MSc Project Dissertation

**Classification of Metabolic Disorders and Development of Personalised Nutrition Plans for Improved Health Management in the UK Population**

**Chapters 1 and 2**

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# Chapter 1: Introduction

## 1.1 Background to the Topic

One of the most urgent community health concerns in the UK regards metabolic disorders, which include type 2 diabetes, obesity, dyslipidemia, and hypertension. These disorders, often interrelated due to a cluster of risk factors, are typified by physiological imbalances in insulin responsiveness, lipid homeostasis, and blood pressure control, collectively known as metabolic syndrome. These disorders are constantly on the increase because of a shift towards the use of less healthy foods, a more sedentary lifestyle, and urbanisation. It was observed that more than 28% of UK adults are already clinically obese, and nearly 4.9 million people are already living with diagnosed diabetes, and are expected to grow further (Alabdullah, 2023).

Identification of metabolic risks at an early stage plays a crucial role in mitigating the burden of chronic illness. Nevertheless, conventional practices of diagnosing and treating with nutrition are more or less generalized, providing dietary recommendations that can be summed up as one size fits all. Although foundational dietary guidance can be accessed by the population through publicly available resources such as the NHS, such resources cannot accommodate the specificities of the individual risk profile, lifestyle, or any comorbidity. Personalised nutrition, where the diet is designed for a person according to his or her health indicators and state of their metabolism, has thus become a factor in the field of clinical practice and even research.

Recent development in machine learning (ML) processes within the healthcare sector presents novel potential to break down the challenging clinical and biometric data to infer disease orientations to recommend personalised medical approaches. Where conventional methods cannot reveal minute links between metabolic parameters like the BMI, glucose, HDL, and triglyceride concentrations, ML can. The decision-making systems have now become more transparent and trusted by the user due to the introduction of explainable AI libraries like SHAP (SHapley Additive Explanations).

An original way to intervene in individual health is to combine the ML classification methods and rule-based nutrition planning. In particular, using data of the anonymised population health, it is possible to classify metabolic disorders effectively by training algorithms like Random Forest and XGBoost. The connection of the model outputs and dietary recommendations according to the NHS and WHO guidelines may allow the creation of dynamic and personalised nutrition planning. Such a strategy can not only increase access to personalised care but also lessen the burden of clinical consultation, hence lessening the burden on the NHS infrastructure.

The availability of open data on healthcare in the UK and the high emphasis on implementing AI in the realm of public healthcare make the case of a data-driven, scalable metabolic disorder-detecting and nutritional recommendation tool unmissable. This dissertation will examine such a possibility through a technical implementation, but with a social impact on health.

## 1.2 Research Rationale

The rationale for conducting the present research is associated with the combination of problems of high prevalence of chronic diseases, the heavy burden of the healthcare system, and the weak individualisation of nutritional recommendations in the UK. Such metabolic diseases like type 2 diabetes, insulin resistance, and cardiovascular risk factors are not limited to particular ages or socio-economic classes. With lifestyle diseases continuing to spread among different populations, there arises a dire need for adaptive tools that can provide early identification and individual health guidance (Mbata et al., 2024).

Although there is an increased availability of health information, the majority of dietary guidelines are still generic and unresponsive to the personal biochemical or metabolic state. As an example, the NHS Eatwell Guide has been developed according to the needs of a typical population, and is not a self-adjusting tool relative to glucose tolerance, lipid profile, or blood pressure category. Because of this, the same dietary recommendation can be drawn up by people with different levels of risk, and this may not work to prevent the progression or reverse it.

Machine learning is a possibility of closing this gap. Several clinical activities, including disease prediction, diagnosis, and triaging, have already demonstrated the good promise of the technology (Stamate et al., 2024). At their best, machine learning algorithms would classify people into risk buckets, using their metabolic biomarkers, when trained on structured health data. Accommodated alongside interpretability methods like SHAP, these modeling systems not only make accurate predictions but also explain them, i.e., they give transparency, which is critical in healthcare-related contexts.

At the same time, personalised nutrition science has developed as it has become more popular to specialise dietary planning to the individual. However, tools that align nutritional recommendations with clinical risk patterns are still in their infancy, and they frequently fail to be integrated with AI-guided diagnostics. This project attempts operationalisation: a prediction model based on classification, coupled with an evidence-based dietary logic, will yield both detection and response, namely, not only being told that one has a problem but being provided with steps they can take in the presence of that problem.

Technically, this study is also a chance to test machine learning models within the context of the field of health, apply a recommendation system built utilizing logic-based programming, and investigate the interpretability of the models through the prism of the state-of-the-art tools.

These applied aspects would not only satisfy the academic requirements but also provide the researcher with the skills that would be applicable in the development of AI techniques, healthcare analytics, and digital health solutions.

Finally, the study is equally socially and technologically significant and can provide an answer to the real-world problems with the help of simple, understandable, and repeatable techniques.

## 1.3 Aim and Objective

### 1.3.1 Aim

The research aim is to test a machine learning classification tool to assist in metabolic disorders, and join it with a personalised nutrition recommendation system. The anonymised health information will be subjected to the system to forecast the metabolic risk categories along with dietary advice compliant with those recommended by the NHS and WHO, thus helping the people in the UK population effectively manage their health.

### 1.3.2 Objectives

* To ensure and preprocess health data applicable to metabolic indicators of the UK population, maintaining data quality and balance.
* To create and compare several supervised machine learning models (such as Random Forest and XGBoost) for the effective classification of metabolic abnormalities.
* To operationalise a rule-based recommendation engine that will associate the results of classifications with personalised dietary plans that are evidence-based.
* To combine or incorporate classification and recommendation components in a single artefact, with diagrams and reporting.
* To measure the performance of the model and the usability of the system, its interpretability (through SHAP), and its compliance with referrals to the guidelines on nutrition in public health.

## 1.4 Research Questions

**RO1:** Which important tendencies and relationships in the UK data of metabolic health can be deployed to categorise metabolic disorders with accuracy?

**RO2:** Which of these supervised learning algorithms (Random Forest, XGBoost, Support Vector Machines) offers the most certifiable predictive ability in terms of disorder classification?

**RO3:** What is the way forward to associate the results of a machine learning classifier with dietary advice to produce feasible and personalized nutrition plans?

**RO4:** How will such personalized recommendations fare as opposed to basing normal dietetic recommendations on a simulated patient scenario?

**RO5:** Both aspects of the research questions are to be devoted to the technical effectiveness of machine learning models and their legitimate embodiment in the area of personalised nutrition.

## 1.5 Thesis Structure

The chapters of the dissertation are structured logically and are divided into six categorized chapters that will lead to the final objective of the project, which is the development and evaluation of a personalised nutrition system concerning metabolic classification:

**Chapter 1: Introduction -** This chapter gives the background, rationale, aims, objectives, research questions, and the general structure of the study.

**Chapter 2: Literature Review -** Reviews related health research on the metabolism disorder, machine learning, personalised nutrition, model interpretability, and combining the classification with a recommendation system.

**Chapter 3: Methodology -** describes the research design, data utilized, machine learning algorithms applied, preprocessing of data, and metrics quality, as well as ethical aspects.

**Chapter 4: Data Analysis and Results -** Gives the results of training and testing the machine learning models, EDA results, the performance statistics, and the output of the recommendation engine.

**Chapter 5: Discussion -** Interpretation of the findings in association with the initial goals and questions of research. Calculates model accuracy, quality of recommendation, and ease of use of the system.

**Chapter 6: Conclusion and Recommendations -** Presents a synthesis of the main findings, states the limitations, proposes future developments, and speaks concerning the future of implementing such systems on a mass scale in public health.

The chapters are structured in such a way that each chapter is based on the earlier one, which makes both the technical and academic sense of the whole dissertation.

# Chapter 2: Literature Review

## 2.1 Nutrition and the Role of AI Review

Kassem and colleagues (2025) provide a narrative review where they discuss the changing place of artificial intelligence (AI) in nutrition science. Various studies on using neural networks, decision trees, and natural language processing (NLP) to evaluate and direct nutrition-based interventions are gathered to form the paper. AI can increasingly track the diet in real-time, forecast the nutrient shortage, and evaluate the personal requirements regarding the health conditions connected to the lifestyle information (Coman et al., 2024). Although in review, it has been affirmed that major progress has been made in the area of predictive modelling, it is also observed that demands have not been met in the implementation of fully automated, personalised nutrition systems.

Among the major conclusions of this article is the request for systems that link AI-mediated health risk estimation with nutrition planning. Even among the numerous attempts to address the idea of AI-assisted nutrient analysis and calorie requirements, few of them employ clinical data to place findings in a diagnostic context (Kaseen et al., 2025). Such a drawback defines an acute research gap, especially when it comes to approaches involving machine learning-assessed categorization of metabolic disorders and subsequent diet-related guidance. The authors indicate the existence of ethical issues where the explainability, transparency, and culturally appropriate dietary recommendations are required.

This dissertation is justified by the article, which addresses the need for custom user-specific dietary suggestions that will be produced based on AI models that will be trained on actual health data. Highlighting the absence of the direct incorporation of health classification algorithms with dietary engines. Although very general, Kassem et al. (2025) establish the technical and ethical foundation of the creation of personalised nutrition systems, which is exactly what this dissertation sets out to accomplish with an explainable ML classification artefact followed by rule-based logic in terms of dietary recommendations.

## 2.2 ML in diagnosing Metabolic Syndrome

Sghaireen et al. (2022) introduce a machine learning scheme for early prediction of MetS, based on a data-augmentation approach and an explainable classification model. The article deploys multiple ML models, including Random Forest, XGBoost, K-Nearest Neighbours (KNN), and Support Vector Machine (SVM), to determine people at risk of MetS according to their anthropometric and biochemical parameters. SMOTE (Synthetic Minority Over-sampling Technique) is used to balance the data and use SHAP values to say how important features are in a decision-making process (Ni et al., 2024).

The Random Forest classifier performed best, with the accuracy rate being more than 90 percent. SHAP visualisations proved that triglycerides, BMI, and HDL cholesterol were the strongest features. It is also of note that the class imbalance is addressed by implementing data augmentation, which increases the model's applicability to real datasets. Further, implementing SHAP, the authors enhance the interpretability of their model, which is one of the essential elements of clinical decision-making.

In various ways, this research paper strongly backs the present dissertation. First of all, it confirms metabolic classification using such ensemble classifiers as Random Forest and XGBoost (Sghaireen et al., 2022). Secondly, it supports the usefulness of explainability through SHAP, which this project will also use to justify dietary doses to the outputs of the classification. Finally, it offers an organized approach to data preprocessing, model training, and evaluation that can be modified to the data obtained through UK-based repositories.

The limitation of the research is that it does not contain intervention or support after classification. The article does mention that there is a need to do some future research in this area, and the dissertation has covered this gap by including a recommendation engine, since it is after the detection of the risk that lacks this guidance.

## 2.3 Evidence-Based Diet for Youth Type 2 Diabetes

White et al. (2024) present a United Kingdom consensus of evidence-based care of type 2 diabetes (T2D) in children and young people (CYP). The study is closely connected to the current project, even though it is not AI-related, since it provides various dietary frameworks that respond to the principles of public health. To treat T2D among youth, the authors came up with a multidisciplinary consensus with clinicians, nutritionists, and experts on public health to advise carbohydrate control, high-fibre diets, and low consumption of saturated fats (Skurk et al., 2024).

The guidelines have specific food group guidelines, energy balance, and meal planning guidelines for young populations. These techniques are particularly used in this project to structure the logic of a recommendation engine. The authors also stress that interventional changes must be sensitive to clinical parameters and include insulin resistance, body mass index, and lipid ratios: variables that match the parameters considered in the ML classification section of this dissertation (White et al., 2024).

The paper is useful due to its UK dietary advice, which is pragmatic. It creates a basis on which categorized levels of risks (i.e., insulin resistance or dyslipidemia) can be mapped to the respective dieting plans. As this project will suggest how to give nutritional guidance after the classification, the diet structure presented by White et al. can be used as a direct reference to formulate the recommendation logic and the development thereof based on the evidence, and not on some generic functions of a diet.

Algorithmic or AI-based personalization is not touched on in this paper. The dynamic adjustment of the plans of diet plans according to individual diversity is lacking beyond the fixed scheme. This study thus helps to justify the practical dietary aspect of the dissertation, and leaves the novelty of this project: automatic production of these recommendations based on the ML-based classification.

## 2.4 Cardiovascular Risk, Explainability, and Data Balancing

Yang, F. et al. (2024) examine the issue of domain-driven explainability and sophisticated data-balancing strategies for the prediction of cardiovascular risk. The authors construct a strong predictive model using SHAP to carry out its interpretability, SMOTE to oversample, and therefore calculated that this method better exceeds the expected outcome compared to other standard models. The author applies the use of clinical variables (including blood pressure, triglycerides, and BMI) that are also used to classify metabolic disorders.

The necessity of transparency is emphasized regarding applications of machine learning in health-related purposes, saying that accuracy is not everything, but its explainability and trustworthiness are needed (Famiglini, 2025). Not only is their model technically competent, but it is ethically conscious and integrates SHAP explainability as a means of integrating clinician-user collaborations. The above-mentioned importance of explainability can be closely seen in the dissertation's use of the SHAP in validating both classification and recommendation steps.

Yang et al. also use such data pre-processing techniques as z-score normalization and feature selection based on recursive feature elimination (RFE), which are by the technical practices in this dissertation (Yang et al., 2024). All these common methods confirm the adequacy of the existing methodology and indicate that open machine learning in healthcare is possible and critical.

The study, however, does not take the time to implement the outputs of the classification to real-life health management tasks like planning a diet or educating a patient. It can only be in the domain of risk forecasting. This dissertation is the logical step forward in further expanding the scope of the study by Yang et al., by transforming classification into a system of dietary recommendations.

## 2.5 Soft Voting Classifier with Explainable AI for Diabetes

Kibria et al. (2022) introduce a strong machine learning ensemble model predicting diabetes mellitus, which uses a soft voting classifier technique that is coupled with explainable AI. The model works with prediction of Random Forest, Gradient Boosting, and Decision Tree classifiers to improve generalisation. The soft voting process imposes probabilities on the outputs of any of the models and picks the most consistent class among all the models, which enhances the confidence in making predictions. SHAP values can be applied to understand the output of the model and determine features of sensitive importance, like glucose, BMI, and levels of insulin.

The study has high predictive indications with the results of the F1-score of 0.88 on the PIMA Indian Diabetes dataset (Kibria et al., 2022). It is worth noting that the authors lay much stress on the interpretability of models and clinician trust as primary objectives of design, which is reminiscent of the growing role of transparency in health-related AI. The SHAP visualisations give a clear idea of the features with the biggest impact on modelling predictions, something that needs to be addressed in the case of sensitive health data (Rezk et al., 2024).

Putting the information and the arguments presented in their context of this dissertation gives two-fold benefits: methodological encouragement and practical reasonability of featuring SHAP in the corresponding artefact. The fact that they have been successful with the ensemble models justifies the decision to explore Random Forest and XGBoost in this project. Moreover, their incorporation of explainability processes fits with the aim of the project to offer rationalised nutrition information together with risk categorisation.

The most obvious weakness of their research is its focus because it ends at predicting the disease, and it does not provide afterward recommendations and supporting tools to patients when they have to leave a diagnostic facility. This is the gap that the present dissertation can complement, by associating the predictions with practicable diet plans-thus overcoming the gap that the ML-based healthcare solutions currently suffer.

## 2.6 ChatDiet: A Nutrition Chatbot Framework

Yang et al. (2024) present ChatDiet, an LLM (large language model)-based chatbot that provides nutrition-focused food advice on a personalised basis. The chatbot is designed on a hybrid framework to incorporate user demographics and health metrics into dietary information that can be used to suggest foods in real time and based on individual circumstances. In contrast to inactive meal planners, ChatDiet can strike up a conversation with the user, updating its recommendations as the user continues to provide it with feedback and background information.

ChatDiet is also a refreshing example of personalised health and nutrition, driven by AI in particular, since its approach involves a population-scale set of dietary rules combined with an individual-scale health profiling. The reasoning system in ChatDiet simulates the approach of the dietician who will need to customize the advice depending on diagnosis, energy needs, and user preferences (Yang et al., 2024).

The second part of this dissertation, the design of a personalised recommendation engine, will be very relevant to this paper. Although the mapping of input data to dietary guidance can be conceptually the same in the context of this project, the classification model employed is not conversational. The chatbots' architecture also facilitates using rule-based engines instead of the fully generative type of AI, which is appropriate to the idea of the dissertation, transparency, and scalability to a low-computation environment (Sapkota et al., 2024).

ChatDiet, however, was established on unnatural user input and was not tested against actual health data or outcomes. It was also not very formal in the model evaluation section- this brings into question the accuracy and the clinical trustworthiness. By contrast, this dissertation can deal with such problems by creating correct classifications using clinical variables first before implementing recommendation logic - a combination of predictive accuracy and personalisation.

## 2.7 Metabolic Obesity Subtypes Review

Lin et al. (2021) presented a multi-centre machine learning study to identify the subtypes of metabolic obesity in communities with various population backgrounds. Their research is particular since they do not identify obesity as some homogeneous entity but as a set of phenotypes that represent metabolically healthy obese (MHO) and metabolically unhealthy obese (MUO). With the help of clustering algorithms and classification methods, the authors examined the dataset containing more than 5,000 patient records in several hospitals to cluster people by including the lipid profile, glucose levels, blood pressure, and inflammatory markers.

The proposed study utilized XGBoost and k-means clustering to divide populations with an area under the ROC (AUC) of 0.91 to distinguish between MHO and MUO. This study indicates that detailed classification, rather than the simplified diagnosis of diseases, can be significantly more predictive and beneficial in terms of interventions because it can be ensured using machines and more detailed machine learning tools (Lin et al., 2021).

This thought directly applies to the current dissertation as it should encourage elaborated clinical features instead of mere measures of such characteristics as BMI. The ML pipeline of this dissertation, moreover, works with several biometrics, such as HDL, triglycerides, glucose, etc., to detect metabolic patterns, which makes diet recommendations specific and dependent on the condition (Panagoulias et al., 2021).

The study conducted by Lin et al. is limited in its aim to be aware of classification only and does not reach post-diagnosis care or intervention. The present project sees this by the development of a logic dietary engine giving specific food advice by the metabolic classification results, with the final gap between classification and action closed.

## 2.8 Prediction of MASLD by Clinical Data

Zhu et al. (2025) explore the ability to forecast metabolic dysfunction-associated steatotic liver disease (MASLD) with the help of typical demographic and clinical characteristics based on machine learning models. The research constructs a binary classification algorithm on Random Forest, Logistic Regression, and XGBoost modalities on a dataset of 6,000 anonymised instances. A liver disorder closely associated with metabolic syndrome is MASLD, which displays low sensitivity when it comes to early physical symptoms and is frequently underdiagnosed because of the necessity to undergo expensive imaging tests (Cusi et al., 2025).

The authors indicate that machine learning models proved to be beneficial in identifying MASLD, not only with a balanced accuracy score of over 85%. Significantly, they do not employ any invasive characteristics but just cheaper ones, including BMI, waist circumference, age, and triglycerides as well, which were also employed in the ML model of this dissertation. The paper is a good indication of machine learning as a front-line screening mechanism of population health management (Zhu et al., 2025).

Zhu et al. use the SHAP analysis to affirm the significance of features and test the possible clinical implementation. The way they have gone about things methodologically, especially feature engineering and model evaluation, is very informative for this dissertation. The authors mention the model transparency, generalisability of the model, and the necessity to have ethical oversight of this issue, which is also mentioned when developing an explainable dietary recommendation system in this project.

As with several other models in this review, even prediction is not followed by the ability to support decisions or to lead the patient. It is based on them, and this dissertation goes a step further and translates the results of classification to personalised dietary plans, providing not only detection but also practical responses.

## 2.9 Gap Analysis

The general synthesis of the eight articles under consideration demonstrates that despite a significant number of achievements related to the utilization of machine learning (ML) and artificial intelligence (AI) in the field of health diagnostics and dietary recommendation systems, there are still some critical gaps. It is these gaps that constitute the basis of this dissertation research direction and motivation.

The first key gap identified concerns the unavailability of integrated systems that would relate health condition classification to personalised eating recommendations. In the majority of investigations, including Sghaireen et al. (2022), Zhu et al. (2025), and Lin et al. (2021), researchers concentrate on the predictive power of ML models. Although they exhibit great precision in identifying risk or subsets of metabolism, they do not go up to any course of action associated with subsequent intervention, i.e., nutritional counsel. This dissertation directly focuses on such a gap by using a logic-based recommendation engine to convert classification results into nutritional guidelines.

The second gap is that they were using generalised or synthetic data. Another example would be ChatDiet (Yang, Z. et al., 2024), which is found promising in terms of individualised nutrition-based logic, yet the experiment is conducted on synthetic profiles and has nothing to do with validated clinical outcomes. Similarly, generalisability is diminished by the implication of region-specific or limited datasets (e.g., the PIMA dataset in Kibria et al., 2022). Conversely, the dissertation applies health characteristics (including NDNS-based profiles) of the UK context, thus guaranteeing the contextual relevance and usefulness.

The next gap is the one related to the low visibility of the recommendation logic. Although SHAP has been hugely deployed in classifying models' explainability (as in the studies of Yang, F. et al., 2024; Kibria et al., 2022), very few researchers utilize it to aid in the formulation of dietary recommendations, which is equally associated with high stakes. In addition to explaining the classification process with the use of SHAP, logical linkages between the identified risks and NHS-compatible diet plans are pursued in this dissertation with a combination of both trust and actionability.

The fourth gap is that the computational practicality is taken into account rather minimally. Although some of the models are dependent on complex LLMs or multi-logged systems, they face limitations when it comes to scaling the systems in the real-life healthcare environment due to limited resources. To achieve scalability and replicability, to support a wider use, a lightweight rule-based system using open-source tools such as Python, scikit-learn, and SHAP was proposed in this dissertation. Lastly, some of the papers highlight the essence of ethical AI, yet there is little implementation of those ideas.

Table Gap Analysis Table

|  |  |  |
| --- | --- | --- |
| Study | Contribution | Gap Identified |
| Kassem et al. (2025) | Overview of AI in nutrition | No integration between classification and recommendation |
| Shireen et al. (2022) | Metabolic risk classification using ML and SHAP | No dietary or post-diagnosis guidance provided |
| White et al. (2024) | Evidence-based dietary guidelines for youth with T2D | Lacks automation, AI integration, or dynamic tailoring |
| Yang, F. et al. (2024) | Explainable cardiovascular risk prediction | Does not connect predictions to practical interventions |
| Kibria et al. (2022) | Ensemble classification for diabetes with SHAP explanations | The dataset is limited, and no action-oriented system has been developed |
| Yang, Z. et al. (2024) | LLM-powered nutrition chatbot (ChatDiet) | Uses synthetic data and lacks clinical dataset validation |
| Lin et al. (2021) | Obesity subtyping using clustering and ML | No dietary recommendations are tied to classification outcomes |
| Zhu et al. (2025) | MASLD prediction using clinical data | Stops at prediction; does not support patient dietary intervention post-diagnosis |

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