variables of the model, while the adjusted R^2 statistic accounts for the number of predictors in the model, thereby expecting a higher R^2 because there are more factors. Thus, the adjusted R^2 represents a comparative measure and was used to evaluate the different regression models. The model with the highest adjusted R^2 was considered the one with more variation explained. In addition, the Bayesian information criterion was used to aid model selection amongst the various set of models, the one with the lowest BIC was preferred.

The process and different stages and models considered before arriving at the best fitting model is included as Appendix 7 due to the large content. A great amount of time approximately 5weeks was devoted to this stage of the regression process. It started with a full model named as stage 0 (full model with all nutrients), then one nutrient was taken out at a time and model fit statistics (R^2, adjusted R^2, BIC, p-values and standardized coefficient) were performed. As the nutrient that was initially removed was returned into the full model and a different nutrient was removed and the model fit statistics were produced once again. This iterative process was carried out until there were 13 different models each one containing a removed nutrient from the full model and each with its respective statistics (i.e., see Appendix 7, stages 1 through to stage 13). The model with the best statistical fit (lowest BIC, highest adjusted R^2 and $R^{2)}$ was chosen to take forward and the process repeated this time producing 13 respective models, each with a variable entered and removed (Table 4.2). This process continued until removing further items provided no further improvement to the model. After comparing the results from 14 models (13 models plus the full model) as shown in Table 4.2, the final model identified as the best fit model was the full model with all nutrients, as it presented the lowest BIC and the highest Adjusted R^2. A detailed summary of this analysis is presented in Table 4.3

which gives the final summary of the various models compared and the model of the optimal statistics and best-fit as identified from the regression analysis arranged in descending order (R^2=0.999, BIC=338.524, p<001).

Table 4.2: Comparison of models according to stages and number of nutrients removed from regression analysis.

Stages	Nutrients entered into the model		Nutrients removed from the model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 0 (Full Model) NRF11.3	Calcium Fibre Folate Iron Magnesium Potassium Protein	Sodium Sugar Total Fat Vita min A Vita min C Vita min E Zinc	None	**0.999**	**0.999**	**338.524**
Stage 1 Model 1	Calcium Fibre Folate Iron Magnesium Potassium	Protein Sodium Sugar Total Fat Vita min A Vita min C Vita min E	Zinc	**0.999**	**0.999**	**437.435**
Stage 2 Model 2	Calcium Fibre Folate Iron Magnesium	Protein Sodium Sugar Total Fat Vita min A Vita min C	Zinc Potassium	**0.998**	**0.997**	**532.312**
Stage 3 Model 3	Calcium Folate Iron Magnesium Protein Sodium	Sugar Total Fat Vita min A Vita min C Vita min E	Zinc Potassium Fibre	**0.993**	**0.992**	**688.134**
Stage 4 Model 4	Calcium Folate Iron Magnesium Protein	Sodium Total Fat Vita min A Vita min C Vita min E	Zinc Potassium Fibre Sugar	**0.986**	**0.985**	**771.253**
Stage 5 Model 5	Calcium Folate Iron Protein Sodium	Total Fat Vita min A Vita min C Vita min E	Zinc Potassium Fibre Sugar Magnesium	**0.978**	**0.976**	**829.737**
Stage 6 Model 6	Calcium Folate Iron Protein Sodium	Vita min A Vita min C Vita min E	Zinc Potassium Fibre Sugar Magnesium Total Fat	**0.969**	**0.968**	**866.802**

Stages	Nutrients entered into the model		Nutrients removed from the model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 7 **Model 7**	Calcium Folate Iron Protein	Vitamin E Vitamin C Vitamin A	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium	**0.960**	**0.957**	**900.077**
Stage 8 **Model 8**	Calcium Folate Iron	Protein Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A	**0.945**	**0.943**	**937.389**
Stage 9 **Model 9**	Folate Iron Protein	Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium	**0.931**	**0.929**	**963.293**
Stage 10 **Model 10**	Folate Protein Iron Vitamin C		Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E	**0.901**	**0.898**	**1008.126**
Stage 11 **Model 11**	Folate Iron Vitamin C		Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E Protein	**0.855**	**0.852**	**1055.730**
Stage 12 **Model 12**	Iron Vitamin C		Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E	**0.787**	**0.784**	**1103.164**

Stages	Nutrients entered into the model	Nutrients removed from the model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
		Protein Folate			
Stage 13 Model 13	Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E Protein Folate Iron	**0.644**	**0.641**	**1169.008**

Table 4.3: Summary of the recommended optimal model.

Model Summary			
			Selection Criteria
Full Model	**R Square**	**Adjusted R Square**	**Schwarz Bayesian Criterion**
1	**.999**	**.999**	**338.524**

Predictors: (Constant), Potassium, Vitamin A, Vitamin E, Calcium, Protein, Iron, Zinc, Vitamin C, Fibre, Folate, Magnesium, Total Fat, Sodium Sugar

Table 4.3 above shows the summary of the optimal GhanaNRF11.3 index for classifying Ghanaian foods items (R^2=0.999, BIC=338.524, p<001) whilst Table 4.4 below presents the contributions of the various nutrients to the model.

Table 4.4: The contributions of the various nutrient to the model

Coefficients[a]									
		Unstandardized Coefficients		Standardized Coefficients		95.0% Confidence Interval for B		Collinearity Statistics	
Model		B	Std. Error	Beta	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.713	.447		.113	-.171	1.597		
	Protein	1.013	.011	.235	.000	.992	1.034	.691	1.447
	Fibre	.968	.041	.079	.000	.887	1.048	.387	2.585
	Calcium	1.008	.021	.114	.000	.968	1.049	.795	1.257
	Folate	1.014	.022	.146	.000	.970	1.058	.415	2.410
	Zinc	.873	.074	.031	.000	.726	1.020	.632	1.583
	Potassium	1.019	.063	.077	.000	.894	1.144	.190	5.274
	Magnesium	1.034	.050	.095	.000	.935	1.132	.206	4.860
	Iron	.989	.014	.229	.000	.961	1.017	.406	2.463
	Vitamin A	1.004	.016	.137	.000	.972	1.037	.847	1.180
	Vitamin C	.995	.007	.410	.000	.981	1.010	.470	2.127
	Vitamin E	.998	.017	.136	.000	.965	1.032	.802	1.248
	Total Fat	-1.025	.023	-.109	.000	-1.069	-.980	.748	1.337
	Sodium	-.995	.018	-.123	.000	-1.031	-.960	.871	1.149
	Sugar	-1.020	.026	-.089	.000	-1.071	-.968	.822	1.217

a. Dependent Variable: Ghanaian NRF11.3

4.7.2.1 Results: Contribution of the various nutrients to the model

After having established the best fit model from the modelling process, the interpretation of the effects of each independent variable used to predict the dependent variable are shown in Table 4.5 with the coefficients. To compare the various variables, the column labelled Beta under the standardised coefficients was used. Standardised suggest that these values for each of the different variables have been transformed to a comparable scale to facilitate comparison. In addition, the standardised Beta coefficients reflect the number of standard deviations that the predictor variable's value would vary by if it underwent a unit standard deviation change in the NRF11.3 index. In this study, as the objective is to compare the contributions of individual independent variables for optimisation of the number of nutrients to include in the final model, therefore the standardised beta values were used (Table 4.4). The largest beta values (ignoring any negative sign) make the greatest distinct impact on the dependent variable (i.e., NRF11.3) after accounting for the variance that each other variable in the model explains. However, in the construction of a regression equation, the unstandardised coefficients are preferred whereby a coefficient represents each independent variable (i.e., β_1 to β_{14}) (Mooi, 2011)**.** Typically, the β shows how, if all other independent variables are maintained constant, a change in one independent variable impacts the dependent variable (Pallant, 2010).

In addition, part correlation coefficients were also generated that gave more information about the contribution of variables. According to Pallant 2010, the square of the part correction correlation coefficient of each independent variable provides an indication of how much that variable contributes to the overall R^2 (Pallant, 2010). Thus, the overall variance in the dependent variable (i.e. NRF11.3 index) is distinctively accounted for by the independent variable and how much R^2 will change if it was not added to the model (Pallant, 2010).

In this analysis, zinc has a part correlation coefficient of 0.024. When it was squared the result was 0.00057, indicating that zinc explained only 0.05 percent of the variance in NRF11.3 index scores which was the lowest. Whereas vitamin C, had a part correlation coefficient of 0.281 and when squared was 0.079, indicating a distinct contribution of 7.89 percent to the explanation of the variance and which was the highest shown (Table 4.5). The total R^2 value included the distinct variance described by each independent variable and shared variance. All the individual variables were seen to be making a significant distinctive contribution to the prediction of the dependent NRF11.3 index.

Table 4.5: Evaluating each of the independent variables from lower to highest contributions

Nutrient included	Standardised coefficients (Beta)	Part correlation coefficients	Squared part correlation coefficients	Percentage explained variance (%)	p-value
Protein	.235	.195	0.038025	3.8025	<0.001
Fibre	.079	.049	0.002401	0.2401	<0.001
Calcium	.114	.101	0.010201	1.0201	<0.001
Folate	.146	.094	0.008836	0.8836	<0.001
Zinc	**.031**	**.024**	**0.000576**	**0.0576**	**<0.001**
Potassium	.077	.033	0.001089	0.1089	<0.001
Magnesium	.095	.043	0.001849	0.1849	<0.001
Iron	.229	.146	0.021316	2.1316	<0.001
Vitamin A	.137	.126	0.015876	1.5876	<0.001
Vitamin C	**.410**	**.281**	**0.078961**	**7.8961**	**<0.001**
Vitamin E	.136	.122	0.014884	1.4884	<0.001
Total Fat	-.109	-.094	0.008836	0.8836	<0.001
Sodium	-.123	-.114	0.012996	1.2996	<0.001
Sugar	-.089	-.081	0.006561	0.6561	<0.001

4.7.2.2 The optimal number of nutrients included in the best fit model

The finding from the regression analysis suggests that the model with all 14 nutrients is the optimal model to use in the classification of Ghanaian foods and beverages (Table 4.2). The BIC values suggested that decreasing the independent variables (i.e., nutrients) beyond 14 individual nutrients does not result in a better fit model for the current dietary data set than the full model with 14 nutrients: BIC=338.524, R^2=0.999, Adjusted R^2=0.999, $p<0.001$. For instance, the model with only 13 nutrients presented a BIC=437.435, R^2=0.999, and Adjusted R^2 =0.999; $p<0.001$, which shows that although the R^2 and Adjusted R^2 looks the same with both 13 nutrients and 14 nutrients the BIC suggest that the better fit model will be the model with the 14 nutrients (i.e., 11 positive nutrients and 3 negative nutrients), and it has the lower BIC which indicated the optimal model.

Secondly looking at the coefficient table taking out zinc from the model makes little or no difference and having it in the model makes it optimal Table 4.2 and Table 4.4. In this case with or without zinc in the model the R2 and Adjusted R2 are the same at 0.99, however the BIC give a clear distinction of 338.524 with zinc and 437.345 without zinc. And the lower BIC presents the best fit model as the model with the BIC of 338.524, which is the model with all nutrients. Therefore, the model which included 11 beneficial nutrients and three nutrients to limit; adding up to a total of 14 nutrients explains 99.9% of the variance in the NRF11.3 index score. Of the 14 variables, vitamin C made the largest unique contribution (beta=0.410). Although zinc (beta=0.031) made the smallest contribution, it was still a statistically significant contribution.

4.7.2.3 Nutrients with high contributions to the NRF11.3 index

The nutrients with relatively higher contributions from food items to the overall index were from vitamin C (beta=0.410), protein (beta=0.235) and iron (beta=0.229) as indicated in Table 4.5. This may be because food items with favourably higher nutrient composition were from the vegetables and fruits category. Secondly probably because models based on 100 kcal result in giving the best scores to food items with higher water content and lower energy density.

4.7.2.4 Nutrients with less or no contribution to the NRF11.3 Index

The least nutrient contributors to the NRF11.3 index were zinc (beta= 0.031), Potassium (beta=0.077) and Fibre (0.079). Although these nutrients contributed less to the model, their inclusion yield the best-fit model as per the BIC. They were also statistically significant (p<.001).

The next section estimates the reliability of the Ghanaian NRF11.3 index.

4.8 Discussion of findings from Study 2 Phase 2

The main research objectives of Study 2 Phase 2, involved the use of secondary data to:

- Develop a context-specific nutrient profiling model for categorising foods and beverages in Ghana.
- Determine the optimal combination of nutrients required in the newly developed Ghanaian NRF index for classifying Ghanaian foods.

4.8.1 The development and optimal combination of nutrients required in the Ghanaian NRF index for classifying Ghanaian foods

The Ghanaian NFR11.3 index was developed based on the proposed guidelines by Drewnowski and colleagues (Drewnowski, 2005; Fulgoni et al., 2009) for the development of the NRF index which ranks food items based on various nutrient. Hence using the highly validated NRF9.3 index as the premise, the Ghanaian NRF11.3 index was developed for classifying Ghanaian foods. Section 4.2 describes the developmental steps of the Ghanaian NRF11.3 index. Given the Ghanaian context (i.e., the double burden of malnutrition), the selected nutrient of public health concern included two more nutrients (folate and zinc), resulting in a final index named the Ghanaian NRF11.3 index. However, because the Ghanaian context may benefit from using only fewer nutrients in a model that produces the same results, due to the unavailability of FCTs, regression analysis was used to determine the optimal number of nutrients in the newly developed Ghanaian NRF11.3 index. The results showed that an optimal model best fit for the Ghanaian context using context-specific dietary data was an index with 11 beneficial and three negative nutrients. From the regression analysis, 14 different indices were modelled and analysed (Appendix 7).

An index with 10 beneficial nutrients (fibre, vitamin A, C, E, protein, calcium, iron, potassium, magnesium, folate) and three nutrients to limit (total fat, total sugar, and sodium) produced similar results (i.e., R^2=0.999, Adjusted R^2=0.999) to the index with 11 beneficial (protein, potassium, fibre, folate, vitamin A, C, E, calcium, iron, magnesium and zinc) and three nutrients to limit (total fat, sugar and sodium) except for their BIC which differed (i.e., BIC for NRF10.3 index = 487.345; and BIC for NRF11.3 index =338.524) when zinc was excluded from the NRF11.3 index. Consequently, it was concluded that the NRF11.3 index presented the lowest BIC and was thus the best fit model according to this analysis. More so, this finding corroborates validation studies that compared nutrient profiling models with independent measures of a healthy diet and produced evidence to suggest that performance optima for a nutrient profiling model is between 9-12 nutrients (Drewnowski et al., 2021). Drewnowski et al. (2009) also writes, that the nutrient profiling model in the nutrient density family yields similar results as further vitamins and mineral beyond some optimum of 10 or 11 (Drewnowski et al., 2009b). Therefore, considering our model with 11 beneficial nutrients also fits well with the recommended amount of nutrients needed for optimal performance.

The nutrients with relatively higher contributions to the Ghanaian NRF11.3 index were vitamin C (beta=0.41), protein (beta=0.235) and iron (beta=0.229) (Table 4.5). The reason for this may be because 100 kcal models tend to assign high scores to foods with the maximum water content and minimal energy density, of which vitamin C is usually found in higher qualities. Particularly vitamin C, or ascorbic acid, a water-soluble vitamin that is naturally available in fruits and vegetables, is known to have comparatively high-water content. More so, a large number of food items from the categories of fruits and vegetables, red meat, poultry, offals & giblets contributed to the food list that was used for the analysis.

Moreover, in the Ghanaian context, like many SSA countries experiencing the double burden of malnutrition, there is the need to have a holistic model that balances the future risk of excess "empty calories" with beneficial nutrient-dense options.

4.9 Summary of key highlights from Chapter 4 (Study 1 phase 1)

In summary, the objectives of Chapter 4 were, firstly develop a context-specific nutrient profiling model for categorising foods and beverages in Ghana. Secondly to determine the optimal combination of nutrients required in the Ghanaian NRF index for classifying Ghanaian foods.

The findings from this chapter showed through regression analysis that (i.e., modelling 14 different stages) an optimal model for classifying Ghanaian food items is one with 11 beneficial and three nutrients to limit. This result corroborates validated studies that compared nutrient profiling models with independent measures of a healthy diet and produced evidence to suggest that performance optima for a nutrient profiling model was between 9-12 nutrients (Drewnowski et al., 2021). Moreover, in the Ghanaian context, there is the need to have a holistic model that balances the future risk of excess "empty calories" with beneficial nutrient-dense options.

5 CHAPTER FIVE: THE RELIABILITY, OPTIMAL CUT-OFF POINT, SENSITIVITY AND SPECIFICITY OF THE GHANAIAN NRF11.3 INDEX (STUDY 2 PHASE 2)

Chapter overview

This chapter describes the second phase of Study 2 (i.e., the development of the Ghanaian NRF11.3 using secondary data), whereby the reliability, optimal cut-off point, sensitivity and specificity of the newly developed Ghanaian NRF11.3 index are determined. The key objectives of this chapter include:

- To obtain an estimate of the reliability of the Ghanaian nutrient profiling index (i.e., internal consistency and inter-rater reliability).
- To determine the sensitivity, specificity and optimal cut-off point for the Ghanaian nutrient profiling index in order to identify the performance

First, the reliability of the Ghanaian NRF 11.3 index is tested for internal consistency by calculating the Cronbach's Alpha. Next, the nutrient profiling scores of Ghanaian food items using the newly developed Ghanaian NRF11.3 index is compared to a context-specific "reference model". Thus, Study 2 Phase 2 is conducted to establish the optimal cut-off, sensitivity and specificity of the Ghanaian NRF11.3, in order to determine the performance of the Ghanaian NRF11.3 index.

A more detailed account of the steps involved in the nutrient profiling of the same foods using the WHO African nutrient profiling model is presented. Thus, a comparison of food. scores generated from the NRF11.3 index and those generated from the WHO African nutrient profiling model, which is used as a "reference standard", as no gold standard nutrient profiling model currently exists for the Ghanaian context.

Then, optimisation of the adapted NRF11.3 index is presented, considering the Ghanaian context and available data. An optimal cut-off point for the Ghanaian NRF11.3 is determined, and the specificity and sensitivity of the model are established using Receiver Operating Characteristics (ROC) curves and Kappa statistics, prior to a discussion of the study findings with reference to relevant literature The chapter concludes with a discussion and summary of the findings.

5.1 Internal consistency – Reliability test

Internal consistency measures the level to which all elements in an instrument measure the same construct; more precisely, it shows how closely correlated the items are to one another. Cronbach's alpha was calculated to establish the internal consistency amongst the 14 components of the NRF11.3 index. Cronbach's alpha determines reliability based on an average of all possible correlations between items and values above 0.7 are considered acceptable by most researchers (Pallant, 2010; DeVellis, 2012; Streiner, 2015). The interclass correlation coefficient (ICC), which ranges from zero (no agreement) to 1 (perfect agreement), is an index of reliability commonly used to measure repeatability and reproducibility. The ICC measures the correlation, consistency or conformance of a dataset by representing the proportion of the variability in the observation that is caused by the differences between pairs (Petrie, 2005; Zaiontz, 2020).

Table 5.1: Cronbach's alpha coefficient for the NRF11.3 index

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	Number of Items
.728	**.792**	**14**

5.1.1 Results: Internal consistency of the Ghanaian NF11.3 index

The Cronbach's alpha for the 14 items in this study was 0.728 (95% CI 0.652 to 0.793) (Table 5.1 and Table 5.2). Table 5.1 above and 5.2 below shows the Cronbach's alpha coefficient and interclass correlations for the NRF11.3 index respectively.

Table 5.2: Cronbach's alpha for intraclass correlation of items in the NRF11.3 index

	Intraclass Correlation Coefficient						
	Intraclass	95% Confidence Interval		F Test with True Value 0			
	Correlation	Lower Bound	Upper Bound	Value	df1	df2	p-value
Single Measures	.160[a]	.118	.215	3.675	123	1599	<.001
Average Measures	**.728**	.652	.793	3.675	123	1599	<.001

The following section determines the optimal cut-off point, sensitivity, and specificity of the Ghanaian nutrient profiling model, i.e. the performance of the model.

5.2 Receiver Operating Characteristics (Roc) Curve and Kappa Statistics

The aim and objective of the secondary data analysis (Study 2 Phase 2) was to determine the optimal cut-off point for the Ghanaian NRF11.3 index. As a new test that generated continuous scores, there is the need to identify an optimum cut-off point to distinguish those foods and beverages that are unhealthy from those that are not. As a gold standard measure is not available for use, a "reference" measure (i.e., the WHO African nutrient profiling model) was employed to determine the optimum cut-off point of the Ghanaian NRF11.3 index and also to establish the specificity and sensitivity of the index.

5.2.1 Brief description and comparison of the "reference" model (WHO African model) and the Ghanaian NRF11.3 index

Nutrient profiling models vary in complexity and detail (Labonte, Poon et al., 2018), but broadly fall into two main categories: (i) the threshold approach, whereby thresholds of specified nutrients (targeted for restriction) are applied; and (ii) a scoring system or continuous model, which uses an algorithm to generate a score from a combination of different nutrients or food components. Each nutrient is subsequently analysed individually in relation to its threshold and any decision to restrict is based on each nutrient taken individually. If one or more of the target nutrients is found to be above the defined threshold, then that food is not permitted or deemed "unhealthy". An example of this is the WHO African nutrient profiling model (World Health Organization Regional Office for Africa, 2019). Developed in 2019 by the WHO for the African region, this model focuses on sodium, sugar, and both saturated and trans-fats because of their association with NR-NCDs such as hypertension, diabetes and cardiovascular diseases. Under this model, food is classified as permitted or not permitted for marketing depending on whether or not it meets the required nutrient threshold. Details of the model's development are extensively described elsewhere (World Health Organization Regional Office for Africa, 2019). This categorical approach has been broadly employed by food retailers and food manufacturers, amongst others, to designate a range of products as either "healthy" or "restricted".

However, the aforementioned scoring system awards points based on the content of each of the target nutrients or food components incorporated (positive or negative or both) and these are summed to obtain the total score. The decision on classifying a food using the scoring system depends on the value or cut-offs applied to the scores and therefore may vary from one model to another. As a result, a continuous model can be transformed into a categorical model by classifying foods depending on whether they score above the criteria as healthy or not.

In Chapter 2 of this thesis, the NRF9.3 index was identified as a suitable and easily adaptable starting point for the development of the Ghanaian NFR11.3 index used for classifying Ghanaian foods. Thus, section 4.2 elaborates on the developmental steps of the Ghanaian NRF11.3 index. Given the public health nutrition context in Ghana (i.e., the double burden of malnutrition), two extra beneficial nutrients (folate and zinc) to promote were used to augment the NRF9.3 index into the NRF11.3 index. Using regression analysis (see sections 4.6-4.8), results showed that a final best fit Ghanaian NRF11.3 index with 11 beneficial and 3 negative nutrients was optimal to be used for categorising food and beverages in Ghana. The Ghanaian NRF11.3 index places emphasis on nutrients to include alongside those to avoid. Therefore, shifting the idea of a "healthy food" based on only the absence of negative nutrients such as fats, sugar, and sodium to a broader definition that encompasses its content of beneficial nutrients such as fibre, calcium, iron, protein, potassium, magnesium, and vitamins A, C and E (Drewnowski et al., 2014). Thus, the index ranks nutrient-rich foods highly, whereas foods that are high in calories but lacking in beneficial nutrients receive a lower rating (Drewnowski, 2010; Drewnowski and Fulgoni, 2008).

In the Ghanaian context, an approach using fewer individual negative nutrient thresholds like the WHO African model may seem easier to adapt and apply; however, given the double burden of malnutrition in Ghana, a model that emphasises both positive and negative nutrients may be more holistic and appropriate.

This study objective therefore seeks to determine the optimum cut-off value for the new test (NRF11.3 index) as well as the specificity and sensitivity against the "reference" measure (the WHO African nutrient profiling model).

5.2.2 Procedure for determining the optimal cut-off point, sensitivity and specificity of the Ghanaian NRF11.3 index:

I. A sample of foods and beverages (henceforth foods) identified as commonly consumed from a dietary 24-hour recall were compiled.

II. The new test (i.e., Ghanaian NRF11.3 index) was used to generate food scores for each individual food.

III. The test scores are then compared against the reference test or model, which in this case was the WHO nutrient profiling model.

IV. The optimal cut-off point for the NRF 11.3 index is determined from the resulting ROC curve.

5.2.3 Compiling the foods item list

A full list containing food and beverage items (n =138) identified as consumed in Ghana was considered for profiling food using the NRF11.3 index. The food list contained 26 food groups and was obtained from a secondary data analysis of 24-hour dietary recalls conducted in Ghana (i.e., Drivers of Food Choice and TACLED projects) (Holdsworth et al., 2020) (Appendix 10).

5.3 Classification of Ghanaian food items using the NRF.11.3 index and WHO African food profiling model as a "reference standard"

In order to classify Ghanaian food items using the NRF11.3 index and the WHO African food profiling model, the following steps were followed. Firstly, the nutrient content (both macronutrients and micronutrients) for each food item was obtained from a combination of FCTs (as described above in section 4.3.3).

5.3.1 How the NRF index scores were obtained

As indicated in section 4.4 above, the Ghanaian NRF11.3 index scores were calculated by subtracting the total percentage DV of negative nutrients from the total percentage DV of positive nutrients.

Ghanaian $NRF_{11.3\ 100\ grams}$ =[(percentage DV protein + percentage DV fibre + percentage DV calcium + percentage DV iron + percentage DV potassium + percentage DV magnesium + percentage DV zinc + percentage DV folate + percentage DV vitamins A + percentage DV vitamin C+ percentage DV vitamin E) - (percentage DV total sugar + percentage DV total fat + percentage DV sodium)] /100grams.

5.3.2 Steps used in classifying food according to the WHO model

The WHO African model is designed for use by governments in identifying foods and non-alcoholic beverages that should not be sold or advertised to children. Food items that should be permitted or not permitted for marketing were classified using the following steps in the diagram below (Figure 5.1):

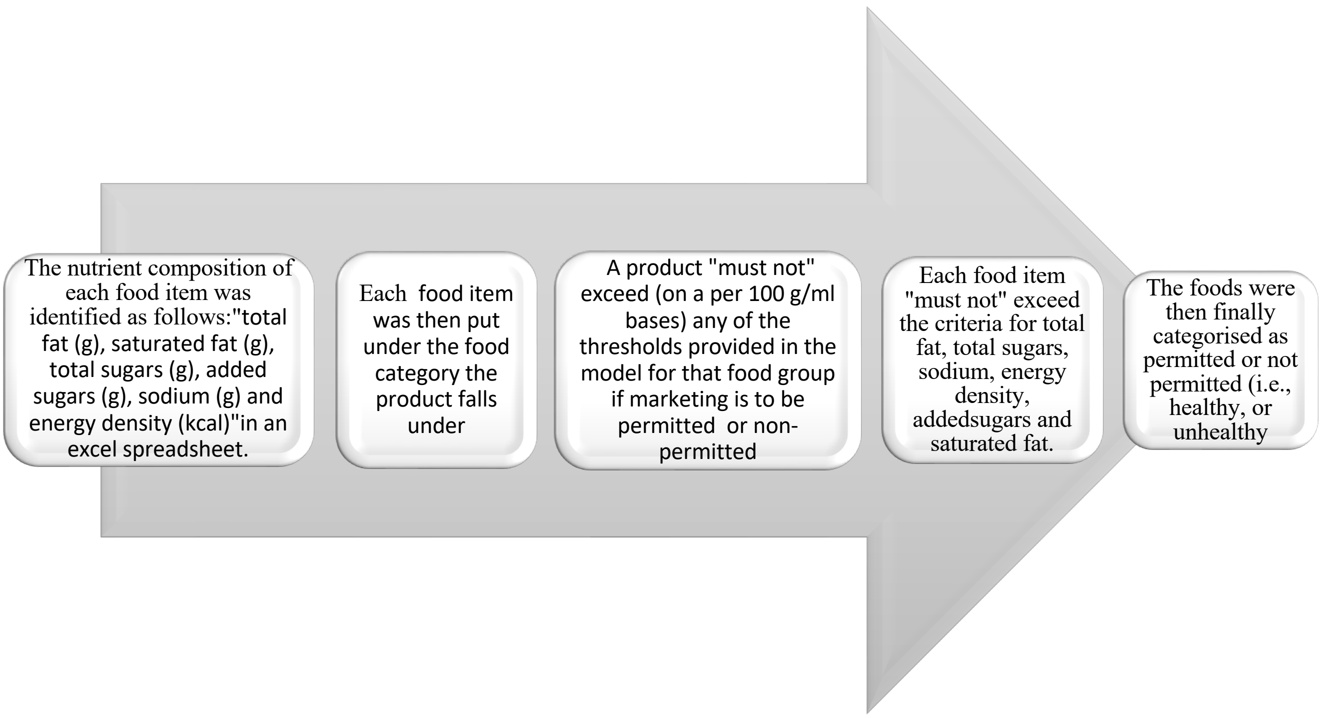

Figure 5.1: Steps used in classifying food according to the WHO African model

Out of 138 food items, seven could not be classified using the WHO model due to missing information on added sugar nutritional content, therefore 131 items were classified and used for the analysis. The details of the classification of foods using both the NRF11.3 index and the WHO model is shown in Appendix 8.

5.4 **Determination of the optimal cut-off point for NRF11.3 (ROC Curve Analysis)**

Reference test

The "gold standard" test that provides a definitive diagnosis of a phenomenon may sometimes not exist (as in this case), hence a "reference standard" provides a reasonable guide to use for the same purpose. In this analysis the WHO African model was used as the "reference standard" to determine the optimal cut-off point, sensitivity and specificity of the Ghanaian NRF11.3 index. A ROC curve was therefore constructed by using the WHO African model (Figure 5.1) for the identification of permitted and non-permitted foods in other words healthy and less healthy foods.

5.4.1 The use of a cut-off value

The NRF11.3 index is a continuous measure and to classify food as healthy or unhealthy as per the classification of the reference model, a cut-off value is required. This is a cut-off value, above or below which food is defined as either healthy or unhealthy. Various "cuts" can be created to form a binary prediction of status, however, when a different cut-off is chosen the sensitivity and specificity of the model in classifying food changes, accordingly, becoming more or less stringent.

5.4.2 The receiver operating characteristic (ROC) curve

The ROC curve allowed for a graphical analysis of the compromises between the test's specificity and sensitivity, to which several cut-offs were applied. Thus a curve was created by calculating the test's sensitivity at each potential cut-off point and plotting "sensitivity" versus "1-specificity" (Akobeng, 2007).

5.4.2.1 Procedure/description of the ROC curve

A ROC curve of "sensitivity" versus "1-specificity" for all cut-off points that would change at least one categorisation was obtained (

Figure 5.2). Conventionally, 1-specificity (proportion of false positives) is indicated on the *x-axis,* going from zero to one or (0 to 100%) (Akobeng, 2007), and sensitivity (proportion of true positives) is displayed on the *y-axis*, going from zero to one or (0 to 100%) (Akobeng, 2007; Nahm, 2022). The upper left corner of the plot denotes a perfect performance. The graph's diagonal line extends from the upper right (1,1) to the lower left hand corner (0,0) to serve as a reference line, indicating an uninformative test (Jones et al., 2005). The test performs better across the range of cut-off points when the area under the curve is greater. The closer a point comes to perfect performance, the better the test results with that single optimum cut-off point (Beck et al., 1986; Jones et al., 2005; Akobeng, 2007; Nahm, 2022).

5.4.3 Determining the optimal cut-off point

To identify the optimal cut-off value in this analysis, the first method used was the assumption that the ideal cut-off point for assessing a test's "sensitivity" and "specificity" was the one located nearest to the (0,1) point on the ROC curve (

Figure 5.2). The area under the curve (AUC) also provided very useful information about the discriminatory power of the test (Nahm, 2022). A theoretical perfect test with 100% specificity and 100% sensitivity is indicated by the AUC's maximum value of 1.0 (Akobeng, 2007).

However, other methods are also recommended; one such method is by calculating the Youden index (J) (Youden, 1950; Akobeng, 2007; Nahm, 2022). Where J denotes the greatest perpendicular distance between the ROC curve and the diagonal line (Youden, 1950; Akobeng, 2007; Nahm, 2022). J is equal to maximum [(sensitivity) +(specificity -1)] (Youden, 1950). The best cut-off points for this measure are those on the ROC curve that correspond to J, or those at which [(sensitivity) plus (specificity -1)] is maximised (Youden, 1950; Akobeng, 2007; Nahm, 2022). J is typically seen as corresponding to the point on the ROC curve that is furthest from chance (Perkins et al., 2006; Akobeng, 2007).

5.5 **Results: Determination of the optimal cut-off point of the Ghanaian NRF11.3 (ROC curve analysis)**

5.5.1 The area under the ROC curve

Figure 5.2 below shows the area under the ROC curve, which was determined as 0.807 (95% CI 0.726 to 0.888, $p<0.001$). Higher values indicate better discrimination in this area under the ROC curve, which can vary from 0.5 to 1.0 (Nahm, 2022). According to Hosmer et al. (2013), a value of 0.807 puts the discrimination of this model at "the lower borderline of excellent" discrimination (Hosmer, 2013). Thus, the better the discrimination, the farther the blue line is above the red straight line (Hosmer, 2013; Nahm, 2022). The area under the ROC curve is considered equivalent to the concordance (Gönen, 2007; Nahm, 2022). The study results showed that the Ghanaian NRF11.3 index has excellent discrimination between foods (Figure5.2).

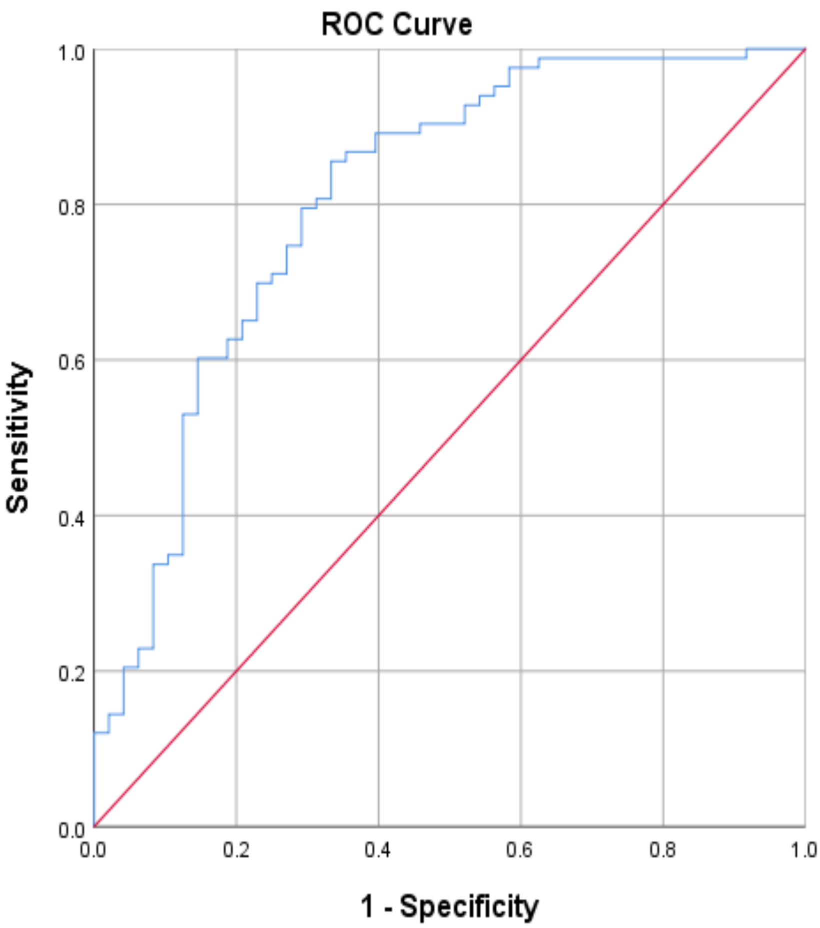

Figure 5.2: An illustration of a ROC curve comparing the Ghanaian NRF11.3 index classification to the WHO African model classification[*]

[*]The top left corner of the plot signifies perfect performance.
The red diagonal line on the graph from the lower left-hand corner (0,0) to the upper right-hand serves as a reference line.
The larger the area under the curve the better the test across the range of cut-off points.
The nearest a point gets to perfect performance, the better the test performance

Table 5.3: Sensitivity and specificity of the ROC curve for NRF11.3 cut-offs

Curve test result variable(s): NRF11.3 index	Sensitivity	1 - specificity	Specificity
15.67	0.867	0.375	0.625
15.74	0.867	0.354	0.646
15.84	0.855	0.354	0.646
16.24	0.855	0.333	0.667
16.59	0.843	0.333	0.667
17.11	0.831	0.333	0.667
18.12	0.819	0.333	0.667
18.97	0.807	0.333	0.667
20.40	0.807	0.313	0.687

Table 5.4: Selected co-ordinates of the ROC curve to calculate Kappa statistic, accuracy, misclassification and Youden index (J)

Cut-off points	Kappa	Accuracy	Misclassification rate	Youden Index (*J*)
15.67	0.508	0.779	0.221	0.532
15.74	0.527	0.786	0.214	0.547
15.84	0.513	0.779	0.221	0.528
16.24	0.531	0.786	0.214	0.543
16.59	0.517	0.779	0.221	0.525
17.11	0.502	0.771	0.229	0.507
18.12	0.488	0.763	0.237	0.490
18.97	0.474	0.756	0.244	0.474
20.40	0.493	0.763	0.237	0.491

As the area under the ROC curve (Figure 5.2) was determined to be 0.807, it meant that there is an 80% chance the model will be able to distinguish between “healthy” and “unhealthy foods”. More so, the value under the ROC curve is between 0.8 and 0.9, which could be deemed as a “good” score.

5.5.2 Optimal cut-off point of the Ghanaian NRF11.3 index

The optimum cut-off point was established by taking the maximum sum of sensitivity and specificity, where the specificity and sensitivity are closest to one (Akobeng, 2007). Thus, the cut-off for the Ghanaian NRF11.3 was identified as 16.24 (Table 5.3). This is the point above and below in which food items could be classified in binary terms, similar to the classification of the reference WHO African model. For instance, at the test optimal cut-off point of 16.24 (Table 5.3), if a food item with a predictive probability of an outcome (e.g. healthy food) is greater than or equal to 16.24, that would be classified as having the outcome (e.g. healthy food), and all food items with predicted probabilities lower than 16.24 would be classified as not having the outcome (i.e., less healthy food). However, other cut-off points as listed (see Table 5.3 and Table 5.4) could be considered; nonetheless, each cut-off changes the specificity and sensitivity of the test, but these may not give the desired optimal performance. A greater cut-off point, for instance, will increase specificity but decrease sensitivity. In other words, cases may be “harder” to classify as having an outcome of interest if the cut-off point is raised, but “easier” to classify as not having the outcome of interest. This is shown graphically in a plot of the ROC curve, which is a graph of sensitivity versus 1-specificity (Figure 5.2).

5.5.3 The sensitivity and specificity of the NRF11.3 index with respect to a reference model (i.e., the WHO African nutrient profiling model)

A total of 131 foods were included in this classification to determine the sensitivity and specificity of the NRF11.3 index (Appendix 8). They represented foods consumed in a 24-hour dietary recall in Ghana. The sample included 26 food groups, of which: fish and shellfish (10.7%); cakes and sweets (6.87%); fruits (8.40%); red meat, poultry, offal & giblets (9.16%); refined cereals (9.16%); roots and tubers (5.34%); vegetables (7%) and traditional mixed dishes (8.4%) were the major contributors of individual food items to the list.

The ability of the NRF11.3 index to predict the health value of an individual food or beverage item is illustrated through the ROC curve analysis.

From this analysis, the optimal cut-off point for the Ghanaian NRF11.3 index was identified as 16.24 NRF per 100kcals (Table 5.3 and Table 5.4). The sensitivity of the nutrient profiling model at the optimal cut-off point was 0.855 and the specificity was 0.667. The Cohen's kappa coefficient calculated at various cut-off points was seen to be highest at 0.531 ($p<0.001$) at the optimal cut-off point of 16.24 (Table 5.4). This indicated a moderate strength of agreement between the two models.

The misclassification rate (0.21) was lowest at the optimal cut-off point (Table 5.4). More so, the accuracy (0.79) and the Youden index were also at their maximum at this optimal cut-off point (Table 5.4). The AUC represents the accuracy of each nutrient profiling model and provides a measure to compare the performance of the WHO African model and the Ghanaian NRF11.3 index. The NRF11.3 index was observed to discriminate between "healthy" and "less healthy" food items as categorised by the WHO African Model (AUC: 0.807; 95% CI: 0.726-0.888; $p< 0.001$). The Ghanaian NRF11.3 index demonstrated a high sensitivity of 85.5% (Table 5.3 and Table 5.4). to identify healthy (permitted) food items at the optimal cut-off point.

Other cut-off points like 15.74 presented similar accuracy and misclassification rates; however, Cohen's kappa (k) = 0.531, $p<0.001$ was highest at 16.24 (Table 5.4).

Table 5.5: The Ghanaian NRF11.3 index at optimal cut-off (16.24) and the WHO African model crosstabulation

			WHO African model		
			0= "Less healthy" (Not permitted)	"Healthy"(permitted)	**Total**
Ghanaian NRF11.3 index cut-off (16.24)	0 = "Less healthy" (Not permitted)	Count	32	12	44
		% Within WHO	66.7%	14.5%	33.6%
	1= "Healthy" (permitted)	Count	16	71	87
		% Within WHO	33.3%	85.5%	66.4%
Total		Count	48	83	131
		% Within WHO	100.0%	100.0%	100.0%

Table 5.5 shows the number of counts and percentages from the crosstabulation table, which was similarly used to determine the sensitivity and specificity of the Ghanaian NRF11.3 index. This assessed new test's accuracy (Ghanaian NRF11.3index) against the "reference" standard model. Sensitivity reflected the percentage of "cases with the condition" that were appropriately identified, whilst specificity represented the percentage of cases "without the condition" that were appropriately categorised as such. In this Study 2 Phase 2, the test assessed the consistency of the classification by the Ghanaian NRF11.3 index against the "reference" model, the WHO African model. Out of the 83 cases identified in Table 5.5 as healthy by the WHO model (acting as the "reference" standard), 71 were also classified as healthy by the Ghanaian NRF11.3 index. This corresponded to a sensitivity value of 85.5% (71/83). On the other hand, the Ghanaian NRF11.3 correctly classified 32 out of 48, representing a specificity rate of 66.7% (Table 5.5)

Table 5.6: Kappa statistics at optimal NRF 11.3 index cut-off of 16.24 symmetric measures

		Value	p-value
Measure of agreement	Kappa	**.531**	<.0001
Number of valid cases		131	

Table 5.6 above details the Ghanaian NRF11.3 index optimal cut-off value of 16.24, which yielded a kappa statistic agreement value of 0.531 with a significance of $p<.0001$.

5.6 Discussion of findings from Study 2 Phase 2

The key objectives of Study 2, through secondary analysis of 24-hour recall dietary data, were:

- To establish an estimated value of the reliability of the Ghanaian nutrient profiling index (i.e., internal consistency).
- To determine the sensitivity, specificity and optimal cut-off point for the Ghanaian NRF11.3 index to identify its performance.

An estimate of the reliability of the Ghanaian nutrient profiling index (i.e., internal consistency and inter-rater reliability)

The reliability of the Ghanaian NRF11.3 index was estimated by calculating the Cronbach's alpha and Cohen's kappa statistic. This examined the scores between each item and the sum of all relevant measures of interest. A coefficient of inter-item correlations showed the relationship between the items within the measurement to estimate the internal consistency. It provides an overall assessment of a measure's reliability on a scale of zero to one. The

Cronbach's alpha coefficient of this study was estimated as 0.728 (95% CI 0.652-0.793), which according to Pallant (2010) is considered acceptable (Pallant, 2010). Even though the criteria for a good coefficient are subjective and dependent on theoretical underpinning of the measure, many academics recommend a minimum alpha coefficient between 0.65 to 0.8 (or more in many circumstances); alpha coefficients lower than 0.5 are typically considered undesirable (Pallant, 2010; Streiner, 2015). Higher alpha coefficients are deemed to possibly measure the same underlying concept, because it implies more items have a shared covariance (Pallant, 2010).

As explained earlier, because a new nutrient profiling model for classifying Ghanaian foods is being developed, there was a need to compare the newly developed nutrient profiling index to an existing model in the same context to establish an agreement. Thus, the reliability of the new model in relation to the reference model (i.e., the WHO African nutrient profiling model). The WHO African model used as the "reference" or "gold standard" is a categorical model focused on separating food items as "good" and "bad" or "permitted" and "not permitted" respectively. In similar studies involving two raters, used for profiling food items, it was necessary to determine the agreement between such raters (Rosentreter et al., 2013; Poon et al., 2018). Therefore, following recommended practice, the Kappa statistic was employed to determine the inter-rater agreement (Viera et al., 2005; Streiner, 2015) between the two nutrient profiling models (i.e., the WHO African nutrient profiling model and the Ghanaian NRF11.3 index). According to Viera and Garrett (2005), the Kappa statistic (k) is an optimistic estimate of the inter-rater agreement comparable to the percentage agreement. This gives the estimated proportion of the agreement above and beyond the chance of agreement (Viera et al., 2005; Streiner, 2015). Thus, Kappa statistical values can range from -1.0 to 1.0 (Viera et al., 2005). The standard interpretations of Kappa use a scale with six categories, ranging from the least chance of agreement to almost perfect agreement. The Kappa statistic (k) for the two models in this study was found to be highest at 0.531, (p<0.0001) at the optimal cut-off point of 16.24 of the Ghanaian NRF11.3 index, with reference to the WHO model; this indicates a moderate strength of agreement. Furthermore, since the p-value was p <0.001, the kappa co-efficient was statistically significant. This result corroborates earlier studies on the agreement of nutrient profiling models (Rosentreter et al., 2013; Poon et al., 2018).

The optimal cut-off, sensitivity and specificity of the Ghanaian nutrient profiling index to identify its performance.

Results from this study showed that the ideal cut-off point for the Ghanaian NRF11.3 index was identified as 16.24 NRF per 100 kcals (Table 5.3 and Table 5.4). Published studies have not established the optimal cut-off point for the NRF family of indices because the emphasis of this approach does not so much dwell on the distinction between “good” and “bad” foods. Rather, it highlights that food items fall along a continuum ranging from those that are relatively low in nutrients to those that are nutrient-dense in relation to calories.

From the ROC curve analysis, the sensitivity of the nutrient profiling model at the optimum cut-off point was 0.855 and the specificity was 0.667 (Table 5.3 and Table 5.4). The area under the curve (AUC) was also determined as 0.807 (95% CI: 0.726-0.888). The Cohen’s kappa coefficient (k) calculated at various cut-off points was seen to be highest at 0.531 (p<0.0001) at the optimum cut-off (Table 5.4). The misclassification rate (0.214) was lowest at the optimal cut-off point. Additionally, at this ideal cut-off point, the accuracy (0.786) and the Youden index were both at their highest levels (Table 5.4). The NRF11.3 index was found to accurately distinguish between “healthy” and “less healthy” food items as classified by the WHO African Model (AUC: 0.807; 95% CI: 0.726-0.888). The NRF11.3 index had a higher sensitivity (85.5%) compared to the specificity (66.7%) and therefore, correctly identified healthy (permitted) food items at the optimum cut-off.

Based on the Ghanaian NRF11.3 index, the most nutrient-dense food categories were fruits, fish, poultry, red-meat, vegetables and traditional mixed dishes. These food items have also been classified as "healthy" or "nutrient-dense" in other studies due to their favourable nutrient density composition. The findings from this study support previous research works in which similar nutrient profiles index reported comparable food groups as nutrient-rich (Drewnowski, 2010; Eyles et al., 2010; Streppel et al., 2014; Sluik et al., 2015; Hess et al., 2017).

The results show that the NRF11.3 index used to classify commonly consumed Ghanaian food items discriminates between "permitted" (i.e. nutrient-dense or healthy) foods and "not permitted" (i.e. nutrient poor or less healthy) foods and consequently, confirms its construct validity. Some discrepancies in the category of food items may be explained by the differences in the nutrient profile models' classification criteria. For example, in "agushi soup", the thresholds for total fat and saturated fat in the WHO criteria were exceeded, hence it was classified by the WHO model as "not permitted" or "unhealthy"; on the other hand, the Ghanaian NRF11.3 gave it a reasonable score above the cut-off point, which meant that it was "permitted" or "healthy". The WHO African model thus lays emphasis on the negative nutrients in the foods, while the NRF11.3 index considers all aspects of the food linked with risk factors for the development chronic illness (i.e., total fat, sodium and total sugars) alongside the positive attributes of the food such as protein, fibre, minerals and vitamins.

5.7 **Summary of key highlights from Chapter 5**

Study 2 Phase 2- Summary

In summary, the objectives of Chapter 5 were to establish an estimate of the reliability of the newly developed Ghanaian NRF11.3 index and to determine its sensitivity, specificity and optimal cut-off point in order to determine its performance.

Firstly, the reliability of the Ghanaian NRF11.3 was estimated by calculating the Cronbach's alpha and Cohen's kappa statistics. The estimated Cronbach's alpha coefficient for this study was 0.728 (95%, CI: 0.652-0.793), which according to Pallant (2010) is considered acceptable (Pallant, 2010). Kappa statistic (k) for the two models in this study was discovered to be at its highest value at 0.531 ($p<0.001$). Thus, moderate strength of agreement between the two models was established. The kappa coefficient was also statistically significant ($p<0.001$). This outcome confirms the findings of previous research on the agreement of nutrient profiling models (Eyles et al., 2010; Rosentreter et al., 2013; Poon et al., 2018).

Secondly, from the ROC curve analysis, the optimal cut-off point was 16.24. Lastly, from the ROC curve analysis the sensitivity of the nutrient profiling model at the optimal cut-off point was 0.855 and the specificity was 0.667. The area under the curve was also determined as 0.807 (95% CI: 0.726-0.888), which means the test has excellent discrimination and good accuracy. The Ghanaian NRF11.3 was identified to have a high sensitivity of 85.5%, i.e., the ability to identify "healthy" (permitted) food items at the optimal cut-off point.

6 CHAPTER SIX: PRIMARY QUANTITATIVE SURVEY (STUDY THREE)

Chapter overview

The third study of this PhD research is described in this chapter. The study aimed to assess how expert nutrition professionals in Ghana classify the healthiness/unhealthiness of commonly consumed Ghanaian foods as compared to the Ghanaian NRF11.3 index. The chapter starts with the methodological underpinning of the research. This is then followed by a description of the design and methods employed in this study, including the steps undertaken.

Since the food list used in this study was the same as that used in study two (described in Chapters 4 and 5), elaborations are not provided in this chapter. This will be followed by the data analysis methods and, thereafter, the results will be presented. A discussion of the key findings of the study concludes the chapter.

6.1 Survey of expert nutrition professionals

As the analysis conducted in Chapters 4 and 5 of this PhD added to the internal validation and reliability of the model, it is therefore essential to further test for the external validity of the Ghanaian NRF11.3 index to determine whether Ghanaian nutrition experts classify foods in the same way as was done with the Ghanaian NRF11.3 index. Accordingly, this chapter then describes how an online survey of Ghanaian nutrition professionals/experts in Ghana was undertaken to create a standard ranking of the healthiness of 138 foods commonly consumed in Ghana to compare the ranking of the same foods by the nutrient profiling model.

6.2 Brief theoretical underpinning of the study

The "Guiding Principles and Framework Manual" for the development or adaptation of nutrient profiling models recommends the comparison of scores generated by a nutrient profiling model with the ranking of the same food items by nutrition experts as an approach to testing the validity of the model (World Health Organization, 2011b). The approach deployed in the development of the Ghanaian NRF11.3 index pays heed to this recommendation It draws on similar methods (i.e., self-completed structured questionnaires) used in previous studies (Scarborough, 2007b; Wentzel-Viljoen et al., 2013). It also aligns with simple, less data-intensive approaches for testing nutrient profiling models, as recommended in the World Health Organization's "Guiding Principles and Framework Manual" (World Health Organization, 2011b)

6.3 Ethical considerations, settings, sampling and recruitment of participants

6.3.1 Ethical considerations

The ethical considerations and information governance for this study have been described and detailed in Chapter 3 of this thesis and all relevant documents are attached in Appendix 2-5. These documents included participants' informed consent, consent form and full food list. The study information sheet and informed consent ensured that participants understood the purpose of the research and voluntarily agreed to participate.

6.3.2 Study tool and setting

This study used an online survey design to address the research objectives. An online questionnaire (Appendix 5) was used to assess Ghanaian nutrition experts' perceptions of the relative healthiness of commonly consumed Ghanaian food and beverages. The study settings and country/location are not discussed here because they have previously been covered in detail in section 4.1.1., which described the same study location.

6.3.3 Sampling and recruitment of participants

All registered members of the Ghana Academy of Nutrition and Dietetics (GAND) were invited to participate in this study. GAND is a registered scientific professional body; a learned group formed by dietitians and nutritionists working as health professionals in Ghana with a common interest in the nutrition agenda in Ghana. All registered members of GAND (approximately 230) were invited to take part. The researcher contacted the president (gatekeeper) of the association to explain the purpose of the study. Emails containing a link to the survey and information sheets were then sent out to the president and secretary of GAND to invite all members to participate in the survey. The email contained the researcher's contact details so that potential participants could get in touch if they had any further questions. The survey was managed online using the University of Sheffield's recommend platform - the Qualtrics system. The next section provides a full overview of the data collection approach and strategies employed in this study.

6.4 **Data collection strategies and approach**

6.4.1 Material preparation for the online questionnaire

Prior to beginning the data collection, a number of documents were prepared and ethical approval obtained (sections 3.6 and 3.6.2). The online questionnaire was then created using the Qualtrics system and it covered five main parts: the participant information sheet, informed consent, three questions on background experience in nutrition, how to classify n=138 food items and finally entry into a voluntary draw to win a nutrition textbook.

6.4.2 Pilot testing of study tools and procedures

The online questionnaire was piloted in two phases: first by all four project supervisors (AL, MH, VH and DG) and then secondly by two external participants. The project supervisory team gave constructive feedback about the general appearance and design of the questionnaire and more so about the sequence of questioning. For instance, with regard to appearance, feedback on the ability to correctly display the questionnaire on both the mobile phone and the PC was essential to getting participants on board to complete the questionnaire. Also, feedback about the content and wording of the Likert scale was helpful as this presented the opportunity of exploring the literature for commonly used terms for Likert scales.

Following this, the online survey questionnaire was again piloted in October 2020 before final data collection began. Two participants (Ghanaian nutritionists' resident in the UK) were requested to help with piloting the online questionnaire. Both participants were expert nutrition professionals with background knowledge of the Ghanaian food items listed for classification. Following this pilot, further improvements were made to the online questionnaire on the Qualtrics system. From this second pilot, amendments were made with regard to the settings to questions that required a response before proceeding to subsequent questions, especially the last part that included a survey.

6.4.3 Compiling the foods and beverages list

A full and comprehensive list containing all foods and beverages identified as commonly consumed in Ghana was comprehensively compiled. As described earlier in Chapter 4, the food item list contained n=138 foods and was obtained from a database of 24-hour dietary recalls conducted in Ghana (Holdsworth et al., 2020). This method of using a food list for testing the extent to which nutrient profile models agree with an external criterion (i.e., classification by expert nutritionists) corroborates work done in previous studies (Azaïs-Braesco et al., 2006; Scarborough, 2007a). For example, Scarborough et al. (2007) compiled and used a master list of 120 food items for the UK nutrient profiling model. In this study, the individual foods were arranged alphabetically and divided into four batches/groups consisting of three groups of n=34 food items and one group of n=36 food items, to make online classification feasible or less overwhelming.

6.5 **Data collection**

All participants were registered members of GAND, meaning that members were considered as nutrition experts in Ghana and thus a benchmark for convergent validity assessment. The questionnaire was administered through the gatekeeper of GAND by sending an email containing the link to the questionnaire to all the members of GAND (November 2020). This link was also shared on GAND's common WhatsApp platform and via email. Each nutrition professional was first asked to complete an informed consent form before proceeding with the questionnaire. Respondents were then requested to answer questions about their background/experience in nutrition, their age group and gender. After this, they were asked to consider the 138 food items from the questionnaire and decide where these foods lie on a five-point scale of relative healthiness, from "very unhealthy" (1) to "very healthy" (5). The respondents were also asked to rate the foods according to their experience and knowledge of the foods' contribution to a healthy, balanced diet. No specific definition of "very unhealthy" or "very healthy" was given and classification was based on their own professional judgements. The questionnaire was estimated to take 25 minutes or longer to complete in one sitting, however, participants could close their browsers and return to complete it at their convenience. After completion of the questionnaire, members were given the option of entry into a voluntary draw to win a nutrition textbook.

6.6 **Data cleaning and management of online survey**

The online data were downloaded (February 2021) from the Qualtrics system directly to SPSS software for data management and analysis. Data management involved creating a codebook that included all variable names, labels and attributes. To improve the quality of data, cleaning was done to check for any errors that might have resulted from the process of transferring data from Qualtrics to SPSS. Missing data that resulted from the non-response pattern were all checked by running descriptive statistics, including frequency tables for each variable.

6.7 **Data quality for Study 3**

For any study to be credibility, evaluating procedures for the study must be present. Quality assessment criteria for a well-designed and carefully executed survey tend to focus on the importance of transparency, objectivity, validity, reliability and coverage/generalisability (Payne, 2004; Bryman, 2016).

Transparency in all phases of the research is vital for assessing the quality of the study. This means deciding on the process for acquiring the sample set and its size, choosing a particular research instrument for implementing the survey, and including special measurement procedures and scales for the phenomena using a generally applied method (Pecakova, 2011). For this study, detailed information about how the survey was designed and implemented has been carefully explained and detailed as subsections. For instance, to improve the quality of this study, a lot of time was spent designing a clear, brief, well-written questionnaire that focused on the survey objectives. This was done by assessing the clarity of the questionnaire and uncovering key missing aspects through a pilot survey. Feedback from the pilot was taken on board and implemented to optimise aspects such as the display of the questionnaire in Qualtrics. Hence, the Qualtrics software settings through which the questionnaire was delivered were adjusted for all device types, such as mobile, tablet and PC, to improve accessibility.
In this study, a set of protocols as approved by the ethics committee were all systematically adhered to (Payne, 2004).

The Likert scaling approach to data collection is a reliable method established for opinion or perception assessment of a construct made up of multiple dimensions (Salkind, 2010). The Likert scale gives an outcome depending on a two-part evaluation of a number of items (Salkind, 2010). One dimension is the “stem” which is a statement of an opinion or viewpoint that the respondent is expected to answer (for instance very unhealthy – very healthy). The other part is the response scale (1 to 5) (Salkind, 2010). There are various debates about using Likert scales related to: the reading level of respondents, employing either an even or odd number of responses, labelling of an intermediate response, dealing with missing data and acquiescence bias. Each of these has the potential to influence the reliability of the score (Salkind, 2010; Bryman, 2016). In this study, reading level was not a problem as the respondents were all literate and professionals. Typically, a reading level of at least 11 years and older is often considered minimal for such self-administered surveys (Salkind, 2010). The Likert scale used in this study was a five-point ordinal scale with the middle category carefully defined to have a neutral response. The direction of response categories was chosen to be from negative responses set to the scale's left side, shifting to the right and turning more positive (1 = very unhealthy to 5 = very healthy). Although, there seems not to be unanimity on which is accurate and better to use, the negative left to positive right scale is frequently chosen or preferred (Salkind, 2010). Efforts were targeted at reducing or eliminating missing data by reminding participants about uncompleted questions as they moved through the questions. Acquiescence bias is the inclination of the respondent to give answers that are deemed positive to all or almost all the items on a questionnaire (Salkind, 2010). Though it may be difficult to distinguish acquiescence bias from reasoned opinions, in this survey, food items were randomly listed to prompt reasoning. More so, a clear description of the instructions for classifying food was repeated on each page to enhance the quality of responses.

Another important issue considered was coverage, that is the degree to which all the components in the survey-defined "target population" were included in the sample frame (Kölln et al., 2019). This study gave participants an opportunity to be a part of the target group that the study was intended to represent. Sampling theory explains that bias in a survey can happen when parts of the target group is left out of the primary sampling frame, especially when those excluded vary significantly from the individuals who were selected (Kadilar et al., 2012; Kölln et al., 2019). For this study, coverage was ensured by contacting the gatekeeper of the target association who in turn sent the link to the survey directly to the target population for the study. A reminder was sent after 2 weeks to ensure participants had received the link.

While it may be arguable, there is evidence to support the claim that direct or indirect incentives can both boost response rate and enhance quality of the data (Singer, 2013). A voluntary draw to win a nutrition textbook was incorporated into the survey to serve as an incentive to increase the number of responses.

6.8 Data Analysis

In order to compare the ranking of a food item by the Ghanaian NRF11.3 index with that of expert classification, the steps below were followed:

First, each food item was ranked according to the nutrient profiling model's algorithm and the food composition data (the same as in section 4.4). In this study, the same 24-hour recall food list that were analysed for the optimal model was used in this investigation. Out of a total of 138 food and beverage items, 137 were profiled. Only one item (wele) was excluded from the food profiles because no nutritional information was found for it in any of the food composition tables (FCTs). Nutrition information for each food item (n=137) was scored using the combined synthesis of FCTs to generate Ghanaian NRF11.3 scores. All the Ghanaian NRF11.3 indices were expressed as per 100 kcals for each food. The food items were ranked with negative scores illustrating the less healthy foods and positive scores for the healthiest. Thus, a score was given to each food item based on the Ghanaian NRF11.3 index. The food list and accompanying nutrient-rich scores were imported into SPSS as continuous variables. Because the objective was to compare scores with those of experts' classification on a five-point Likert scale, these scores were transformed, thus creating a new variable. This was undertaken by partitioning the continuous scores into five groups (quintiles) arranged from negative scores through to positive, according to the Ghanaian NRF11.3 index score using the percentiles function (i.e., 20, 40, 60, 80 and 100) in SPSS version 25 (SPSS Statistics, IBM, New York). Each corresponding percentile score was used as the upper and lower range for the partitioning process. As a result, a new variable for Ghanaian NRF11.3 scores was created for all food from the lowest scores represented as 1 – "very unhealthy" to the highest scores as 5 – "very healthy".

At the second stage, responses from the participant in the online Qualtrics system were downloaded into SPSS. All foods (n=138) were labelled as per the rank given by the experts on the five-point scale (from 1 – "very unhealthy" to 5 – "very healthy"). The final score attributed to each food item was calculated as the median value of the five-point scale score across all participants. As the main purpose was to test the degree of agreement between the judgements of Ghanaian nutritionists and the Ghanaian NRF11.3 index, statistical tests were conducted as the last step to establish if there was a correlation.

For comparisons of the Ghanaian NRF11.3 scores and median ranks by Ghanaian nutrition experts, Spearman correlation coefficient values were calculated. This statistical approach was used in previous studies (Azaïs-Braesco et al., 2006; Scarborough, 2007a) to determine the correction between expert rankings and nutrient profile model scores. Thus, it was deemed fit to use in the present study. The set-up (i.e. comparing two ordinal variables) lends itself naturally to Spearman correlation (non-parametric) (Azaïs-Braesco et al., 2006).

A perfect positive association of ranks is shown by a correlation value of +1, whereas a perfect negative association is indicated by a correlation of -1, whereas a correlation of 0 denotes no associations at all (Spearman, 1904; Cohen, 1988; Pallant, 2010; Spearman, 2010). While no specific guidelines are outlined for determining the strength of the associations for different values (Peat, 2002), there is consensus on interpretations, according to which the relationship between ranks is stronger when the correlation coefficient is closer to +1 or -1 than when it is closer to zero (Altman, 1991; Peat J., 2002). The guidelines as recommended by Cohen (1988) suggest the following cut-offs: "small (r=0.10 to 0.29), medium (r=0.30 to 0.49) and large (r=0.50 to 1.0) associations" (Cohen, 1988; Pallant, 2010).

In previous studies (Azaïs-Braesco et al., 2006; Scarborough, 2007a) comparison of such standard rankings provides one way of validating nutrient profiling models. Whilst other studies referred to this kind of comparison as a measure for testing criterion-related validity (Scarborough et al., 2007a), others referred to it as convergent validity (Arambepola et al., 2008) as in this study. The term convergent validity was preferred for use in this study because it was deemed appropriate.

The key findings of the study are presented in the next section. Firstly, a description of the characteristics of the study participants from the online survey is given. This is followed by the list of food items and the various classifications by both experts and the nutrient profiling model.

6.9 **Results**

6.9.1 Characteristics of study participants

Descriptive statistics were performed and results summarised in Table 6.1 (i.e., frequencies, percentages, range, mean, standard deviation and variance). A total of 129 responses were received. Out of these 129 responses, 96 participants presented complete responses to all questions, representing 74.4% of completed questionnaires. The majority of the participants were male, n=77, representing 63.1% of the participants. The most frequent age group in terms of those who answered the questionnaire was between 31-40 years, representing 68.9%, and 77.9% of participants indicated that they were nutritionists (Table 6.1). About 44.3% of the participants indicated they had 5-10 years of work experience, 34.4% had less than five years of work experience, whilst 21.3% had more than 10 years work experience.

Table 6.1: Characteristics of online survey participants[‡]

Characteristics of participants		Frequency	Percent	Valid Percent	Cumulative Percent	Mean	Standard Deviation	Variance
Profession	Dietitian	4	3.1	3.3	3.3			
	Nutritionist	95	73.6	77.9	81.1			
	Dietitian and Nutritionist	14	10.9	11.5	92.6			
	Other (please specify)	9	7	7.4	100			
	Total	122	94.6	100		2.23	0.627	0.393
Employment Category	Academic	21	16.3	17.5	17.5			
	Hospital	34	26.4	28.3	45.8			
	Community	33	25.6	27.5	73.3			
	Private consultancy	8	6.2	6.7	80			
	other (specify)	24	18.6	20	100			
	Total	120	93	100		2.83	1.356	1.838
Work Experience	< 5	42	32.6	34.4	34.4			
	5 to 10	54	41.9	44.3	78.7			
	>10	26	20.2	21.3	100			
	Total	122	94.6	100		1.87	0.738	0.545
Gender	Male	77	59.7	63.1	63.1			
	Female	44	34.1	36.1	99.2			
	Prefer not to say	1	0.8	0.8	100			
	Total	122	94.6	100		1.38	0.503	0.253
Age, years	<20	1	0.8	0.8	0.8			
	21-30	32	24.8	26.2	27			
	31-40	84	65.1	68.9	95.9			
	41-50	4	3.1	3.3	99.2			
	>50	1	0.8	0.8	100			
	Total	122	94.6	100		2.77	0.557	0.311

[‡] Profession; Employment category; Gender and Age – number missing =7
Work experience – number missing =9

6.9.2 Results and interpretations

As highlighted in Figure 6.1, the median is considered the most reliable and informative measure of central tendency that describes a set of data. The mean, median and mode are all reliable indicators of central tendency, but only in different circumstances. In this study, the median – "middle value" – was used because the data presented a skewed distribution and, more so, the variable was ordinal which satisfied the guidance/assumption for use of the present test. In this case, the median serves as the best indicator of the central location of the data, unlike mean or mode, as the impact of extreme values or outliers is not as strong for median. The difference between the median and the mean increases with the skewness of the distribution. For example, the ranking for Tuo zaafi (T.Z.) presented a mean score of 4.34, which falls in the category of "slightly healthy" as opposed to a median of 5, in the category of "very healthy". However, with regard to some food items, the median and the mean were not appreciably different.

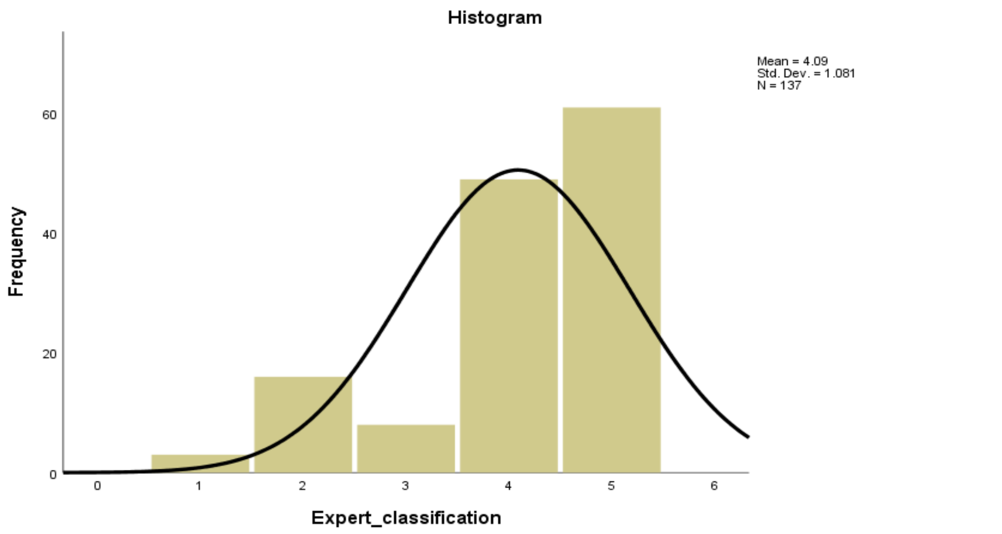

Figure 6.1: Illustration of the left skewed data of expert classification (from 1= "very unhealthy" to 5= "very healthy")

Table 6.2 below gives a breakdown of the frequencies of median ranking by the nutrition experts. The majority of the median scores of food items were classified by the experts as “very healthy” (n=61; 44.2%) and “slightly healthy” (n=49; 35.5%), whilst only small proportions were classified as “very unhealthy” or “slightly unhealthy”, representing (n=3; 2.2%) and (n=16; 11.6%) respectively.

Table 6.2: Frequencies of median classification of food items by Ghanaian nutrition experts

Median ranking per Ghanaian Nutrition Experts	Frequency	Percent
Very unhealthy	3	2.2
Slightly unhealthy	16	11.6
Neither healthy/unhealthy	9	6.5
Slightly healthy	49	35.5
Very healthy	61	44.2
Total	138	100.0

To compare the Ghanaian NRF11.3 index scores to those of expert classification, quintiles were created. Table 6.3 presents those percentiles and cut-offs that were used to categorise the model scores. For instance, the smallest quintile (i.e., 20th percentile) was all scores from the lowest score through to 6.54, and the highest quintile (i.e., 100th percentile) was from 75.09 through to the highest.

Table 6.3: Percentiles used for partitioning the Ghanaian NRF11.3 scores into quintiles for 137 food items

Percentiles	Value
20	6.54
40	22.21
60	43.89
80	75.09
100	351.70

Table 6.4 show the ranking of food items by both the Ghanaian NRF11.3 index and the Ghanaian experts. Largely the classifications were in agreement, however, there were some discrepancies observed with regard to some foods like anchovies, koose, banana, gaari and boiled corn meal.

Table 6.4: Classification of food items by Ghanaian NRF11.3 Index and Ghanaian Experts

Food items	NRF11.3 scores	Ranks NRF11.3 Partitioned into quintiles	Ranks Expert Classification
Abeduro, turkey berries	159.39	5	5
Aboloo	27	3	4
Ademe, jute leaves	271.76	5	5
Adziado	56.95	4	5
Agushi soup	40.91	3	5
Akple	15.28	2	4
Aluguntugui, sweetsop	110.35	5	5
Amma, spinach broth	69.79	4	4
Anchovies	4.24	1	5
Avocado, pulp, raw	44.03	4	5
Baked beans	81.08	5	4
Banana, raw	32.63	3	5
Banku	46.32	4	4
Bean cake, koose	13.06	2	5
Bean stew	92.21	5	5
Beef, meat, boiled	65.19	4	5
Biscuits, sweet	2.4	1	2
Blolovi	48.44	4	5
Bofrot	-3.25	1	3
Boiled corn meal	-35.84	1	4
Burkina drink	11.88	2	4
Cabbage stew	139.05	5	5
Candy and toffee	-14.92	1	1
Carrots, raw	176.95	5	5
Cassava, boiled	43.9	4	4
Chicken, boiled	15.72	2	4
Chicken, grilled	19.29	2	4
Chinese and White Cabbage	339.55	5	4
Chips, snack	36.49	3	2
Chocolate	-2.41	1	4
Cocoa milk drink	14.87	2	4
Coconut, mature, raw	8.19	2	5

Cookies	-3.33	1	2
Corned beef	15.92	2	2
Crab	102.05	5	5
Doughnuts	-2.43	1	3
Duck	4.34	1	4
Egg stew	27.16	3	5
Egg, chicken, boiled	35.39	3	5
Evaporated milk	25.05	3	4
Fish pie	44.43	4	4
Flavoured yoghurt	39.65	3	4
Fried chicken	0.52	1	3
Fried egg	21.5	2	4
Fried sausage	-12.86	1	2
Fruit juice, unsweetened	148.57	5	5
Fufu	47.01	4	4
Gaari	17.59	2	4
Garden egg stew	36.19	3	5
Goat, meat, boiled	43.85	3	5
Green leaf, relish with oil	143.81	5	5
Grilled beef	68.53	4	4
Grounded pepper, raw	199.79	5	4
Groundnut soup	57.38	4	5
Groundnuts	32.5	3	5
Guinea fowl, boiled	65.77	4	5
Hausa koko	16.55	2	4
Hot cereal, maize	2.14	1	5
Ice-cream	-5.81	1	2
Indomie	25.36	3	2
Jollof rice	15.34	2	4
Kenkey	53.33	4	4
Konkonte	26.01	3	4
Kontomire soup	287.38	5	5
Kontomire stew	56.29	4	5
Koobi	25.35	3	2
Kpanla	49.27	4	5
Lentil-pea and bean, stew	38.1	3	5
Lettuce	299.82	5	5
Light and diet drinks	-26.4	1	4
Light soup	91.99	5	5
Liver and giblets	208.26	5	5
Local brown rice, boiled	27.47	3	5
Macaroni	23.9	3	3
Maize, roasted/boiled	34.85	3	5
Mango, raw	156.36	5	5
Margarine, regular	-14.52	1	2
Mashed kenkey	11.91	2	4

Meat pie	15.61	2	4
Melon seeds	40.92	3	5
Milk	37.1	3	4
Millet porridge	-2.22	1	5
Moringa stew	351.7	5	5
Mudfish, grilled	50.81	4	5
Oats, porridge	22.13	2	5
Octopus fried	16.63	2	4
Offal, beef tripe, boiled	50.54	4	4
Okro soup	61.67	4	5
Okro stew	51.3	4	5
Onions and Garlic	161.39	5	5
Orange, raw	145.02	5	5
Palm nut soup	96.01	5	5
Palm oil, red	8.83	2	4
Pasta, boiled	22.53	3	3
Pastry	6.8	2	2
Pear, raw	29.4	3	5
Peppers	301.72	5	4
Pineapple, raw	114.55	5	5
Plantain, dried, chips	13.91	2	4
Plantain, Eto	12.14	2	5
Plantain, ripe, boiled	40.52	3	5
Plantain, ripe, fried	26.88	3	4
Pork, approx.20% fat	5.59	1	3
Powdered milk	40.76	3	4
Red, red	48.91	4	5
Rice porridge	-3.81	1	4
Salmon fried	4.89	1	4
Sardine in oil, canned	46.21	4	3
Scrambled egg	10.05	2	4
Shito	21.93	2	4
Smoked fish	52.5	4	4
Sobolo	338.59	5	4
Sodas, sweetened sodas	-27.9	1	1
Sugar, white	-6.79	1	1
Sweet pie or tart	-4.76	1	2
Sweet potato yellow	43.47	3	5
Sweetened coffee	-29.94	1	2
Sweetened condensed milk	1.63	1	2
Sweetened tea	-29.79	1	2
Tilapia, fried	114.5	5	4
Tilapia, non- fried	130.7	5	5
Tomato sauce and stew	14.21	2	4
Tomatoes, red, ripe, raw	217.12	5	5

Tombrown	23.85	3	5
Tuna, fried	46.22	4	4
Tuna, non-fried	71.09	4	5
Tuo Zaafi (T.Z)	15.75	2	5
Turkey (fried)	49.94	4	4
Unsweetened tea	-23.93	1	4
Vegetable soup	6.14	1	5
Waakye	47.01	4	5
Watermelon	56.15	4	5
White, sugar bread	12.17	2	2
White crisp bread	13.76	2	2
White rice, boiled	11.8	2	3
Yam, boiled	56.25	4	5
Yam, fried	18.65	2	4

A Spearman's rank correlation coefficient was calculated to assess the relationship between the ranking of 137 food items by Ghanaian nutrition experts and the Ghanaian NRF11.3 index. There was a statistically significant, strong positive correlation between the ranking of experts and the Ghanaian NRF11.3 index, the Spearman correlation coefficient, R_s = 0.549, p <.001. This measured the strength and direction of the association between the two variables and means.

However, when the Ghanaian NRF11.3 scores were not partitioned into quintiles, as in previous studies, the Spearman's correlation coefficient was found to be slightly higher (R_s = 0.580, p<0.001) than when the Ghanaian NRF11.3 score were in quintiles (R_s=0.549, p<.001). In both cases, there was a strong positive correlation between the ranking by the nutrient profiling model and the experts' classification

6.10 Discussion: Experts classification of Ghanaian foods as compared to the Ghanaian NRF11.3 index

The aim of this study was to compare expert nutrition professionals' ranking of commonly consumed Ghanaian food items with the healthiness of the same foods as ranked by the Ghanaian NRF11.3 index. Comparison of such measures provides one way of validating nutrient profiling models.

To establish comparisons of the Ghanaian NRF11.3 index scores and median ranks of food by Ghanaian nutrition experts, Spearman correlation coefficient values were calculated. This statistical approach was used in previous studies (Azaïs-Braesco et al., 2006; Scarborough, 2007a) to determine the correlation between expert rankings and nutrient profile model scores. Thus, it was deemed fit to be used in the present study. The set-up (i.e. comparing two ordinal variables) lends itself naturally to Spearman correlation (non-parametric test) (Azaïs-Braesco et al., 2006). The finding from the study by Azai-Braesco et al. (2006) showed that using four different across-the-board nutrient profiling models to compare with expert classification, the spearman correlations revealed correlation coefficients that were within the same range of 0.65, whether they were calculated on ranks or in quintiles using the same list of 125 food items. These findings by Azai-Braesco et al. (2006) corroborated the results of this current study, which also showed that there was a statistically significant and positive correlation between the ranking of the experts and the Ghanaian NRF 11.3 index ($Rs = 0.549$, $p < 0.001$). This congruence in ranking denotes convergent validity

Performance of each classification approach

The Ghanaian NRF11.3 index tested here achieved good agreement with the rankings derived from the online survey, with a Spearman correlation coefficient of $R_s = 0.549$, $p < .0001$.

Each ranking system (i.e., Ghanaian NRF11.3 and the expert classification) ranked fruits and vegetables highly, followed by fish, soup, meat and traditional mixed dishes. Particularly for the Ghanaian NRF11.3 index, the inclusion of zinc and folate amongst the beneficial nutrients may have contributed to the meat group also gaining higher scores, alongside the fruit and vegetables group. Cakes and sweet snacks, refined cereals, visible fat and caloric beverages tended to receive the lowest scores because they were energy-dense and had lower nutrient density. However, dairy products had scores in the mid-range classification.

Even though there was a general pattern for some food categories, it was more challenging to characterise the classification of food groups distributed throughout several quintiles. The Ghanaian NRF11.3 provided a classification to which most fruit and vegetables were in the fifth quintile, and fish/shellfish, lean meat and traditional mixed dishes were in the fourth quintile. Whereas cakes and sweets, sugar-sweetened beverages, sweetened tea and coffee were in the first quintile and the second quintile contained refined cereals, red meat, root/tubers – fried, savoury pie and some traditional mixed dishes. Dairy products, fatty seeds/nuts, such as agushi and groundnuts, eggs, roots/tubers – not fried, were grouped as intermediary foods in the third quintile, probably because total fats and total sugars were considered instead of saturated fats and added sugars in the system's calculation. However, it remained puzzling to see some fruits (i.e., pear and banana) in the intermediate quintile, whereas fruit juices (unsweetened) were classified by both experts and the Ghanaian NRF11.3 index in the fifth quintile. In addition, probably because of the combination of FCT tables used, minor differences in food composition may affect scores. On the other hand, it may also be due to the misconceptions experts have in relation to the healthiness of some foods.

The experts' classifications were largely distributed in the fifth quintile (i.e., very healthy) and least in the first quintile (i.e., very unhealthy). Vegetables, vegetable soups, fruits, pulses and starchy foods were distributed across the fifth quintile, while milk and milk products, fish, meat and eggs were in the fourth quintile. The third quintile contained foods including starchy grains, fried foods and fatty meat. Surprisingly, only three food items that were sugary products were classified in the first quintile (i.e., sweetened sodas, white sugar and candy and toffee) by Ghanaian experts

Some minor inconsistencies remain, however, in the classification of food by both the experts and models in quintiles, such as the classification of oat porridge in the second quintile by the model and in the fifth quintile by the experts. On the other hand, the classification of bananas is in the intermediate group of the third quintile by the NRF11.3 index, whereas they are classified by the experts in the fifth quintile.

Although there were some minor differences, these classifications largely corroborate with the categorisation of food in the literature as there was a remarkable consistency in the groupings of foods in the "very unhealthy" category (Drewnowski, 2005).

6.11 **Summary of chapter**

In summary, Study 3 aimed to determine the convergent validity of the NRF11.3 index by assessing how expert nutrition professionals in Ghana classified commonly consumed Ghanaian foods as compared to the Ghanaian NRF11.3 index. The findings showed that there was a statistically significant and strong positive correlation between the ranking of experts and the NRF11.3 index with a Spearman correlation coefficient, $R_s = 0.549$, $p < 0.001$. This measured the strength and direction of the association between the two measures. These findings corroborate results from previous studies that compared nutrient profiling models classifications to experts' opinions (Azaïs-Braesco et al., 2006; Scarborough, 2007a)

The next chapter discusses all the studies conducted in this PhD thesis.

7 CHAPTER SEVEN: DISCUSSION AND CONCLUSION

7.0 Introduction

The overall aim of this PhD research was to develop and test the validity of a nutrient profiling model for categorising the healthiness of commonly consumed Ghanaian foods. A systematized review was first carried out to identify the terms used to define food as healthy or unhealthy and to critically appraise the validity and public health applications of these methods. This was followed by secondary data analysis to develop a context-specific nutrient profiling model for Ghana (the Ghanaian NRF11.3 index). The process took into account the optimal number of nutrients, optimal cut-off point, sensitivity, specificity, and reliability. The third study was a cross-sectional study conducted to examine the convergent validity of the Ghanaian NRF11.3 index.

The preceding chapters (Chapters 2-6) contained the various methodological approaches, results and in-depth discussion of the findings of each study. This current chapter consolidates and triangulates these discussions to facilitate simultaneous interpretation of the findings from all three studies. The chapter starts by summarising the study rationale that explains why the study was needed, followed by a summary of the aims and objectives, the research methods used and a summary of the findings from the three different studies. The contributions of this thesis to existing knowledge on the development and validation of nutrient profiling models in the Ghanaian context is also presented. The chapter finally presents the strengths and limitations of the study and the implications of the research findings for policy, further research and practice.

7.1 Summary of why the study was needed

The rising prevalence of obesity and NR-NCDs, accompanied by persistent micronutrient deficiencies in Ghana, needs urgent attention (Ministry of Health Ghana, 2012; Bosu, 2015; Agyemang et al., 2016; Ofori-Asenso et al., 2016; Osei-Kwasi et al., 2020). A key driver of obesity and NR-NCDs is the increased consumption of unhealthy foods that may be high in sugar, salt and fat, with decreased consumption of fruits and vegetables and pulses (Popkin, 2004, 2012; Bosu, 2015; Imamura et al., 2015; Holdsworth et al., 2019; Holdsworth et al., 2020). The high prevalence of overweight or obesity in Ghana is paralleled by increasing incidences of NR-NCDs, including cardiovascular diseases, type 2 diabetes (Institute for Health Metrics and Evaluation, 2021) and some forms of cancer (de-Graft Aikins, 2012). Also, micronutrient deficiencies, particularly of vitamin A, folate and iron are a major concern, which continues to undermine health and development across all age groups in Ghana (Ghana Statistical Service, 2015; Wegmüller et al., 2020). Consequently, the coexistence of these multiple forms of malnutrition is currently recognised as a serious public health challenge in the country. This therefore warrants the development of reliable and validated models (Laar et al., 2020) for categorising the healthiness of commonly consumed Ghanaian food and beverages. Such tools, including a nutrient profiling model, are prerequisites for relevant food policies geared towards addressing the escalating obesity and the NR-NCDs pandemic.

To achieve the study aim, a quantitative multimethods design was adopted to collect and analyse data to develop a nutrient profiling model for defining and categorising Ghanaian foods based on the nutrient composition of the food and according to scientific and pragmatic principles. The multimethods design used in this thesis involved the combination of secondary data and primary survey, particularly from the quantitative methodological approach to address the research questions (Brewer, 2006; Hesse-Biber, 2015).

The specific objectives which were achieved through the three studies were to:

I. Identify terms used in defining food as healthy or unhealthy.

II. Appraise the methods used in defining and categorising foods as healthy or unhealthy, including their validity and public health applications.

III. Develop a context-specific nutrient profiling model (the Ghanaian NRF11.3 index) for categorising food and beverages in Ghana.

IV. Determine the reliability of the Ghanaian NRF11.3 index

V. Test the convergent validity of the Ghanaian NRF11.3 index

7.1.1 Discussion of key findings

7.1.2 Terms used to define and categorise food as healthy or unhealthy

Previous research suggests that there is no consensus in the definition of food as healthy or unhealthy (Drewnowski, 2005; Drewnowski et al., 2008; Lobstein, 2009). Indeed, the findings of this present research support this. A systematized review conducted in Study 1 to identify the terms used in defining food as healthy or unhealthy from 56 studies showed heterogeneity in the definitions. Thirty-eight different "terms" were identified for defining food as healthy (n=16) or unhealthy (n=22). "Nutrient-dense" and "healthier" were common terms for "healthy foods", whereas "energy-dense nutrient-poor" and "less healthy" were common terms for "unhealthy foods". Other terms that were also sparingly used to describe "unhealthy foods" included: "extra foods", "empty calorie foods", "non-essential foods", "snack foods", "superfluous foods", "ultra-processed foods", "fast foods", "non-core foods", "occasional foods" and "junk foods". Whilst "unprocessed foods" and "traditional dishes" were also used to define "healthy foods".

However, whilst this investigation suggests that studies used a wide variety of definitions for healthy and unhealthy foods, there was a great overlap in definitions of unhealthy foods with regard to food categories. Similar food categories, such as those high in salt, containing refined grains, added sugar and visible or added fats, were consistently referred to as "unhealthy" using the various terms for "unhealthy" as identified above. These findings are consistent with terms used in previous studies to define food and beverages as healthy and unhealthy (Guthrie, 1977; Thomson, 1980; Lackey et al., 2004; Drewnowski, 2005; Franck et al., 2013; Chandran et al., 2014; Kelly et al., 2015; Hess et al., 2017; Holdsworth et al., 2020). These findings agree with both earlier and recent studies that have used similar terms to define healthy and unhealthy foods.

Overwhelmingly, the wide range of terms identified in Study 1 led to the subsequent research questions, which sought to further investigate and identify a more transparent and less "agnostic" categorisation method other than this plethora of terms used for referring to unhealthy or healthy foods. For example, some of these terms seemed to be limiting and imprecise, as in the case of "junk foods" which may only apply to a subset of foods also known as "fast foods" or "snack foods" or "extra foods" (Rangan et al., 2009; Chandran et al., 2014). This approach is less relevant to the Ghanaian context, where there is little evidence about meal patterns and eating occasions (Holdsworth et al., 2020)

More so, with the existence of numerous terms characterising food as healthy or unhealthy, policy makers seeking to limit the advertising of unhealthy foods to children or impose a tax on unhealthy foods may find it challenging to identify which foods to label as such.

Hence, having identified the distinguishing terms used to describe healthy and unhealthy foods, this research went on to critically appraise the methods used in categorising foods, including their validity and public health applications geared towards providing evidence for policy in Ghana.

7.1.3 Food categorisation approaches

To identify and describe the methods commonly used in classifying foods as healthy or unhealthy, the systematized review analysis identified three comparative methods for categorising food: Food-based (n=18); nutrient-based (n=35) and food processing (n=3) (i.e., Chapter 2, Study 1). The nutrient-based approach was shown to have been the most validated previously, using transparent quantitative criteria for defining and categorising "healthy" and "unhealthy" food, compared to food-based and food processing approaches, e.g., NOVA classification (Monteiro et al., 2011; O'Halloran et al., 2017).

Methods based on the food-based approach and food processing approaches did not include the food's nutrient composition as fully as nutrient-based approaches, which meant the latter were relatively more able to discriminate between the healthiness of products.

This finding aligns with a study that previously analysed these three comparative approaches to food classification (Crino et al., 2018), suggesting that nutrient profiling demonstrates a positive way to inform customers about the nutritional qualities of food and beverages. Nutrient density scores thus present a useful means to classify foods based on their nutritional qualities or composition by allocating each food item with unitary scores to reflect its nutrient quality (Arambepola et al., 2008; Drewnowski et al., 2008; Drewnowski et al., 2014).

Nutrient-dense foods scored highly whereas foods that provide lesser nutrients received a lower rating as explained by Drewnowski and colleagues who have shown that the NRFn.3 family of indices use such a scoring system that ranks foods according to their nutrient content and can support consumer education and guidance unlike other approaches such as those based solely on food-based dietary guideline and food processing (Drewnowski, 2008)

Even in the case of nutrient-based approaches, others have argued that "focusing only on nutrients to limit may not necessarily guide consumers towards healthier options" (Mobley et al., 2009), especially in settings where multiple burdens of malnutrition exist. Consequently, taking the nutrient density approach implies that accompanying nutrition programs can emphasise both foods to include and those to limit, hence changing the notion of “healthy” food from just being low in fat, sugar and/or sodium to also include the beneficial nutritional contents (Drewnowski, 2005, 2008)

The findings of Study 1, identified the NRF9.3 index (Drewnowski et al., 2014) amongst various existing nutrient profiling models, i.e., SAIN: LIM (Darmon et al., 2009); HSR,(Food Standard Australia New Zealand, 2021) PAHO (Pan American Health Organization, 2016) and the Ofcom model (Rayner M, 2005a) as robust and adaptable to inform the basis for the development of the Ghanaian NRF11.3 index in Study 2 using secondary data analysis.

Other studies have applied the NRF family of indices widely, which supports these findings (Streppel et al., 2012; Streppel et al., 2014; Wu et al., 2020; Drewnowski et al., 2021)

More recently, a novel nutrient-based profiling approach known as the “food compass” has been proposed for assessing the healthfulness of foods (Mozaffarian et al., 2021). However, this approach is anticipated to be useful in contexts with comprehensive food composition databases but less relevant and of limited applicability in the Ghanaian context, where food composition data are scant and reliable data on phytochemicals and food additives do not exist.

These findings informed aspects of the PhD Study 2, wherein the nutrient density approach (including nutrients to “encourage” and nutrients to “limit”) was employed in the development of the Ghanaian NRF11.3 index.

7.1.4 Development of a context-specific nutrient profiling model for classifying Ghanaian foods

Studies that have, like this study, focused on nutrient density have conducted nutrient profiling using the NRFn.3 index proposed by Drewnowski and colleagues (Streppel et al., 2012; Drewnowski et al., 2014; Streppel et al., 2014; Wu et al., 2020; Drewnowski et al., 2021). In the development of the Ghanaian NRF11.3 index (see section 4.1), the following were the key steps deliberated on:

Step 1: Deciding on the purpose and starting point

The previous study (i.e., Study 1) has shown that the NRF9.3 index was found to have been extensively validated for its construct, predictive validity and appropriate to use as a platform for the development of the Ghanaian NRF11.3 index. More so, this approach was found to be easily adaptable for optimisation and use in classifying food and beverages in the Ghanaian context, where NR-NCDs co-exist with undernutrition (chapter 2, section 2.4.1). Due to the high levels of micronutrient deficiency, two additional nutrients (folate and zinc) were included in the final model. Meanwhile, Drewnowski (2021) proposes that adding positive nutrients beyond 12 may have no impact on the nutrient profiling model. Therefore, the use of the NRF11.3 index was considered reasonable. The results from the regression analysis conducted in Study 2 revealed that the optimal index for classifying Ghanaian foods had 11 beneficial nutrients to encourage and three negative nutrients to limit (see section 4.7.2). The 11 beneficial nutrients were: calcium, protein, fibre, potassium, folate, iron, magnesium, vitamin A, C and E and zinc. This aligns with the findings from Fulgoni et al. (2009), suggesting that the performance optimum of a nutrient profiling algorithm is approximately 9 to 12 nutrients to encourage (Fulgoni et al., 2009; Drewnowski et al., 2021). Similarly, studies that have used the NRF11.3 index to determine the macro and micronutrient components of diverse potato cultivars report that this scoring system was found to be useful and can contribute to human nutrition and daily diet (Wu et al., 2020).

The NRF approach lays emphasis on nutrient density to assist consumers to choose the most nutrient-rich foods first and then the less nutrient-dense foods as calorie needs allow. By including multiple beneficial nutrients, the index shifts the emphasis from “negative” nutrients to “positive” and therefore “better” foods.

Step 2: An across-the-board or category-specific nutrient profiling model.

An across-the-board nutrients model was chosen because it applied the same standards across all foods and beverages in the data (Drewnowski et al., 2008). Based on this approach, evidence indicates that some food categories may rank low, even if they are a major source of a "healthy" diet (Drewnowski et al., 2021). Fruits and vegetables are found to be favoured by this approach when unprocessed (i.e., without adding salt, sugar, or fat) (Drewnowski et al., 2013). On the other hand, foods that are energy dense and poor in nutrients tend to score poorly (Hess et al., 2017). Nuts and seeds score low because of their "high" energy density and fat content. These findings were evident in this study and confirm previous studies that have applied this across-the-board approach to nutrient profiling.

Category-specific nutrient profiling models on the contrary apply various nutrition standards to different food categories to help identify "best of category" items within a specific food group. This approach is said to favour the food industries (Scarborough, 2010) and therefore was not applied in this study. Moreover, allocating foods into groups, subcategories and categories posed a challenge and thus a limitation to the use of this approach in the Ghanaian context. Study 1 of this study also found that food groups/categories ranged from a least two to 43, while the total number of food items categorised into food groups ranged from 102 (Guidetti et al., 2014) to 12,618 food items (Kelly et al., 2010). Thus, using the category-specific approach may increase subjectivity and inconsistency in scoring mixed foods or traditional meals. Therefore, the across-the-board approach was considered simple and easy to use in this study, processing parameters uniformly across categories to help guide toward healthy food choices and policy actions.

Step 3: Selection of nutrients to include in the model.

This phase involves the identification and selection of “qualifying” and “disqualifying” nutrients in other words “positive” and “negative” nutrients. Thus aligning nutrients with public health goals, which are specific to the context in which the model is to be used. Thus far, it has been justified that the inclusion of folate and zinc in the model would serve the public health needs of Ghana due to the importance of the aforementioned nutrients to the well-being of the population. The beneficial nutrients incorporated into the Ghanaian NRF11.3 index were folate, fibre, calcium, potassium, protein, magnesium, iron, vitamin A, C and E, and zinc, whilst the disqualifying nutrients were total fat, total sugar, and sodium. However, there were limitations with regard to food composition tables (FCTs). Ghana does not have a country-specific FCT, which led to the robust synthesis of nutrient values from six other FCTs relevant to the Ghanaian context. In addition, nutrient composition information on vitamins and minerals and especially sugar were mostly lacking and were systematically and methodically supplemented from other sources (see section 4.3.3).

Thus, one caution is that data on total sugar were mainly sourced from European FCT (i.e., McCance Widdowson UFCT), wherein there may be regional variations in the sugar contents of foods. Moreover, the Ghanaian NRF11.3 index reacts to changes in FCTs. This study explored secondary analysis to determine the optimal numbers of nutrients needed for optimal performance in the Ghanaian NRF11.3 index, as a smaller number of nutrients in a model may be helpful in this context. However, a regression analysis revealed that the full model with all 11 beneficial nutrients to encourage and three nutrients to limit was the optimum and favourable in this context with a double burden of malnutrition. These findings are similar to those found in previous studies (Wu et al., 2020; Drewnowski et al., 2021)

Step 4: Selection of nutrient standards

The nutrient standard used for the development of the Ghanaian NRF11.3 index closely followed the regulatory guidelines of the FDA reference daily values, which are equally recognised in Ghana. This was chosen because there are no existing locally available recommendations. Nonetheless, the classification of foods by applying these standards in the Ghanaian NRF11.3 index provided results consistent with studies observed in the literature (Drewnowski et al., 2008; Holdsworth et al., 2020). Fruits and vegetables were ranked highly, followed by fish, soup, meat and traditional dishes, whilst cakes, sweet snacks, refined cereals, visible fats and caloric beverages attained the lowest scores because of being nutrient-poor.

Step 5: Deciding on the bases of the calculation

Nutrient profiling models are typically calculated on the bases of different reference amounts: per 100 kcals, per100 grams or per serving. Local regulatory requirements usually determine the choice of the calculation bases (Azaïs-Braesco et al., 2006; Drewnowski et al., 2008; U.S. Food and Drug Administration, 2019). However, no government-certified serving size calculation bases exist in Ghana at this time, hence the Ghanaian NRF index scores were calculated per 100 kcals. By contrast, 100 grams was not considered as the bases because models based on 100 grams can be strongly influenced by water content and also have difficulty handling servings size customarily consumed as per food group (Drewnowski et al., 2008; Scarborough, 2010; Labonté et al., 2017; Poon et al., 2018). For instance, Mozaffarian et al., (2021) demonstrated that 150 kcals of soda weighs 245 grams, while 150 kcal of fruit-flavoured candy weighs 37.5 grams. Therefore, sugar, sodium and fats calculated per 100 grams of food and consumed in small amounts tend to be penalised for small items of food (i.e., nuts and dried fruits which may be nutrient-dense), while awarding favourable scores to sugary drinks of low energy density.

As the focus of the Ghanaian NRF11.3 index was on nutrient density, the NRF nutrient scores were calculated per 100 kcal (418.4 KJ) to make it easier to use a single scoring base for a diverse range of items, from small to large foods that varied in size or volume. This also meant that one could compare the different profiles of food items in there of their nutrient density, thereby selecting the option that is nutrient-dense over those that may be nutrient-poor.

Step 6: Deciding on the balance of nutrients in the model

The NRF index is countercyclical because it is based on the arithmetic difference between two scores (positive and negative, respectively) (Drewnowski, 2005; Drewnowski et al., 2021). It takes into consideration whether the presence of beneficial nutrients such as fibre, protein, etc., can compensate for the recommended levels of fat, sugar and salt. Thus, the Ghanaian nutrient profiling model takes this compensatory approach (Drewnowski et al., 2021). The results from the classification were found to be largely consistent with the literature (Scarborough, 2007a; Arambepola et al., 2008) and also with those from nutrition experts, although a few discrepancies exist (Azaïs-Braesco et al., 2006).

Step 7: Deciding on the nutrient profiling algorithm

The Ghanaian NRF index algorithm incorporates two sub-scores: the nutrient-rich scores (NR_n) and the nutrient-to-limit scores (LIM). The NR_n sub-scores were based on 11 variable nutrient components to encourage. While the nutrient limiting (LIM) sub-score was based only on three nutrients' components, expressed as percentage DV per reference amount. The final NRF index algorithm was derived from the calculation of the arithmetic difference between the positive (NR_{11}) and the negative (LIM) components. A food's entire nutritional value may be obscured by a focus on only its negative components. In this study, "agushi soup", for example, exceeded thresholds for total fat and saturated as per the WHO criteria and hence was classified by the WHO African model as not permitted or unhealthy; on the other hand, the Ghanaian NRF11.3

gave it a reasonable score above the cut-off point which meant that it was permitted or healthy. The effectiveness of the use of this algorithm has been exemplified in a study by Fulgoni et al. (2019). However, weighing nutrients equally could also fail to take into consideration how different interact with one another. For example, Dawson-Hughes et al. (2015) write that dietary fat promotes the absorption of vitamin D.

Step 8: Testing and validation of the Ghanaian NRF11.3 index.

After ascertaining that the optimal number of nutrients in the Ghanaian NRF11.3 index was at its optimum, the next phase was then to assess its reliability and validity. The optimal cut-off point represented the maximum value for sensitivity and specificity for the Ghanaian NRF11.3 index. Cut-offs were calculated because they represented the points above and below which food items can be categorised as "healthy" or "unhealthy" with reference to a "gold standard" or "reference standard". Using the WHO African model as a "reference standard", a cut-off of 16.24 was established for the Ghanaian NRF11.3 index. This is the first time a cut-off point has been established for the NRF11.3 index. This cut-off point was used to compare with the binary WHO African model's classification, which was useful for determining the performance of the NRF11.3 index. Nonetheless, other profiling models such as the Health Star Rating System, which is a continuous model, have used 3.5 stars as an appropriate cut-off point to identify healthier packaged food options (Dunford, 2015; Food Standard Australia New Zealand, 2021). The sensitivity and specificity of the Ghanaian NRF11.3 index were also determined using ROC curve analysis. The accuracy of the Ghanaian NRF11.3 index was evidenced by the AUC which provided a measure of how well the NRF11.3 discriminated between "healthy" and "less healthy" food items as classified by the reference model. (AUC: 0.807; 95% CI:0.726-0.888; p< 0.001). The Ghanaian NRF11.3 demonstrated a high sensitivity of 85.5% in the identification of healthy (permitted) food items at the optimal cut-off point and a specificity of 66.7%. These results serve to confirm the accuracy and performance of the Ghanaian NRF11.3 index in classifying Ghanaian foods.

The reliability of the Ghanaian NRF11.3 was estimated by calculating the Cronbach's alpha and Cohen's kappa statistics. The Cronbach's alpha coefficient (0.728, 95% CI: 0.652-0.793) was acceptable. The Kappa statistic (k) for the two models in this study was observed to be highest at 0.531 ($p<0.001$), at the optimal cut-off point of 16.24 of the Ghanaian NRF11.3 index with reference to the WHO model. Thus, a moderate strength agreement was indicated. This result corroborates earlier studies on the agreement of nutrient profiling models (Eyles et al., 2010; Rosentreter et al., 2013; Poon et al., 2018).

The findings illustrated similarities and differences in the classification of food, for example, when using the Ghanaian NRF11.3 index and a reference model which was based on negative nutrients. Several of the food and beverage items considered in the analysis such as all fruits, traditional dishes, fish and vegetables had comparatively high NRF index scores suggesting nutrient density. Some commonly consumed food and beverages, including doughnuts, cookies, ice cream and soft drinks had negative NRF scores and consequently low nutrient density. A restricted focus on only the negative aspects of a food item may conceal its overall nutritional quality. For example, flavoured yoghurt may contain added sugar and total sugars but due to a lack of data on added sugar, which is a criterion for classification using the WHO model, this item in the food list was not able to be classified under the WHO African model because it is strictly focused on negative nutrients. Nonetheless, yoghurt may also be rich in calcium and other beneficial nutrients. This explains why seven foods were not classified by the WHO model but classified by the NRF11.3 index(i.e., n=137 by the NRF index and n=131 by WHO). Thus, policy makers trying to identify an all-inclusive nutrient profiling model that is able to classify the majority of foods may consider the rigour of the Ghanaian NRF11.3 index in classifying a wide range of items under its scoring algorithm. Furthermore, given the public health landscape in Ghana – undernutrition, micronutrient malnutrition, overweight /obesity amongst other diet-related chronic illnesses, a reliable nutrient profiling model that includes "negative" and also "positive" nutrients is a practical option. Moreover, studies have shown the NRF family of indices to be consistently more persuasive or adaptive (Fulgoni et al., 2009; Hess et al., 2017; Wu et al., 2020; Drewnowski et al., 2021). This analysis provides evidence to support the reliability of the Ghanaian NRF11.3 index, which has been shown to be a more objective and holistic model in determining the nutritional value of commonly consumed Ghanaian foods.

7.1.5 Convergent validity of the Ghanaian NRF11.3 index

The Ghanaian NRF11.3 index demonstrated strong agreement with the rankings derived from expert nutrition professionals, with a Spearman correlation coefficient of $R_s = 0.549$, $p < .0001$. This corroborates similar studies that were conducted to determine the agreement between expert classification and nutrient profile models (Azaïs-Braesco et al., 2006; Scarborough, 2007a). The ranking of food items by experts also appears to be in agreement with general healthy eating guidelines (Scarborough, 2007a). The highest median rankings (showing very healthy food items) were attained by foods in the vegetable and fruits group and the lowest ranking (showing very unhealthy) was the sugary foods group. Whereas the experts ranked the same food items on a 5-Likert scale, the Ghanaian NRF11.3 and the expert classification both ranked vegetables and fruits highly, followed by fish, soup, meat and traditional mixed dishes. Particularly regarding the Ghanaian NRF11.3 index, the inclusion of zinc and folate amongst the beneficial nutrients may have contributed to the meat group also gaining higher scores alongside the fruits and vegetable group. Cakes and sweet snacks, refined cereals, fats and calorie-containing beverages typically received the lowest scores, possibly because they were energy-dense and had lower nutrient density. However, dairy products had scores in the mid-range classification. This finding reflects an earlier study by Drewnowski et al. (2010), that suggests that low-energy-dense vegetables and fruits followed by beans and legumes, and then eggs attained the highest scores of the NRF index. Meanwhile, grains, sweets, fats and oils have lower nutritional content per calorie and higher energy density. Whole foods scored higher than refined grains within food groups, while 100 per cent fruit juices scored higher than soft drinks which collaborates with previous findings (Drewnowski, 2005, 2010). According to Drewnowski et al. (2010), NRF indices calculated on 100 kcals, 100 grams or serving size bases provide different outcomes. In this study, the Ghanaian NRF11.3 calculations were based on 100 kcals and foods that benefited the most from 100 kcals calculations were vegetables with low-calorie content such as lettuce, cabbage, and green vegetables. However, foods that are considered to benefit from 100 grams calculation are energy-dense foods, particularly nuts, seeds and cereals, whilst per-serving size calculations benefited foods eaten in quantities greater than 100 grams or 100 milligrams, including fruits and fruit juices milk and yoghurt and mixed dishes which were not used as the bases for this current study. These findings corroborate the finding of Drewnowski et al. (2013), as the classification has shown that the foods that benefited the most from 100 kcals were the low energy-dense vegetables and fruits. Similar calculations have been done in France to show this, using the SAIN: LIM model (Maillot et al., 2018).

The Ghanaian NRF11.3 classification and corresponding nutrition expert ranking of some food items were however surprising. For instance, anchovies, boiled meal, and millet porridge received a median ranking by nutrition experts of 5 = “very healthy” but were all considered as 1= “very unhealthy” by the nutrient profiling model. This may be due to the nutrient composition of negative nutrients that contributed largely to the NRF score. Thus, anchovies had a high negative sodium value of 3668 mg, boiled cornmeal a high sugar value of 14.6 grams and millet porridge a high sugar value of 14.5 grams which may have affected the overall

NRF score. Similar trends in their results from previous studies have been attributed to the use of descriptive prompts by participants to guide their judgements (Scarborough, 2007a).

Also, another interesting food item was banana which was classified as “neither healthy nor unhealthy” in the third quintile according to the Ghanaian NRF11.3 score of 32.63 but was classified in the fifth quintile by the experts. Of note, if one were to consider the suggested cut-off point of the Ghanaian NRF11.3 index of 16.24 in this current study and the score of banana of 32.63 would be considered very healthy and not in the intermediate group. Moreover, probably because a combination of FCTs was used, minor differences in food composition may have had an effect on scores. But this was largely controlled for through rigorous synthesis.

Lastly, comparing the Ghanaian NRF11.3 index scores in quintiles (R_s=0.549; $p<0.001$) or as continuous scores (R_s=0.58.; $p<0.001$) to expert scores on the 5 Likert scale, both showed a significant and positive strong correlation coefficient. More so, the guidelines as recommended by Cohen (1988) suggest a large positive correlation (r=0.5 to 1.0). Hence, irrespective of using quintiles or continuous scores the Spearman correction coefficient for the Ghanaian NRF11.3 index and the expert classification still showed a significant positive strong correlation.

Overall, the findings from this multimethods PhD study complements and confirm each other to suggest that the newly developed Ghanaian NRF11.3 index is a reliable and validated nutrient profiling model for classifying the healthiness of Ghanaian food items (Figure 7.1) Findings from this PhD extend practical tools that can be used to curb the changing trend in the Ghanaian diet that is increasingly becoming energy-dense but nutrient-poor (Holdsworth et al., 2020; Rousham et al., 2020). Thus, the increased intake of energy-low but nutrient-dense foods through interventions or policies based on a reliable and validated model like the Ghanaian NRF11.3 index may achieve both the objectives of lowering daily caloric intake and increasing the nutrient density of the overall diet. Drewnowski et al. (2021) and Fulgoni et al.

(2009) have also shown that the NRF index, like many other nutrient profile models, aims to encourage people to consume fewer calories and more healthy foods containing beneficial nutrients (Fulgoni et al., 2009; Drewnowski et al., 2021), therefore, moving away from the traditional dietary advice that places emphasis on what foods to avoid. The concept of what defines a “healthy food” appears to be centred more on the avoidance of saturated fat, added sugars and sodium than on the incorporation of healthful components. Such unfavourable dietary advice has not been proven effective, as evidenced by the dramatic rise in obesity and diabetes over the past 20 years (Drewnowski, 2008; Miller et al., 2009). A more positive approach of focusing on nutrient density may ultimately prove to be more effective in the long term. Moreover, in Ghana, significant gaps exist in the implementation of policies to create “healthy” food environments (Laar et al., 2020). This may partly be due to the lack of a reliable and validated nutrient profiling model. Thus, by developing such nutrition tools that are reliable and valid to classify the healthiness of Ghanaian foods may then easily lead to policies and interventions that can easily be formulated or adapted to promote a healthy food environment, which may consequently lead to reducing the disease burden in the country.

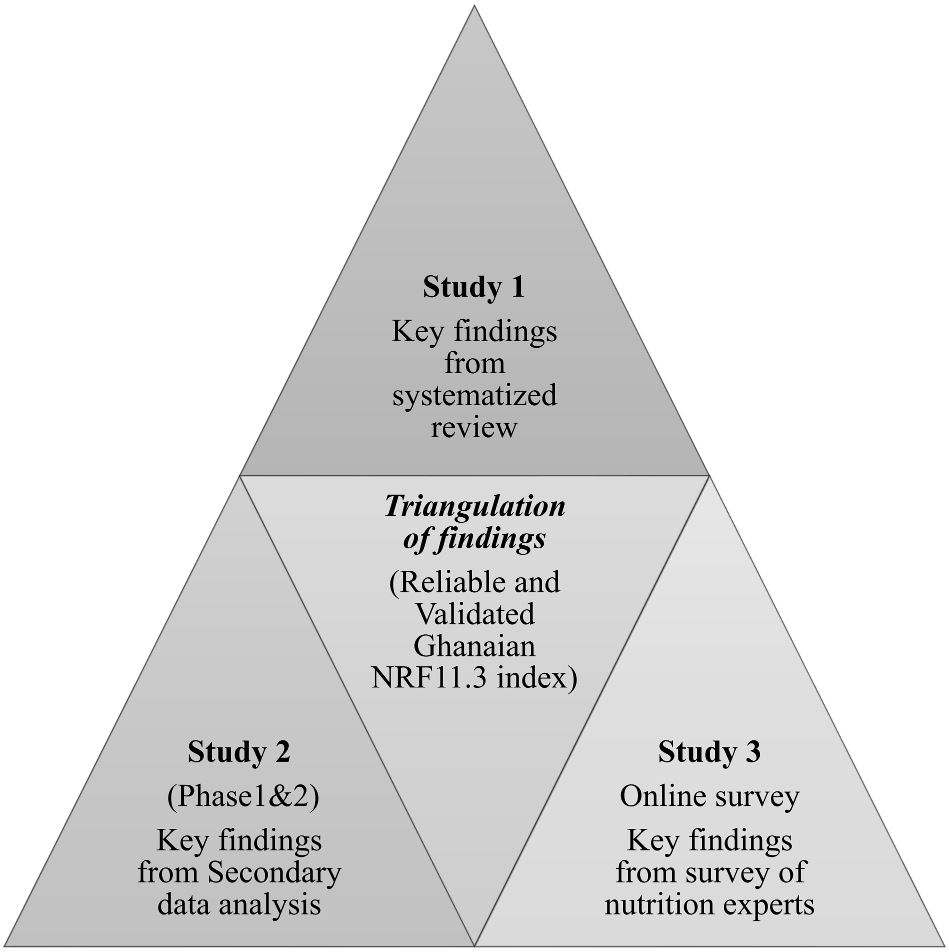

Figure 7.1:Provides a pictorial summary of how the findings of the three studies complement each other (triangulation of key findings) to confirm the reliability and validity of the Ghanaian NRF11.3 index.

7.2 **Strengths and Limitations of Study**

7.2.1 Study 1: a systematized review

Foremost, the inclusion of the systematized review in this PhD is a key strength of the study. More so, the literature was searched systematically in several academic databases, which also serves as a key strength This approach helped in identifying and reviewing a large number of studies (n=56). Evidence identified in the literature for defining and categorising food was not restricted by time limits or publication date for eligible studies, which also represents a strength of the current review. This review provided strong evidence that led to the identification of a suitable model as a starting point for the development of a context-specific nutrient profiling model: the GhanaianNRF11.3 index for use in Ghana.

However, a key limitation of this review is that only papers published in English were included. This means that relevant studies published in other languages and could have been used to enrich the evidence might have been missed. More so, the quality appraisal of articles was not included and the last search was done in 2018.

Another limitation of this systematized literature review was that most studies were from high-income countries and thus presented nutrient profiling models that were designed to tackle dietary excess and NR-NCDs which may not readily be transferable to LMICs such as Ghana where dietary deficiencies persist.

7.2.2 Study 2 Phase 1: The development of the Ghanaian NRF11.3 index

The secondary data used in this study represented the most relevant dietary data from Ghana, at the time of conducting this research which is a major strength of this study. The dietary 24-hour recall data were collected over a period of seven months between June to December covering both rainy and dry seasons hence seasonal variation did not affect the dietary data, which is also a strength. Given that dietary survey data has its own limitations including recall bias, especially for 24-hour recall data, measures were put in place to minimize it.

The newly developed Ghanaian NRF11.3 is a holistic model that is optimised for use in the Ghanaian context. This model focuses on measuring nutrient density, which is prudent for countries experiencing the double burden of malnutrition. Moreover, the inclusion of specific nutrients of public health concern (folate and zinc) to the positive nutrients discussed in this study represents another great strength of this study. Whilst access to country-specific electronic food composition tables was a limitation, a thorough synthesis of relevant food composition tables was used from similar contexts (as far as possible) was implemented to supplement or fill the gaps. This has also revealed the need for a country-specific food composition database for use in Ghana.

7.2.3 Study 2 Phase 2: The reliability, optimal cut-off point, sensitivity and specificity of the Ghanaian NRF11.3 index

To the best of our knowledge, this is the first time that the WHO Africa Nutrients profiling Model has been used as a reference model in a study examining a nutrient profiling model's reliability, optimal cut-off points , sensitivity and specificity. The fact that individual foods and not diets were assessed using a nutrient profiling model that emphasised a wide range of both micronutrients and macronutrients rather than only emphasising one aspect of nutrients is a great strength of this study, especially for the context in which it is meant to be applied. Furthermore, many nutrient profiling models do not have a nutrient density focus to address the double burden of malnutrition, unlike the newly developed Ghanaian NRF11.3, which is a strength of the model. In addition, findings from this chapter have shown good internal consistency and inter-rater reliability which supports that the Ghanaian NRF11.3 is a reliable model.

7.2.4 Study 3: The convergent validity of the Ghanaian NRF11.3 index

The expert nutrition professionals were not given any nutritional information to aid the classification of the food items serves as a strength of this study. However, it is likely that the experts might have given the food items different scores if they had access to detailed nutrition profiles of the food items. This would have affected the results of the comparison between the expert ranking and the way the Ghanaian NRF11.3 index categorises foods. One main advantage that this method presents is that the opinion of the nutrition professionals were gathered without prior awareness of the classification of the same foods by the nutrient profiling model, and therefore their views were not influenced by the model under investigation. However, interpreting results obtained using only the classification of foods derived from the opinion of nutrition experts to assess the validity of a nutrient profiling tool should be done with caution. This is due to the fact that experts' classification of food is not always consistent, as past research have shown (Scarborough, 2007b). In a previous study where food items were classified by a large sample-size of nutritionists (over 700) (Scarborough, 2007b), this was deemed insufficient to discriminate amongst a number of nutrient profiling models. Multiple types of evidence are needed to demonstrate that a test measures the intended construct. It is recommended that simpler and less complicated measures like expert opinions to be used during the developmental stage of a nutrient profiling model to first ensure the robust classification of foods. To broaden the evidence base and boost confidence in the model, other more sophisticated and data-intensive approaches to validity testing have been proposed. These include the assessment of predictive validity against health outcomes in longitudinal studies. Despite the value of obtaining predictive validity, it was beyond the scope of this study to measure this type of validity.

7.2.5 A reflection on the research process

Based on this research process and the resultant findings, it is critical to highlight the lessons learned and reflect on the entire process. In this PhD, a systematised literature review was conducted in Study 1 to determine a context-specific nutrient profiling model for classifying Ghanaian foods as healthy or unhealthy, critically appraise the validity of the methods and consider their public health applications. A plethora of definitions and categorisation methods were found to be widely available for profiling food as such, but most of these approaches were developed and validated in HICs. Only a few studies originated from LMICs and the nutrient-based approach emerged as the most validated and transparent approach using quantitative criteria for defining and classifying foods. However, this systematised review process fell short of the full requirement for a comprehensive systematic literature review due to the lack of quality appraisal of all the studies included in this review process. More so, an update of the search was needed since the last search was conducted in November 2018. The inability to update the whole review process again was due to the limited time left for the completion of the PhD, which resulted from challenges beyond the researcher's control, including the COVID-19 pandemic. However, through new citation alerts and expert consultation, efforts were made to include the recent articles written after the last search date in the discussion chapter of this PhD. Nonetheless, research regarding nutrient profiling methods and their validity, particularly in LMICs, is limited It is therefore essential for researchers to conduct further studies in this topic area.

Secondly, Study 2 was based on the analysis of 24-hour recall dietary data derived from food consumed by a sample of participants living in deprived Ghanaian neighbourhoods at different stages of the nutrition transition. The nutrient composition of the commonly consumed Ghanaian foods identified from the 24-hour dietary recall of participants was used in regression analysis to explore the optimal combination of nutrients needed for developing a context-specific model for use in Ghana. This process was challenging because of the lack of a local food composition table specific to Ghana. Thus, a careful synthesis of other food composition tables with similar foods was employed, which made the entire process challenging and prolonged. Therefore, it would be beneficial if the required government agencies and research organisations made significant efforts to develop a high-quality and comprehensive electronic food composition database for use in Ghana. Although the best combinations of FCTs were used, results should be interpreted with caution.

Lastly, Study 3 of this PhD was an online survey of Ghanaian nutrition experts conducted to determine the validity of the newly developed nutrient profiling model. This study was conducted during the COVID-19 pandemic lockdown period and therefore getting ethical approval and conducting the study, in general, took an unusually longer time than expected, although the participant participation was satisfactory.

7.3 Implication for policy and practice

The results of this study provide evidence of an optimal nutrient profiling model for use in interventions and policies that can address the double burden of malnutrition in Ghana. The Ghanaian NRF11.3 index incorporates 11 positive nutrients and only three negative nutrients. The positive nutrients are potassium, fibre, magnesium, calcium, vitamin C, E, & A, folate, iron, protein and zinc. Thus, public health agencies seeking to balance the risk of overnutrition against the persistent danger of undernutrition in Ghana may require such optimised nutrient profiling models.

Furthermore, the findings from this study provide evidence supporting recommendations made by other such studies (Holdsworth et al., 2019; Holdsworth et al., 2020; Laar et al., 2020; Rousham et al., 2020; Akparibo et al., 2021; Booth et al., 2021; Laar, 2021b), all of which call for the implementation of various food environment policies (e.g. labelling, marketing regulations, provisioning, fiscal policies, etc.), indicating that a nutrient profiling model is a prerequisite for the development and implementation of such policies. Additionally, over the past ten years, the Ghanaian government has demonstrated its political will and dedication to the control and prevention of NR-NCDs by creating a national policy (Ministry of Health Ghana, 2012) and, in 2021, environmental policies relating to unhealthy foods and NCDs have been proposed (Laar et al., 2020) (i.e. interventions including the regulation of advertisements of “unhealthy foods” and non-alcoholic beverages to children, limiting the levels of sugar, trans fat and sodium in ultra processed foods as well as food-related health taxes).

For instance, this novel Ghanaian NRF11.3 index was presented at a consultative meeting in Ghana for the MEAL4NCDs project. The Ghanaian NRF11.3 stood out amongst other models that were also presented as a model that used context-specific robust dietary data to develop a validated model tailored for the specific population's needs. This novel model aligned as a fit-for-purpose model for the MEAL4NCDs project which aims to "support public sector actions that create healthy food marketing retail and provision environment for children" in Ghana (Laar, 2021a). Therefore, the Ghanaian NRF11.3 index can practically help facilitate the implementation of similar food promotion and provision programmes as well as contribute to the development of nutrition standards and food dietary-based guidelines for the Ghanaian populace.

Apart from directly supporting the implementation of policies and interventions, this novel Ghanaian NRF11.3 index could contribute largely to the current discussions on reliable and validated nutrient profiling models for use in Ghana.

In a statement delivered by the President of Ghana at the Food Systems Summit 2021, he highlighted the need for a fit-for-purpose nutrient profile model to facilitate the implementation of food-based policies by 2022 (Nana Addo Dankwa Akufo- Addo, 2021). Thus, the study provides a context-specific reliable and validated nutrient profiling model for the categorisation of Ghanaian foods and beverages.

7.4 Suggestions for future research

Despite the inclusion of a wide range of studies in Study 1, only a few studies were from LMICs in relation to the classification of food as healthy or unhealthy were from LMICs, which suggests the need for researchers to explore approaches to the classification of food as healthy or unhealthy in Ghana. The results from Study 2 of this research provided evidence that the Ghanaian NRF11.3 index is a reliable and valid nutrient profiling model; thus follow-up research that evaluates the utility of the NRF11.3 index in implementing public health interventions and policies is needed. The findings of Study 3 showed the convergent validity of the Ghanaian NRF11.3 index nonetheless, other forms of validity, such as the assessment of predictive validity may also be needed. For example, an assessment of whether consuming healthy foods as defined by the Ghanaian NRF11.3 index protects against undesirable diet-related health outcomes such as obesity, type 2 diabetes and the prevalence of cardiovascular illness may be required to increase the evidence-based supporting the model. This research can also serve as the basis to explore further research in the subject area of nutrient profiling models in Ghana.

7.5 Conclusion

In conclusion, the findings from all three studies in this PhD thesis confirm that it is possible to develop a reliable and validated nutrient profiling model for classifying Ghanaian foods. This study successfully developed a locally relevant model, the Ghanaian NRF11.3 index, for classifying Ghanaian food items. It is anticipated that the Ghanaian NRF11.3 index will serve as a useful tool for a more objective and holistic classification of commonly consumed food items in Ghana. Being able to identify nutrient-rich foods has implications for public health policy and practice. Expert nutrition professionals and other professionals with the challenging task of providing categorising local foods as healthy or unhealthy, or government agencies seeking better ways to regulate the advertisement of unhealthy foods to children or food labelling could use the Ghanaian NRF11.3 index to classify foods based on their overall nutrient profiles.

The current public health situation underscores the urgent need to consider the newly developed Ghanaian NRF11.3 index proposed for classifying Ghanaian foods. In the Ghanaian context with the double burden of malnutrition, where obesity and type-2 diabetes are among the leading causes of mortality and morbidity, such comprehensive and evidence-based models that align with nutrition-related policies and international recommendations are needed to regulate unhealthy food environments, especially those directly associated with these diseases (total and added sugar).

This model may also be useful for other countries with the same or similar contexts and food items; however, caution should be taken. There is a need for further research to establish other forms of validity, like the predictive validity of the Ghanaian NRF11.3 index.

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9 Appendix

Appendix 1: Example of a search strategy carried out from a search engine: Medline via Ovidsp

#	Searches	Results
1	((unhealth* or health*) and food*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]	108519
2	(Defin* or Categori* or Classif* or 'Nutri* Profil*').mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]	1647396
3	1 and 2	11452
4	(defin* or categori* or classif* or 'Nutri* Profil*').m_titl.	130468
5	((unhealth* or health*) and food*).m_titl.	5084
6	4 and 5	34

Appendix 2: Ethics Approval letter (Ghana Health Service Ethics Review Committee)

GHANA HEALTH SERVICE ETHICS REVIEW COMMITTEE

In case of reply the number and date of this Letter should be quoted

Research & Development Division
Ghana Health Service
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24th August, 2020

MyRef. GHS/RDD/ERC/Admin/App/20/246
Your Ref. No.

Zakia Abdul-Haq
School of Health and Related Research (ScHARR)
University of Sheffield
30 Regent Street, S1 4DA, UK.

The Ghana Health Service Ethics Review Committee has reviewed and given approval for the implementation of your Study Protocol.

GHS-ERC Number	**GHS-ERC001/04/20**
Study Title	Nutrition Experts' Classification of Commonly Consumed Ghanaian Foods and Beverages: Testing Validity and Reliability of Two Nutrient Profiling Models
Approval Date	24th August, 2020
Expiry Date	23rd August, 2021
GHS-ERC Decision	**Approved**

This approval requires the following from the Principal Investigator

- Submission of yearly progress report of the study to the Ethics Review Committee (ERC)
- Renewal of ethical approval if the study lasts for more than 12 months,
- Reporting of all serious adverse events related to this study to the ERC within three days verbally and seven days in writing.
- Submission of a final report **after completion** of the study
- Informing ERC if study cannot be implemented or is discontinued and reasons why
- Informing the ERC and your sponsor (where applicable) before any publication of the research findings.

You are kindly advised to adhere to the national guidelines or protocols on the prevention of COVID -19

Please note that any modification of the study without ERC approval of the amendment is invalid.

The ERC may observe or cause to be observed procedures and records of the study during and after implementation.

Kindly quote the protocol identification number in all future correspondence in relation to this approved protocol

SIGNED…… ……………
Professor Moses Aikins
(GHS-ERC Vice Chairperson)

Appendix 3: Ethics Approval letter (University of Sheffield)

The University Of Sheffield.

Downloaded: 13/09/2021
Approved: 29/04/2020

Zakia Abdul-Haq
Registration number: 160103933
School of Health and Related Research
Programme: Mapping the factors in the social and physical food environments that drive consumption of energy dense nutrient-poor (EDNP) foods and beverages, to identify interventions targeting women and adolescent girls throughout the reproductive life course.

Dear Zakia

PROJECT TITLE: Nutrition experts' classification of commonly consumed Ghanaian foods and beverages: testing validity and reliability of two nutrient profiling models.
APPLICATION: Reference Number 032486

On behalf of the University ethics reviewers who reviewed your project, I am pleased to inform you that on 29/04/2020 the above-named project was **approved** on ethics grounds, on the basis that you will adhere to the following documentation that you submitted for ethics review:

- University research ethics application form 032486 (form submission date: 26/04/2020); (expected project end date: 01/10/2020).
- Participant information sheet 1074563 version 6 (26/04/2020).
- Participant consent form 1076499 version 2 (18/03/2020).
- Participant consent form 1074564 version 2 (26/04/2020).

If during the course of the project you need to deviate significantly from the above-approved documentation please inform me since written approval will be required.

Your responsibilities in delivering this research project are set out at the end of this letter.

Yours sincerely

Jennifer Burr
Ethics Administrator
School of Health and Related Research

Please note the following responsibilities of the researcher in delivering the research project:

- The project must abide by the University's Research Ethics Policy: https://www.sheffield.ac.uk/rs/ethicsandintegrity/ethicspolicy/approval-procedure
- The project must abide by the University's Good Research & Innovation Practices Policy: https://www.sheffield.ac.uk/polopoly_fs/1.671066!/file/GRIPPolicy.pdf
- The researcher must inform their supervisor (in the case of a student) or Ethics Administrator (in the case of a member of staff) of any significant changes to the project or the approved documentation.
- The researcher must comply with the requirements of the law and relevant guidelines relating to security and confidentiality of personal data.
- The researcher is responsible for effectively managing the data collected both during and after the end of the project in line with best practice, and any relevant legislative, regulatory or contractual requirements.

Appendix 4: Ethics Approval letter (University of Sheffield)

The University Of Sheffield.

Downloaded: 13/09/2021
Approved: 29/04/2020

Zakia Abdul-Haq
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School of Health and Related Research
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- The researcher must comply with the requirements of the law and relevant guidelines relating to security and confidentiality of personal data.
- The researcher is responsible for effectively managing the data collected both during and after the end of the project in line with best practice, and any relevant legislative, regulatory or contractual requirements.

Appendix 5: Information sheet and consent

Nutrition experts' classification of commonly consumed Ghanaian foods and beverages: testing validity and reliability of two nutrient profiling models.

Online survey

Survey information sheet

Thank you for your interest in completing this survey. Before you decide to participate, it is important that you understand why the research is being done and what it will involve. Please take the time to read the following information carefully.

The essence of this project is to adapt a reliable and validated nutrient profiling model for Ghana. This is why this project is asking for your help in completing this questionnaire. An essential part of this exercise is to test whether a scientific model adapted for classifying commonly consumed Ghanaian foods and beverages as healthy or unhealthy reflects the expertise of nutrition and dietetics professionals.

Participating involves answering three questions about your background/experience in nutrition and your age group and gender. Then, you will be asked to classify a list of foods and beverages on a five-point scale of relative healthiness based on your opinion and knowledge about the food/beverage.

You are free to choose whether or not to take part. If you do decide to take part, you will be asked to complete a consent form confirming that you have agreed to participate. There is no risk involve in completing the consent form. You can still withdraw at any point before submitting the survey online. You may do so by closing your internet browser and you do not have to give reasons for your withdrawal. Once the survey has been submitted online you will not be able to withdraw your data.

It should take you between 15-20 minutes to complete the questionnaire. Once survey has been submitted, there will be a chance to enter into a voluntary draw to win a nutrition textbook (this will be clarified when sending out this invitation).

All the information that we collect about you during the course of the research will be kept strictly confidential and will be accessible to members of the research team only. No report or publication written out of this study will identify any person.

The handling of personal data is controlled by the General Data Protection Regulation (GDPR) and associated legislation : 'according to data protection legislation, we are required to inform you that the legal basis we are applying in order to process your personal data is that 'processing is necessary for the performance of a task carried out in the public interest' (Article 6(1)(e)). Further information can be found in the University's Privacy Notice https://www.sheffield.ac.uk/govern/data-protection/privacy/general.'

This study is being conducted by Mrs Zakia Abdul-Haq: a student at the School of Health and Related Research in the University of Sheffield (UK) as part of her PhD research project. Zakia will be under the supervision of academics at the University of Sheffield and Dr Amos Laar (University of Ghana, Legon)

Consent

Please tick (yes/no) below to show that you have/have not accepted to participate in this study:

I confirm that I have read and understood the information sheet explaining the above research project.

Yes ☐

No ☐

I understand that my participation is voluntary. I am free to withdraw from the study at any point before the survey is submitted online, by closing my browser. I do not have to give any reason for withdrawal and there will be no negative consequences.

Yes ☐

No ☐

I understand that my responses will be anonymous and I will not be identified or identifiable. I agree for data collected from me to be used in future research respecting my anonymity.

Yes ☐

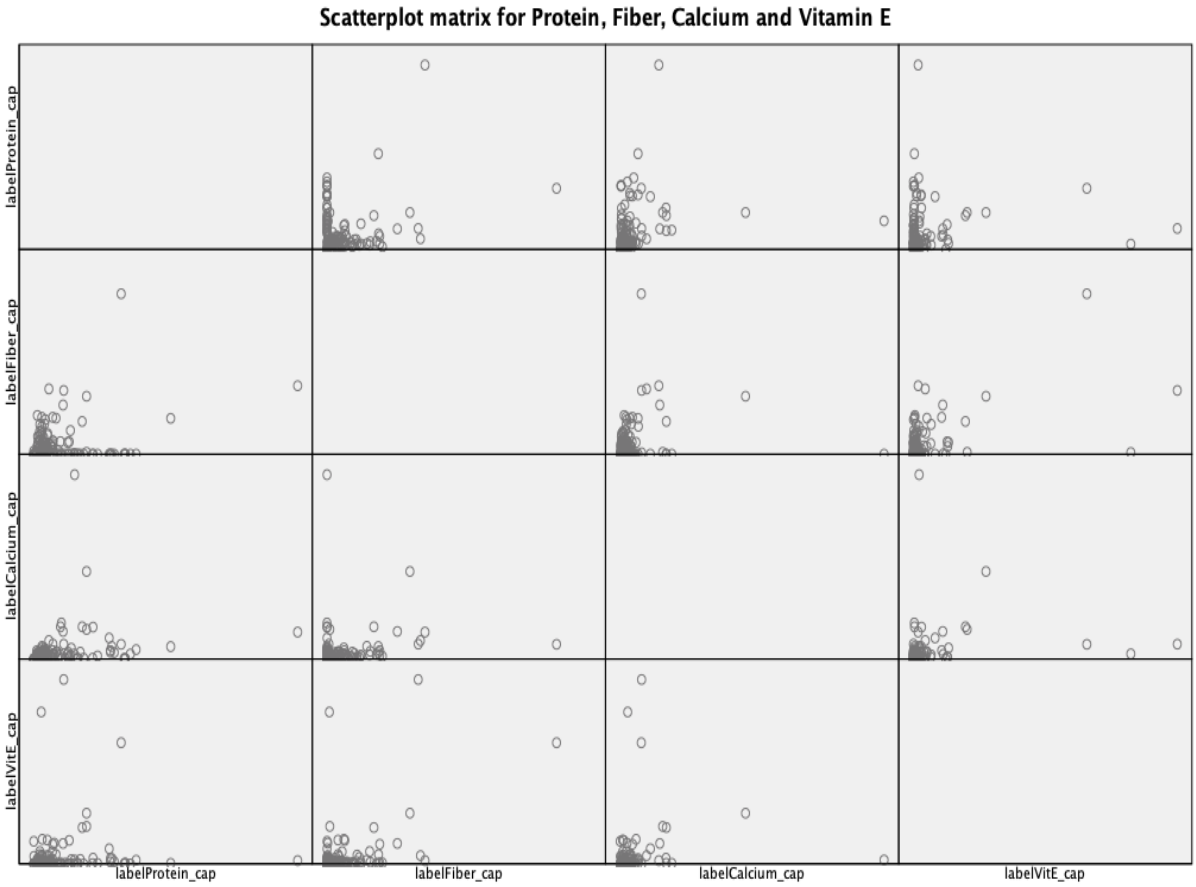
No ☐

I agree to participate in the project.

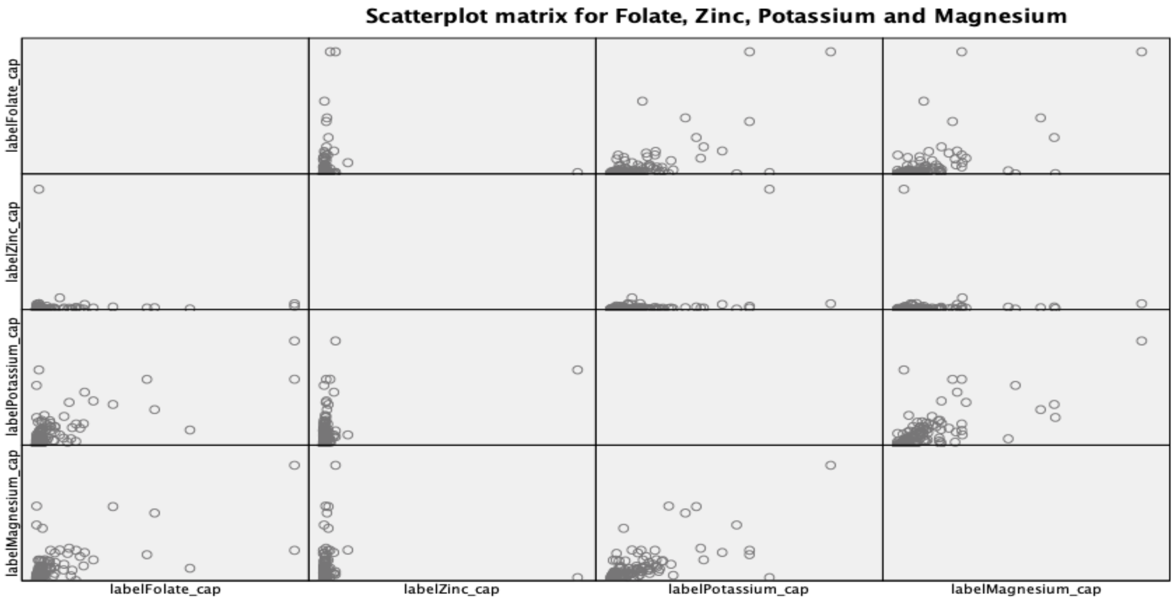
Yes ☐

No ☐

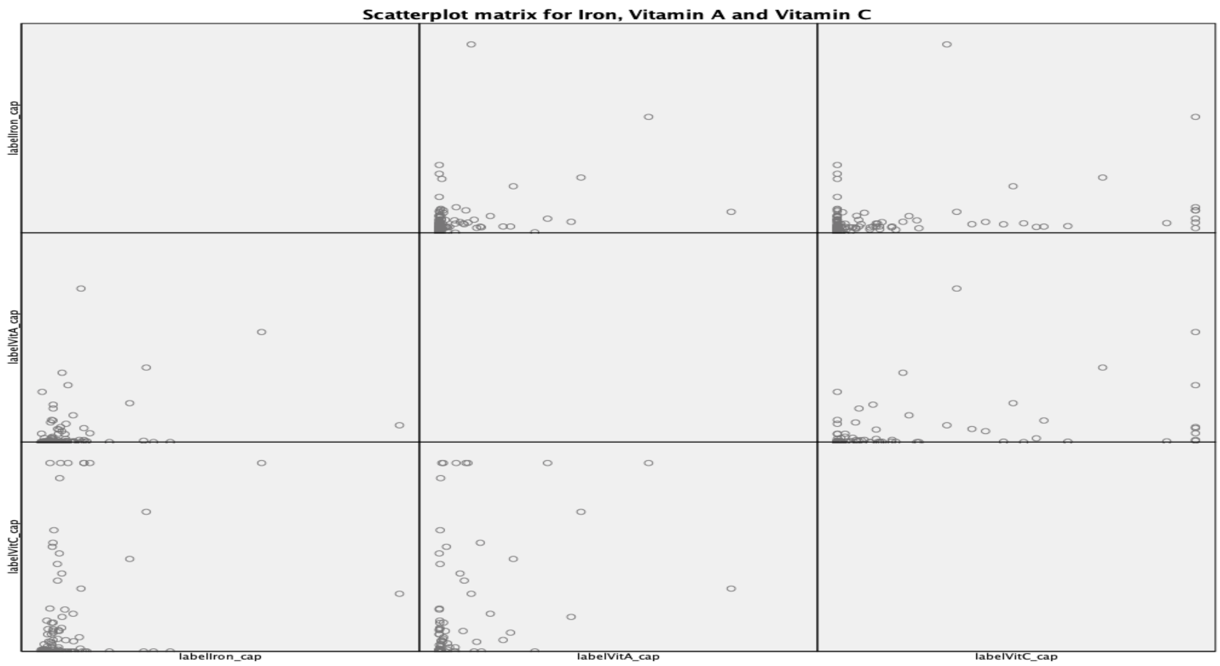
Appendix 6: Assumption for regression model



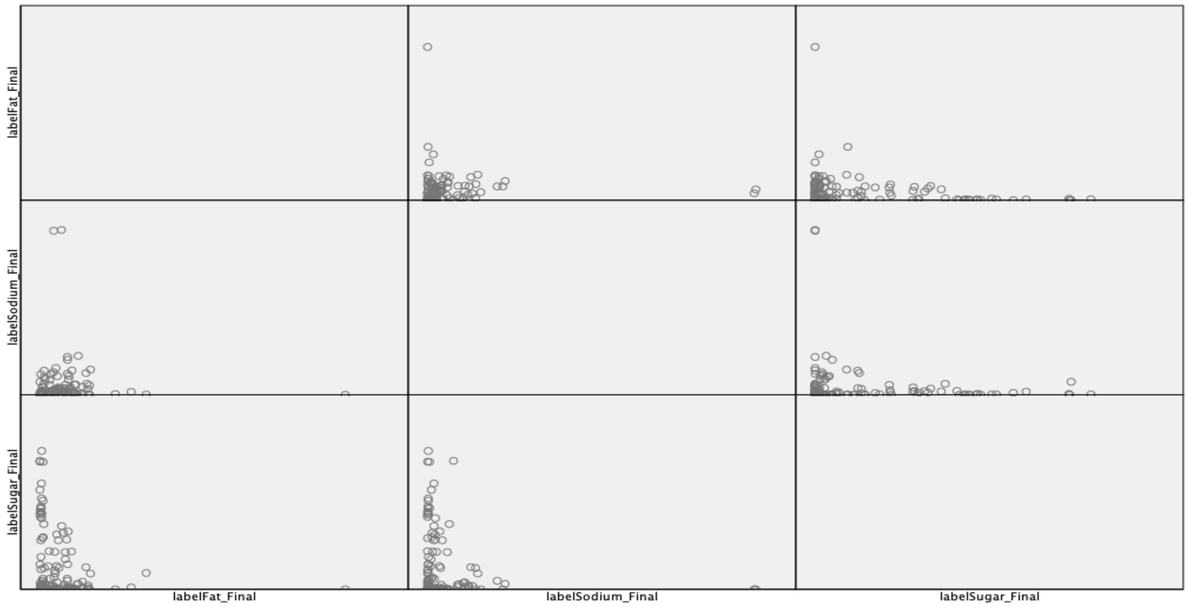
Appendix 6 Figure 1: Scatterplot matrix for Protein, Fibre, Calcium and Vitamin E



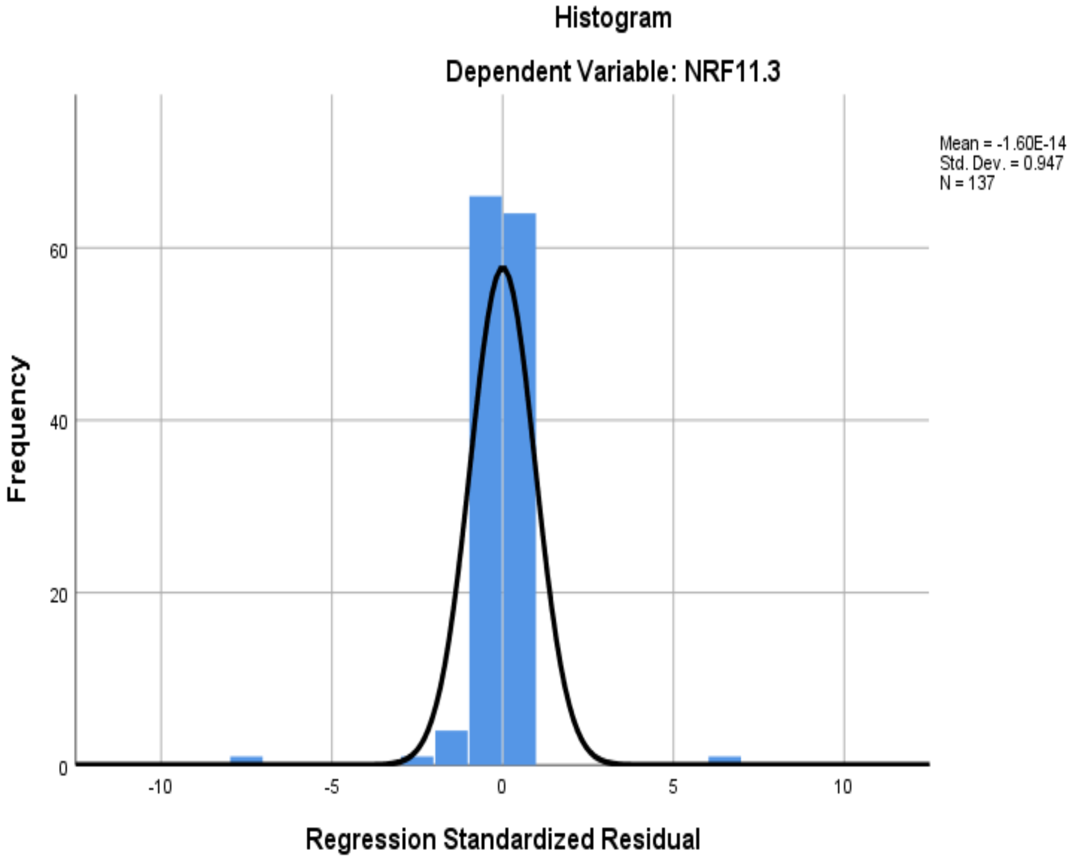
Appendix 6 Figure 2: Scatterplot matrix for Folate, Zinc, Potassium and Magnesium



Appendix 6 Figure 3: Scatterplot matrix for Iron, Vitamin A and Vitamin C



Appendix 6 Figure 4: Scatterplot matrix for Fat, Sodium and Sugar



Appendix 6 Figure 5: Histogram of regression standardized residual

Appendix 7: Summary of regression analysis modelling

Table 7.1: Summary of regression analysis modelling

Table 7.1: Stage 0 and Stage 1

Stages/ Models NRF11.3	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 0 (Full Model)	Calcium Fibre Folate Iron Magnesium Potassium Protein	Sodium Sugar Total Fat Vitamin A Vitamin C Vitamin E Zinc	None	**0.999**	**0.999**	**338.524**
Stage 1 Model 1.1	Calcium Fibre Folate Iron Magnesium Potassium	Protein Sodium Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc	**0.999**	**0.999**	**437.435**
Model 1.2	Calcium Fibre Folate Iron Magnesium Protein Sodium	Sugar Total Fat Vitamin A Vitamin C Vitamin E Zinc	Potassium	**0.998**	**0.998**	**490.431**
Model 1.3	Calcium Fibre Folate Iron	Sodium Sugar Total Fat Vitamin A	Magnesium	**0.998**	**0.997**	**540.969**

Stages/ Models NRF11.3	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
	Potassium Protein	Vitamin C Vitamin E Zinc				
Model 1.4	Calcium Folate Iron Magnesium Potassium Protein	Sodium Sugar Total Fat Vitamin A Vitamin C Vitamin E Zinc	Fibre	**0.997**	**0.997**	**571.408**
Model 1.5	Calcium Fibre Folate Iron Magnesium Potassium Protein Sodium	Total Fat Vitamin A Vitamin C Vitamin E Zinc	Sugar	**0.993**	**0.992**	**691.307**
Model 1.6	Calcium Folate Fibre Iron Magnesium Potassium Protein	Sodium Sugar Vitamin A Vitamin C Vitamin E Zinc	Total Fat	**0.991**	**0.990**	**729.449**
Model 1.7	Calcium Fibre Iron Magnesium Potassium Protein Sodium	Sugar Total Fat Vitamin A Vitamin C Vitamin E Zinc	Folate	**0.991**	**0.990**	**729.532**

Stages/ Models NRF11.3	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 1.8	Fibre Folate Iron Magnesium Potassium Protein Sodium Sugar	Total Fat Vitamin A Vitamin C Vitamin E Zinc	Calcium	**0.989**	**0.988**	**749.081**
Model 1.9	Calcium Fibre Folate Iron Magnesium Potassium Protein	Sugar Total Fat Vitamin A Vitamin C Vitamin E Zinc	Sodium	**0.986**	**0.985**	**780.507**
Model 1.10	Calcium Fibre Folate Iron Magnesium Potassium Protein Sodium	Sugar Total Fat Vitamin C Vitamin A Zinc	Vitamin E	**0.985**	**0.983**	**797.153**
Model 1.11	Calcium Fibre Folate Iron Magnesium Potassium Protein Sodium	Sugar Total Fat Vitamin C Vitamin E Zinc	Vitamin A	**0.984**	**0.982**	**806.176**
Model 1.12	Calcium	Sugar	Iron	**0.978**	**0.976**	**844.792**

Stages/ Models NRF11.3	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
	Fibre Folate Magnesium Potassium Protein Sodium	Total Fat Vitamin A Vitamin C Vitamin E Zinc				
Model 1.13	Calcium Fibre Folate Iron Magnesium Potassium Sodium	Sugar Total Fat Vitamin A Vitamin C Vitamin E Zinc	Protein	**0.961**	**0.957**	**923.672**
Model 1.14	Calcium Fibre Folate Iron Magnesium Potassium Protein	Sugar Total Fat Vitamin A Vitamin E Zinc	Vitamin C	**0.920**	**0.912**	**1022.929**

Table 7.2: Stage 2

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 2 **Model 2.1**	Calcium Fibre Folate Iron Magnesium	Protein Sodium Sugar Total Fat Vitamin A Vitamin C	Zinc Potassium	**0.998**	**0.997**	**532.312**
Model 2.2	Calcium	Protein	Zinc	**0.997**	**0.997**	**572.631**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
	Fibre Folate Iron Potassium	Sodium Sugar Total Fat Vitamin A Vitamin C	Magnesium			
Model 2.3	Calcium Folate Iron Magnesium Potassium Protein	Sodium Sugar Total Fat Vitamin A Vitamin C	Zinc Fibre	**0.996**	**0.996**	**592.731**
Model 2.4	Calcium Fibre Folate Iron Potassium Magnesium Protein	Sodium Total Fat Vitamin A Vitamin C	Zinc Sugar	**0.991**	**0.990**	**714.960**
Model 2.5	Calcium Fibre Iron Magnesium Potassium Protein	Sodium Sugar Total Fat Vitamin A Vitamin C Zinc	Zinc Folate	**0.990**	**0.989**	**739.080**
Model 2.6	Calcium Fibre Folate Iron Magnesium Potassium Protein	Sodium Sugar Vitamin A Vitamin C Vitamin E	Zinc Total Fat	**0.989**	**0.988**	**742.650**
Model 2.7	Calcium Folate Fibre Iron Magnesium Potassium Protein	Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Sodium	**0.986**	**0.985**	**777.075**
Model 2.8	Fibre	Sugar	Zinc	**0.986**	**0.984**	**783.862**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
	Folate Iron Magnesium Potassium Protein	Sodium Total Fat Vitamin A Vitamin C Vitamin E	Calcium			
Model 2.9	Calcium Fibre Folate Iron Magnesium Potassium	Protein Sodium Sugar Total Fat Vitamin C Vitamin A	Zinc Vitamin E	**0.984**	**0.982**	**798.333**
Model 2.10	Calcium Fibre Folate Iron Magnesium Potassium Protein	Sodium Sugar Total Fat Vitamin C Vitamin E	Zinc Vitamin A	**0.981**	**0.979**	**824.041**
Model 2.11	Calcium Fibre Folate Magnesium Potassium Protein	Sodium Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Iron	**0.977**	**0.975**	**846.800**
Model 2.12	Calcium Fibre Folate Iron Magnesium Potassium	Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Protein	**0.957**	**0.953**	**932.703**
Model 2.13	Calcium Fibre Folate Iron Magnesium Potassium	Protein Sodium Sugar Total Fat Vitamin A Zinc	Zinc Vitamin C	**0.920**	**0.912**	**1018.664**

Table 7.3: Stage 3

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 3 **Model 3.1**	Calcium Folate Iron Magnesium Protein Sodium	Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre	**0.993**	**0.992**	**688.134**
Model 3.2	Calcium Fibre Folate Iron Magnesium	Protein Sodium Total Fat Vitamin A Vitamin C	Zinc Potassium Sugar	**0.991**	**0.990**	**718.799**
Model 3.3	Calcium Fibre Folate Iron Magnesium Protein	Sodium Sugar Vitamin A Vitamin C Vitamin E	Zinc Potassium Total Fat	**0.989**	**0.988**	**737.760**
Model 3.4	Calcium Fibre Folate Iron	Protein Sodium Sugar Total Fat Vitamin A Vitamin C	Zinc Potassium Magnesium	**0.989**	**0.988**	**744.241**
Model 3.5	Calcium Folate Fibre Iron Magnesium Protein	Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Sodium	**0.986**	**0.984**	**778.583**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 3.6	Calcium Fibre Iron Magnesium Protein	Sugar Sodium Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Folate	**0.985**	**0.984**	**783.070**
Model 3.7	Fibre Folate Iron Magnesium Protein	Sugar Sodium Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Calcium	**0.984**	**0.983**	**793.570**
Model 3.8	Calcium Fibre Folate Iron Magnesium Protein	Sugar Sodium Total Fat Vitamin A Vitamin C	Zinc Potassium Vitamin E	**0.984**	**0.982**	**795.710**
Model 3.9	Calcium Fibre Folate Iron Magnesium Protein	Sodium Sugar Total Fat Vitamin C Vitamin E	Zinc Potassium Vitamin A	**0.980**	**0.978**	**824.429**
Model 3.10	Calcium Fibre Folate Magnesium Protein	Sodium Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Iron	**0.977**	**0.975**	**841.897**
Model 3.11	Calcium Fibre Folate Iron Magnesium	Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Protein	**0.952**	**0.947**	**944.947**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 3.12	Calcium Fibre Folate Iron Magnesium	Protein Sodium Sugar Total Fat Vitamin E	Zinc Potassium Vitamin C	**0.915**	**0.908**	**1021.238**

Table 7.4: Stage 4

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 4 **Model 4.1**	Calcium Folate Iron Magnesium Protein	Sodium Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar	**0.986**	**0.985**	**771.253**
Model 4.2	Calcium Folate Iron Protein	Sodium Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Magnesium	**0.984**	**0.982**	**790.472**
Model 4.3	Calcium Fibre Iron Magnesium Protein	Sodium Sugar Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Total Fat	**0.980**	**0.979**	**816.522**
Model 4.4	Calcium Folate Iron Magnesium Protein	Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sodium	**0.979**	**0.977**	**827.705**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 4.5	Folate Iron Protein Magnesium Sodium	Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Calcium	**0.977**	**0.975**	**836.140**
Model 4.6	Calcium Folate Iron Magnesium Protein	Sodium Sugar Total Fat Vitamin C Vitamin E	Zinc Potassium Fibre Vitamin A	**0.976**	**0.974**	**842.166**
Model 4.7	Calcium Folate Magnesium Protein Sodium	Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Iron	**0.975**	**0.973**	**849.571**
Model 4.8	Calcium Folate Iron Magnesium Protein	Sodium Sugar Total Fat Vitamin A Vitamin C	Zinc Potassium Fibre Vitamin E	**0.975**	**0.973**	**851.527**
Model 4.9	Calcium Iron Protein Magnesium Sodium	Sugar Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Folate	**0.967**	**0.964**	**889.255**
Model 4.10	Calcium Fibre Folate Iron Magnesium	Sodium Sugar Total Fat Vitamin C Vitamin E	Zinc Potassium Fibre Protein	**0.947**	**0.942**	**952.991**
Model 4.11	Calcium Folate Iron Magnesium Protein	Sodium Sugar Total Fat Vitamin A Vitamin E	Zinc Potassium Fibre Vitamin C	**0.880**	**0.871**	**1063.641**

Table 7.5: Stage 5

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 5 **Model 5.1**	Calcium Folate Iron Protein Sodium	Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium	**0.978**	**0.976**	**829.737**
Model 5.2	Calcium Folate Iron Protein Magnesium	Sodium Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Total Fat	**0.976**	**0.975**	**837.133**
Model 5.3	Calcium Fibre Iron Magnesium Protein	Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Sodium	**0.973**	**0.971**	**856.346**
Model 5.4	Folate Iron Magnesium Protein Sodium	Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Calcium	**0.969**	**0.967**	**871.739**
Model 5.5	Calcium Folate Iron Protein Magnesium	Sodium Total Fat Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Vitamin A	**0.969**	**0.967**	**874.033**
Model 5.6	Calcium Folate Iron Magnesium Protein	Sodium Total Fat Vitamin A Vitamin C	Zinc Potassium Fibre Sugar Vitamin E	**0.965**	**0.963**	**889.807**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 5.7	Calcium Folate Magnesium Protein Sodium	Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Iron	**0.965**	**0.963**	**889.826**
Model 5.8	Calcium Iron Magnesium Protein Sodium	Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Folate	**0.959**	**0.956**	**911.106**
Model 5.9	Calcium Folate Iron Magnesium Sodium	Total Fat Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Protein	**0.933**	**0.929**	**978.706**
Model 5.10	Calcium Folate Iron Magnesium Protein	Sodium Total Fat Vitamin E Vitamin A	Zinc Potassium Fibre Sugar Vitamin C	**0.880**	**0.872**	**1058.826**

Table 7.6: Stage 6

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 6 **Model 6.1**	Calcium Folate Iron Protein Sodium	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat	**0.969**	**0.968**	**866.802**
Model 6.2	Calcium Folate Iron Protein Total Fat	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Sodium	**0.968**	**0.966**	**872.286**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 6.3	Calcium Fibre Iron Magnesium Protein	Total Fat Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Vitamin A	**0.964**	**0.961**	**890.749**
Model 6.4	Folate Iron Protein Sodium Total Fat	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Calcium	**0.960**	**0.958**	**903.196**
Model 6.5	Calcium Folate Iron Protein Sodium	Total Fat Vitamin C Vitamin A	Zinc Potassium Fibre Sugar Magnesium Vitamin E	**0.946**	**0.943**	**944.825**
Model 6.6	Calcium Iron Magnesium Protein Sodium	Total Fat Vitamin A Vitamin C	Zinc Potassium Fibre Sugar Magnesium Folate	**0.940**	**0.936**	**958.916**
Model 6.7	Calcium Folate Iron Sodium Total Fat	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Protein	**0.921**	**0.916**	**996.476**
Model 6.8	Calcium Folate Protein Sodium Total Fat	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Iron	**0.903**	**0.897**	**1024.807**
Model 6.9	Calcium Folate Iron Protein Sodium	Total Fat Vitamin A Vitamin E	Zinc Potassium Fibre Sugar Magnesium	**0.874**	**0.867**	**1060.600**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
			Vitamin C			

Table 7.7: Stage 7

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 7 **Model 7.1**	Calcium Folate Iron Protein	Vitamin E Vitamin C Vitamin A	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium	**0.960**	**0.957**	**900.077**
Model 7.2	Calcium Iron Protein Sodium	Vitamin E Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Vitamin A	**0.955**	**0.953**	**914.803**
Model 7.3	Folate Iron Protein Sodium	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Calcium	**0.951**	**0.948**	**926.403**
Model 7.4	Calcium Folate Protein Iron	Sodium Vitamin A Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat Vitamin E	**0.939**	**0.936**	**957.002**
Model 7.5	Calcium Iron Protein Total Fat	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Folate	**0.936**	**0.933**	**962.652**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 7.6	Calcium Folate Iron Sodium	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Protein	**0.913**	**0.909**	**1004.620**
Model 7.7	Calcium Folate Protein Sodium	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Iron	**0.894**	**0.888**	**1032.682**
Model 7.8	Calcium Folate Iron Protein	Sodium Vitamin A Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Vitamin C	**0.855**	**0.847**	**1075.364**

Table 7.8: Stage 8

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 8 **Model 8.1**	Calcium Folate Iron	Protein Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A	**0.945**	**0.943**	**937.389**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 8.2	Folate Iron Protein	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Calcium	**0.945**	**0.942**	**938.168**
Model 8.3	Calcium Folate Iron	Protein Vitamin A Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin E	**0.930**	**0.927**	**970.266**
Model 8.4	Calcium Protein Iron	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Folate	**0.925**	**0.922**	**979.810**
Model 8.5	Calcium Iron Folate	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Protein	**0.910**	**0.905**	**1005.819**
Model 8.6	Calcium Folate Protein	Vitamin A Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Iron	**0.883**	**0.878**	**1041.042**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 8.7	Calcium Folate Iron	Protein Vitamin E Vitamin A	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin C	**0.836**	**0.829**	**1086.872**

Table 7.9: Stage 9

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 9 **Model 9.1**	Folate Iron Protein	Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium	**0.931**	**0.929**	**963.293**
Model 9.2	Calcium Folate Iron	Protein Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Vitamin E	**0.916**	**0.913**	**990.944**

Stages/ Models	Nutrients entered into model		Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 9.3	Calcium Folate Iron	Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Protein	**0.895**	**0.891**	**1020.841**
Model 9.4	Calcium Protein Iron	Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Folate	**0.895**	**0.891**	**1021.281**
Model 9.5	Calcium Folate Protein	Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Iron	**0.870**	**0.865**	**1051.024**
Model 9.6	Calcium Folate Iron	Protein Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Vitamin C	**0.825**	**0.819**	**1091.062**

Table 7.10: Stage 10

Stages/ Models	Nutrients entered into model	Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 10 **Model 10.1**	Folate Protein Iron Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E	**0.901**	**0.898**	**1008.126**
Model 10.2	Folate Iron Vitamin E Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Protein	**0.877**	**0.873**	**1038.023**
Model 10.3	Iron Protein Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Folate	**0.876**	**0.872**	**1039.407**
Model 10.4	Folate Protein Vitamin C Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Iron	**0.842**	**0.837**	**1072.416**

Stages/ Models	Nutrients entered into model	Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 10.5	Folate Iron Protein Vitamin E	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin C	**0.810**	**0.805**	**1097.413**

Table 7.11: Stage 11

Stages/ Models	Nutrients entered into model	Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 11 **Model 11.1**	Folate Iron Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E Protein	**0.855**	**0.852**	**1055.730**
Model 11.2	Iron Protein Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E Folate	**0.833**	**0.829**	**1075.040**
Model 11.3	Folate Protein Vitamin C	Zinc Potassium Fibre Sugar	**0.818**	**0.814**	**1086.907**

Stages/ Models	Nutrients entered into model	Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
		Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E Iron			
Model 11.4	Folate Protein Iron	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E Vitamin C	**0.760**	**0.754**	**1124.918**

Table 7.12: Stage 12

Stages/ Models	Nutrients entered into model	Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 12 **Model 12.1**	Iron Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E Protein Folate	**0.787**	**0.784**	**1103.164**
Model 12.2	Folate Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat	**0.779**	**0.776**	**1108.289**

Stages/ Models	Nutrients entered into model	Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
		Sodium Vitamin A Calcium Vitamin E Protein Iron			
Model 12.3	Iron Folate	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E Protein Vitamin C	**0.597**	**0.591**	**1190.925**

Table 7.13: Stage 13

Stages/ Models	Nutrients entered into model	Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Stage 13 **Model 13.1**	Vitamin C	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E Protein Folate Iron	**0.644**	**0.641**	**1169.008**

Stages/ Models	Nutrients entered into model	Nutrients removed from model	R^2	Adjusted R^2	Bayesian information criterion (BIC)
Model 13.2	Iron	Zinc Potassium Fibre Sugar Magnesium Total Fat Sodium Vitamin A Calcium Vitamin E Protein Folate Vitamin C	**0.320**	**0.315**	**1257.486**

Appendix 8: Classification of Ghanaian foods with by both WHO model and NRF11.3 index

Table 8.1

Food items	NRF11.3/100kcals	WHO Classification 1= healthy; 0=unhealthy
Abeduro (turkey berries)	159.39	1
Aboloo	27	1
Ademe (jute leaves)	271.76	1
Adziado (herring stock, grilled)	56.95	1
Agushi soup	40.91	0
Akple (unfermented cornmeal)	15.28	1
Aluguntugui (sweetsop)	110.35	1
Amma (spinach broth) with oil	69.79	1
Anchovies, canned in oil (drained)	4.24	0
Avocado, pulp, raw	44.03	1
Baked beans	81.08	1
Banana, raw	32.63	1
Banku (fermented corn and cassava dough mixed with water, cooked)	46.32	1
Bean cake, koose	13.06	1
Bean stew	92.21	1
Beef, meat, lean (boiled)	65.19	1
Biscuits (sweet)	2.4	0
Blolovi (catfish, steamed)	48.44	1
Bofrot (donut, African)	-3.25	0
Boiled corn meal	-35.84	0
Cabbage stew	139.05	1
Candy and toffee	-14.92	0
Carrots, raw	176.95	1
Cassava, tuber (boiled) without salt	43.90	1
Chicken, dark meat, flesh, and skin (boiled)	15.72	0
Chicken, dark meat, flesh, and skin (grilled)	19.29	0
Chinese and White Cabbage	339.55	1
Chips (snack made from bread flour dough fried)	36.49	0
Chocolate	-2.41	0
Coconut, mature kernel, fresh, raw	8.19	1
Cookies	-3.33	0
Corned beef	15.92	0
Crab	102.05	1
Doughnuts	-2.43	0
Duck	4.34	1
Egg stew	27.16	0
Egg, chicken (boiled)	35.39	1

Evaporated milk	25.05	0
Fish pie	44.43	1
Fried chicken	0.52	0
Fried egg	21.5	1
Fried sausage	-12.86	0
Fruit juices (unsweetened)	148.57	0
Fufu	47.01	1
Gaari	17.59	1
Garden egg stew	36.19	1
Goat, meat (boiled) without salt	43.85	1
Green leaf, medium, relish with oil	143.81	1
Grilled beef	68.53	1
Grounded pepper (raw)	199.79	1
Groundnut soup	57.38	0
Groundnuts	32.50	1
Guinea fowl (boiled)	65.77	1
Hausa koko	16.55	1
Hot cereals/maize porridge	2.14	1
Ice-cream	-5.81	0
Indomie (noodles, egg, dried, boiled in unsalted water)	25.36	1
Jollof rice	15.34	1
Kenkey (Fante and Ga)	53.33	1
Konkonte	26.01	1
Kontomire soup	287.38	1
Kontomire stew	56.29	0
Koobi (dried, salted fish) 2	25.35	1
Kpanla	49.27	1
Lentil-pea and bean soup/stew	38.1	1
Lettuce	299.82	1
Light soup	91.99	1
Liver and giblets	208.26	1
Local brown rice (boiled)	27.47	1
Macaroni	23.90	1
Maize (boiled, roasted)	34.85	0
Mango, raw	156.36	1
Margarine (regular)	-14.52	0
Mashed kenkey	11.91	0
Meat pie	15.61	0
Melon seeds (agushi)	40.92	1
Millet porridge, with sugar	-2.22	0
Moringa stew	351.70	1
Mudfish (grilled)	50.81	1
Oats, porridge	22.13	1

Octopus fried	16.63	1
Offal, beef tripe, (boiled)	50.54	1
Okro soup	61.67	1
Okro stew	51.30	0
Onions	161.39	
Orange, raw	145.02	1
Palm nut soup	96.01	0
Palm oil, red	8.83	0
Pasta, white (boiled)	22.53	1
Pastry	6.80	0
Pear, raw	29.40	1
Peppers	301.72	1
Pineapple, raw	114.55	1
Plantain, dried, chips	13.91	0
Plantain, mashed, with palm oil (Eto)	12.14	0
Plantain, ripe (boiled) without salt	40.52	1
Plantain, ripe (fried)	26.88	0
Pork, meat, approx.20% fat, grilled	5.59	0
Powdered milk	40.76	0
Red (plantain and beans)	48.91	1
Rice porridge	-3.81	0
Salmon fried	4.89	1
Sardine in oil, canned	46.21	0
Scrambled egg	10.05	1
Shito	21.93	0
Smoked fish	52.50	1
Sodas and minerals (sweetened sodas)	-27.9	0
Sugar, white	-6.79	0
Sweet pie or tart	-4.76	0
Sweet potato yellow (boiled)	43.47	1
Sweetened coffee	-29.94	0
Sweetened condensed milk	1.63	0
Sweetened tea	-29.79	0
Tilapia (non- fried)	130.7	1
Tilapia (fried)	114.50	0
Tomato sauce and stew	14.21	0
Tomatoes, red, ripe, raw	217.12	1
Tombrown	23.85	1
Tuna (fried)	46.22	1
Tuna (non-fried)	71.09	1
Tuo Zaafi (T.Z)	15.75	1
Turkey (fried)	49.94	1
Unsweetened tea	-23.93	1

Vegetable soup	6.14	1
Waakye	47.01	1
Watermelon	56.15	1
White bread (sugar bread)	12.17	0
White crisp bread	13.76	0
White rice (boiled)	11.80	1
Yam (boiled)	56.25	1
Yam (fried)	18.65	1
Burkina drink	11.88	Missing data
Cocoa milk drink (Milo, chocolim, richoco)	14.87	Missing data
Flavoured yoghurt	39.65	Missing data
Light and diet drinks	-26.40	Missing data
Milk	37.10	Missing data
Sobolo drink	338.59	Missing data
Wele (cow skin and cow feet)	Missing data	Missing data

Appendix 9: Rankings of Commonly Consumed Foods and Beverages by Ghanaian Experts

Table 9.1 Rankings of Commonly Consumed Foods and Beverages by Ghanaian Experts.

Food items	Number of Food Items Classified	Missing	Mean	Median	Mode	Std. Deviation	Range
Abeduro	100	29	4.64	5.00	5	0.871	4
Aboloo	101	28	3.92	4.00	4	1.036	4
Ademe	102	27	4.58	5.00	5	0.750	4
Adziado	101	28	4.50	5.00	5	0.856	4
Agushi soup	102	27	4.83	5.00	5	0.375	1
Akple	102	27	4.13	4.00	4	0.886	4
Aluguntugui	101	28	4.49	5.00	5	0.832	3
Amma	100	29	4.26	4.00	5	0.787	3
Anchovies	100	29	4.57	5.00	5	0.977	4
Avocado, pulp, raw	101	28	4.71	5.00	5	0.726	4
Baked beans	102	27	3.75	4.00	4	1.087	4
Banana, raw	102	27	4.66	5.00	5	0.814	4
Banku	102	27	4.34	4.00	5	0.711	3
Bean cake, koose	102	27	4.42	5.00	5	0.989	4
Bean stew	102	27	4.87	5.00	5	0.390	2
Beef, meat, lean	103	26	4.39	5.00	5	0.888	4
Biscuits (sweet)	103	26	2.45	2.00	2	1.144	4
Blolovi	102	27	4.55	5.00	5	0.766	4
Bofrot	103	26	2.88	3.00	2	1.207	4
Boiled corn meal	103	26	4.30	4.00	4	0.712	3
Burkina drink	103	26	3.92	4.00	4	1.073	4
Cabbage stew	103	26	4.67	5.00	5	0.772	4
Candy and toffee	103	26	1.56	1.00	1	0.987	4
Carrots, raw	103	26	4.83	5.00	5	0.466	3
Cassava, tuber	103	26	4.12	4.00	4	0.745	3
Chicken (boiled)	103	26	4.24	4.00	4	0.846	3
Chicken (grilled)	103	26	4.14	4.00	5	1.029	4
Chinese and White Cabbage	99	30	4.20	4.00	5	0.915	4
Chips	103	26	2.68	2.00	4	1.254	4
Chocolate	103	26	3.64	4.00	4	1.119	4
Cocoa milk drink	103	26	3.83	4.00	4	0.974	4
Coconut, mature kernel, fresh, raw	103	26	4.58	5.00	5	0.721	4
Cookies	103	26	2.48	2.00	2	1.267	4
Corned beef	103	26	2.79	2.00	2	1.194	4
Crab	103	26	4.56	5.00	5	0.723	3
Doughnuts	100	29	2.72	3.00	4	1.272	4

Food items	Number of Food Items Classified	Missing	Mean	Median	Mode	Std. Deviation	Range
Duck (boiled)	100	29	4.33	4.00	5	0.829	4
Egg stew	100	29	4.51	5.00	5	0.785	3
Egg, chicken (boiled)	100	29	4.60	5.00	5	0.603	2
Evaporated milk	100	29	4.18	4.00	4	0.833	4
Fish pie	100	29	3.85	4.00	4	1.086	4
Flavoured yoghurt	100	29	3.96	4.00	4	0.875	4
Fried chicken	100	29	2.91	3.00	4	1.207	4
Fried egg	100	29	3.26	4.00	4	1.186	4
Fried sausage	100	29	2.65	2.00	2	1.313	4
Fruit juices	100	29	4.57	5.00	5	0.769	3
Fufu	100	29	3.97	4.00	4	0.937	4
Gaari	100	29	3.82	4.00	4	0.968	4
Garden egg stew	100	29	4.71	5.00	5	0.556	3
Goat, meat (boiled) without salt	100	29	4.37	5.00	5	0.787	4
Green leaf, relish	100	29	4.53	5.00	5	0.658	3
Grilled beef	100	29	3.97	4.00	4	1.049	4
Grounded pepper	100	29	3.77	4.00	3	1.014	4
Groundnut soup	100	29	4.36	5.00	5	0.871	4
Groundnuts	98	31	4.60	5.00	5	0.605	3
Guinea fowl (boiled)	100	29	4.69	5.00	5	0.563	3
Hausa koko	99	30	4.20	4.00	5	0.990	4
Hot cereals/maize porridge	100	29	4.41	5.00	5	0.753	3
Ice-cream	100	29	2.29	2.00	2	1.140	4
Indomie (noodles)	99	30	1.90	2.00	1	1.015	4
Jollof rice	100	29	4.30	4.00	5	0.847	3
Kenkey (Fante& Ga)	100	29	4.36	4.00	5	0.718	3
Konkonte	100	29	3.86	4.00	4	1.064	4
Kontomire soup	99	30	4.89	5.00	5	0.375	2
Kontomire stew	100	29	4.76	5.00	5	0.534	3
Koobi (salted fish)	100	29	2.81	2.00	2	1.220	4
Kpanla	96	33	4.40	5.00	5	0.761	3
Lentil-pea and bean soup/stew	100	29	4.83	5.00	5	0.403	2
Lettuce	100	29	4.88	5.00	5	0.327	1
Light and diet drinks	97	32	3.20	4.00	4	1.426	4
Light soup	98	31	4.51	5.00	5	0.777	3
Liver and giblets	98	31	4.60	5.00	5	0.743	3
Local brown rice	98	31	4.86	5.00	5	0.476	3
Macaroni	99	30	3.03	3.00	4	1.191	4

Food items	Number of Food Items Classified	Missing	Mean	Median	Mode	Std. Deviation	Range
Maize(boiled,roasted)	99	30	4.46	5.00	5	0.611	2
Mango, raw	98	31	4.66	5.00	5	0.786	4
Margarine (regular)	99	30	2.25	2.00	2	1.091	4
Mashed kenkey	99	30	4.09	4.00	4	0.949	4
Meat pie	99	30	3.17	4.00	4	1.270	4
Melon seeds (agushi)	99	30	4.86	5.00	5	0.350	1
Milk	99	30	4.31	4.00	5	0.829	4
Millet porridge	98	31	4.72	5.00	5	0.570	3
Moringa stew	99	30	4.82	5.00	5	0.482	3
Mudfish (grilled)	99	30	4.58	5.00	5	0.757	3
Oats, porridge	99	30	4.75	5.00	5	0.541	3
Octopus fried	98	31	3.64	4.00	4	1.124	4
Offal, beef tripe,	99	30	4.00	4.00	5	1.134	4
Okro soup	99	30	4.78	5.00	5	0.442	2
Okro stew	99	30	4.54	5.00	5	0.644	3
Onions and Garlic	99	30	4.91	5.00	5	0.353	2
Orange, raw	98	31	4.80	5.00	5	0.703	4
Palm nut soup	99	30	4.22	5.00	5	1.006	4
Palm oil, red	99	30	4.10	4.00	4	0.985	4
Pasta, white (boiled)	99	30	3.09	3.00	4	1.213	4
Pastry	98	31	2.56	2.00	2	1.149	4
Pear, raw	99	30	4.54	5.00	5	0.837	4
Peppers	99	30	3.91	4.00	5	1.001	4
Pineapple, raw	98	31	4.69	5.00	5	0.765	4
Plantain, dried, chips	98	31	3.66	4.00	4	1.201	4
Plantain, (Eto)	99	30	4.30	5.00	5	0.886	4
Plantain, ripe (boiled) without salt	99	30	4.43	5.00	5	0.771	3
Plantain, ripe (fried)	98	31	3.37	4.00	4	1.255	4
Pork, meat, approx.20% fat, grilled	99	30	2.99	3.00	4	1.411	4
Powdered milk	99	30	3.86	4.00	4	1.040	4
Red, red	96	33	4.48	5.00	5	0.833	3
Rice porridge	95	34	4.22	4.00	4	0.801	3
Salmon fried	96	33	3.95	4.00	4	0.999	4
Sardine in oil, canned	95	34	3.13	3.00	4	1.178	4
Scrambled egg	94	35	4.21	4.00	5	0.890	3
Shito	95	34	3.58	4.00	4	1.037	4
Smoked fish	96	33	4.23	4.00	5	0.946	3
Sobolo drink	95	34	4.35	4.00	5	0.782	3

Food items	Number of Food Items Classified	Missing	Mean	Median	Mode	Std. Deviation	Range
Sodas (sweetened)	96	33	1.74	1.00	1	1.028	4
Sugar, white	96	33	1.79	1.00	1	1.035	4
Sweet pie or tart	96	33	2.35	2.00	2	1.231	4
Sweet potato yellow	95	34	4.61	5.00	5	0.624	3
Sweetened coffee	96	33	2.08	2.00	2	1.043	4
Sweetened condensed milk	96	33	2.09	2.00	1	1.206	4
Sweetened tea	96	33	2.40	2.00	2	1.192	4
Tilapia (non- fried)	96	33	4.71	5.00	5	0.521	2
Tilapia (fried)	95	34	3.81	4.00	4	0.982	4
Tomato sauce and stew	96	33	4.27	4.00	5	0.864	4
Tomatoes, red, ripe, raw	93	36	4.81	5.00	5	0.449	2
Tombrown	95	34	4.79	5.00	5	0.459	2
Tuna (non-fried)	94	35	4.76	5.00	5	0.522	3
Tuna (fried)	95	34	3.75	4.00	4	1.041	4
Tuo Zaafi (T.Z)	96	33	4.34	5.00	5	1.024	4
Turkey (fried)	96	33	3.35	4.00	4	1.231	4
Unsweetened tea	96	33	3.97	4.00	4[a]	1.031	4
Vegetable soup	96	33	4.90	5.00	5	0.340	2
Waakye	94	35	4.74	5.00	5	0.567	3
Watermelon	95	34	4.88	5.00	5	0.481	4
Wele (cow skin and feet)	96	33	2.83	3.00	3	1.092	4
White bread	96	33	2.27	2.00	2	1.090	4
White crisp bread	95	34	2.47	2.00	2	1.100	4
White rice (boiled)	96	33	3.01	3.00	4	1.261	4
Yam (fried)	96	33	3.18	4.00	4	1.142	4
Yam (boiled)	96	33	4.40	5.00	5	0.703	3

Appendix 10: Food and beverage items consumed from 24-hour recall

Table 10.1 Food and beverage items consumed from 24-hour recall (Holdsworth et al., 2020)

	Food group	Food items : n=138 foods
1	Fats and oils (oils, spreading fats and fats)	Palm oil, margarine, coconut oil
2	Sugar and sweet spreads	Sugar, other sugar and sweet spreads
3	Red meat, poultry, offals & giblets	Pork, fried chicken, boiled chicken, grilled chicken, turkey, goat, beef, grilled beef, fried beef, wele (cow hide or /feet), liver and giblets, offal, guinea fowl, duck
4	Fish and Shellfish	Fish non-fried (barracuda, tuna, tilapia, salmon, cassava fish, mudfish, sardine, kpanla/adziador (marine-sourced fish, usually smoked), fish fried (tilapia fried, tuna fried, kyenam (fried fish), seafood/shellfish (snail, clams, /adodi, crab, oysters, octopus), dried fish (anchovies), canned fish, smoked fish, kako (salted fish)
5	Eggs	Scrambled egg, fried egg, boiled egg
6	Processed meat	Fried sausage, corned beef
7	Dairy products	Sweetened condensed milk, powdered milk, evaporated milk, milk, flavoured yoghurt, burkina drink (ground millet/maize and pasteurized milk)
8	Sweetened tea & coffee	Sweetened tea, sweetened coffee
9	Sugar-sweetened Beverages (except tea/coffee)	Light and soft drinks, sodas and sweetened beverages, fruit-based drinks, cocoa milk drink (milo, chocolim, richoco), sobolo (hibiscus tea: dried hibiscus leaves and sweetened with sugar)
10	Alcoholic beverages	Beer, wine,
11	Cakes and sweets	Sweet pie or tart, pastries, biscuits(imported/local), chocolate, sweets and toffee, ice cream, groundnut cake, doughnuts, bofrot (dry doughnuts)
12	Crisps and crackers	Plantain crisps, chips (snack made from bread flour dough fried)
13	Modern mixed dishes	Fried rice, fried noodles
14	Traditional mixed dishes	Bean stew, eto (boiled plantain or yam with palm oil), waakye (cooked rice and beans meal), red (fried plantain with bean stew), jollof rice, egg stew, garden egg stew, cabbage stew, tomato sauce and stew, okro stew, nkontomire stew (local spinach stew), moringa stew (made with moringa oleifera leaves)
15	Condiments	Shito (a traditional condiment/very hot sauce), pepper sauce
16	Wholegrain cereals	Local brown rice, boiled corn meal, maize sorghum, whole grain bread (seeded), whole (brown) bread, maize (boiled, roasted), millet porridge, other wholegrain cereals
17	Refined cereals	White bread (sugar bread, butter bread, tea bread), white crisp bread, oats, white rice, pasta, macaroni, hot cereals/porridge/maize porridge/rice porridge, tapioca, tombrown (porridge of roasted corn/cereal flour), indomie/noodles, Hausa koko (spicy millet porridge)
18	Roots/tubers not fried	Plantain (roasted/boiled), cassava (boiled), gaari/gari (cassava powder), yam, fufu (boiled cassava, yam, plantain or cocoyam), konkonte (fufu made solely from cassava flour/water)
19	Roots/tubers fried	Plantain fried, sweet potatoes fried, yam fried
20	Legumes and pulses	Baked beans, red beans
21	Nuts and seeds	Agushi (melon seeds), groundnuts
22	Fruit	Aluguntungui (sour soup), banana, watermelon, avocado, orange, pineapple, pear, mango, coconut, fruit juices (unsweetened), pawpaw
23	Vegetables	Green leaves, spinach, lettuce, chinese and white cabbage, tomatoes, peppers, carrots, cucumber, eggplant, green beans, onions and garlic, mushrooms, pumpkin, bottle gourd, okro, turkey berries, other locally available leaves and traditional vegetables
24	Savoury pies	Meat pie, fish pie, koose (bean cake;spicy black-eyed pea fritter)
25	Fermented and non-fermented grain products	Akple (unfermented cereal meal), t.z/tuo zaafi (unfermented cereal meal), kenkey-ga/fante (fermented cereal meal), banku (fermented cereal meal), aboloo (fermented cereal meal), mashed kenkey (kenkey with sugar, milk and possibly peanut)
26	Soups	Ademe soup (made from leaves of jute plant), light soup, vegetable soup, agushie soup (melon seeds), amma soup (green leafy vegetable), groundnut soup, lentil pea and bean soup, okro soup, palmnut soup, nkontomire soup (made from local spinach leaves), other soup

Source : (Holdsworth et al., 2020)

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