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Health-aware food recommendation system with dual attention in heterogeneous graphs

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ABSTRACT

Recommender systems (RS) have been increasingly applied to food and health. However, challenges still remain, including the effective incorporation of heterogeneous information and the discovery of meaningful relationships among entities in the context of food and health recommendations. To address these challenges, we propose a novel framework, the Health-aware Food Recommendation System with Dual Attention in Heterogeneous Graphs (HFRS-DA), for unsupervised representation learning on heterogeneous graph-structured data. HFRS-DA utilizes an attention technique to reconstruct node features and edges and employs a dual hierarchical attention mechanism for enhanced unsupervised learning of attributed graph representations. HFRS-DA addresses the challenge of effectively leveraging the heterogeneous information in the graph and discovering meaningful semantic relationships between entities. The framework analyses recipe components and their neighbours in the heterogeneous graph and can discover popular and healthy recipes, thereby promoting healthy eating habits. We compare HFRS-DA using the Allrecipes dataset and find that it outperforms all the related methods from the literature. Our study demonstrates that HFRS-DA enhances the unsupervised learning of attributed graph representations, which is important in scenarios where labelled data is scarce or unavailable. HFRS-DA can generate node embeddings for unused data effectively, enabling both inductive and transductive learning.

1. Introduction

A healthy diet is crucial for meeting essential nutrients, and poor eating habits have led to a rise in non-communicable diseases such as obesity and diabetes [1–3]. Unhealthy diets are a significant contributor to malnutrition, and excess weight, and lead to preventable deaths, with an estimated 11 million lives lost annually [4]. As a result, the field of food recommendation systems [5,6] has emerged as an important research area, aiming to provide individuals with suitable food options that align with their dietary preferences and meet their biological and physiological requirements for daily activities and overall well-being [7–9]. The system can recommend recipes or ingredients that are rich in essential nutrients such as vitamins, minerals, and proteins, based on the individual's dietary preferences and requirements [6,10]. This approach can empower users to make informed decisions about their food choices, leading to improved dietary habits and better overall health outcomes. The goal of food recommendation systems is to offer users a curated list of food items that are tailored to their individual preferences and requirements. The concept of "food" with *heterogeneous information networks* (HIN) [5,11] encompasses a wide range of food-related elements, including meals, recipes, coffee shops, and restaurants [12–14].

Recommender systems have shown promising applications in the domain of food recommendation, particularly when leveraging the power of heterogeneous graphs [5,11]. Heterogeneous graphs are effective in representing the complex relationships between diverse entities in the food domain, such as ingredients, nutrients, recipes, cuisines, and user preferences. For instance, a heterogeneous graph can capture the relationships between ingredients and their nutritional content, recipes and their ingredients, and users and their preferred cuisines. By utilizing meta-paths, which are sequences of non-repeated nodes and edges, recommendation systems can effectively capture the intricate structural relationships between nodes of varying classes, enabling accurate and personalized food recommendations [15–18]. The utilization of heterogeneous graphs in food recommendation systems can enhance the

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accuracy and effectiveness of these recommendations by capturing the complex relationships between nutrients, ingredients, and other entities in the food domain, and enabling personalized and context-aware recommendations. By representing the diverse relationships with HIN in the food domain in a graph structure, the recommendation system gains a comprehensive understanding of the interplay between different components. Moreover, heterogeneous graphs allow the integration of various data sources, such as nutritional databases, user preferences, and reviews, expanding the breadth and depth of knowledge available for recommendations. This wealth of information further enhances the system's ability to consider individual dietary needs, restrictions, and flavour preferences when suggesting suitable food items [19–21].

In the realm of food recommender systems, previous studies have predominantly focused on homogeneous graphs [5,6,22,23]; however, they fall short in considering the diverse practical components that constitute foods. Consequently, attempting to apply these systems to homogeneous graphs proves impractical, as the relationships between these components remain undiscovered due to their distinct types. As the number of entities within a graph increases, so does the complexity of relations, resulting in a multitude of links between nodes and intricate relationships [24,25]. Heterogeneous graph neural networks have emerged as a solution within *recommendation systems based on heterogeneous information networks* (RS-HIN) [26,27]. RS-HINs effectively capture and extract meaningful relationships between different types of nodes, with each connection serving a specific purpose. Particularly, RS-HINs that extract semantics-based relationships have garnered attention due to the wealth of purpose-specific relationships between diverse node types. One notable breakthrough in overcoming these challenges is the utilization of meta-paths, which have garnered attention in important research endeavours [28]. Meta-paths offer a solution to encapsulate crucial connections between nodes in a heterogeneous graph. It is important to note; however, that not all meta-paths hold equal significance, leading to additional challenges. In recent years, neural network models, especially attention mechanisms, have garnered considerable interest among researchers [29,30]. Despite the popularity of neural network models in recommendation systems, their application in the domain of food recommendation is still in its early stages.

In this paper, we introduce a novel recommender system called *health-aware food recommendation system with dual attention in heterogeneous graphs* (HFRS-DA). We integrate the *attention* mechanism from *graph attention networks* (GAT) [5,31] to capture nuanced relationships between recipe items and user preferences, enhancing recommendation accuracy. This combination of attention mechanisms with *graph neural networks* (GNN) creates a powerful framework for personalized recommendations. GNNs excel at capturing complex relationships with user–item interaction graphs, while attention mechanisms selectively focus on relevant information, improving recommendation effectiveness. HFRS-DA incorporates a dual attention mechanism to identify popular and healthy recipes concurrently. Popular recipes are defined based on research findings, while healthy recipes align with World Health Organization (WHO) guidelines for healthy eating [4]. The attention mechanism operates in two steps: the *node level of attention* (NLA) and the *semantic level of attention* (SLA) [31,32]. NLA plays a crucial role in identifying significant nodes by applying weighted attention to the nodes that have properties of popular recipes. It effectively prunes paths with lower values, thereby reducing noise and eliminating irrelevant information from the recommendation process. On the other hand, SLA utilizes edge weighting to prioritize more important paths that indicate recipes with healthy features. By incorporating both NLA and SLA, our refined approach enables the recommendation of popular and healthy recipes. HFRS-DA demonstrates its effectiveness in handling complex relationships with a heterogeneous graph by seamlessly integrating attention mechanisms at multiple levels. It represents the first proposed solution that specifically addresses the challenges of heterogeneous graph embedding in the context of food recommendations. The main contributions of this research can be summarized as follows:

1. We propose HFRS-DA that utilizes a dual attention technique, taking into account the user's interests in popular and healthy recipes.
2. HFRS-DA is the first system that proposes recommending healthy meals based on a heterogeneous graph and the dual attention mechanism.
3. HFRS-DA can discover popular and healthy recipes to recommend to the user through recipe properties and analysis of their neighbours of recipes in the heterogeneous graph
4. HFRS-DA can generate node embedding for unused data effectively. Hence, it can be used for both inductive and transductive learning.

The rest of the paper is structured as follows: Section 2 provides an overview of related works, encompassing food recommendation systems and recommender systems that employ graph neural networks. Section 3 presents the methodology, which includes preliminaries and the framework. Section 4 presents the experiments and results, and Section 5 offers a discussion of the findings. Finally, Section 6 provides the conclusion.

2. Related work

The field of recommendation systems (RS) has witnessed significant growth and importance in recent years, attracting a substantial amount of research attention. This trend extends to the domains of healthcare and food, as evidenced by the increasing number of papers exploring their applications [8,33–37]. Machine learning models have played a pivotal role in recommendation systems, with a surge in published papers utilizing these approaches [38–40]. We first focus on research pertaining to food recommendation systems, and then examine studies that employ graph neural networks for recommendation systems.

2.1. Food recommendation systems

Food recommendation systems enable applications to guide users in choosing their favourite foods. Current studies in the food domain consider user preferences and/or health issues when recommending favourite foods [8,41]. Gao et al. [5] proposed an innovative food recommendation system that incorporated user ratings, food ingredients, and images as data to provide recommendations. Asani et al. [42] introduced a novel method to determine customer food preferences based on online restaurant reviews. In the context of local restaurant recommendations, Freyne et al. [43] employed recipe and ingredient ratings to enhance content-based recommendations to facilitate the transition from unhealthy to healthy diets by learning users' dietary preferences. Furthermore, Begam et al. [44] developed a recommender system to suggest different foods to users based on the raw foods available in their refrigerators. Context-aware food recommendation systems have also been developed; Maia et al. [45] utilized mobile devices and medical records to provide personalized recommendations. Similarly, Sookrah et al. [46] proposed a diet recommendation system to suggest healthy menus and dishes. Furthermore, Wang et al. [23] developed a personalized health-conscious food recommendation system called *Market2Dish* that helped users find personalized foods and maintain a healthy diet to prevent health complications caused by poor eating habits.

Heterogeneous graphs (HG), also known as HIN, are widely used in real-world systems [47,48]. HIN provides a unified framework for understanding latent features of users and items [49]. In the context of food recommendation, several studies have explored deep learning models for HGs. Gao et al. [6] proposed a meal recommendation system based on graph convolutional networks and embedding propagation layers, which capture high-order relationships and enhance representation learning. Manoharan et al. [50] introduced an automated food recommendation system for dieting, utilizing deep learning techniques. Rostami et al. [51] developed a food recommendation system that incorporates visual food content through the utilization of deep learning-based image clustering and community detection methods. This system aims to provide explanations for the recommended dietary choices. They introduced a similarity score that employs a tendency measure to quantify the extent to which a user community prefers a specific food category. This similarity score is integrated into the recommendation process.

Mokdara et al. [52] proposed a recommendation system that leveraged deep learning models and user preferences to create a checklist of recommended dishes based on users' profiles. Herlocker et al. [53] employed a *convolutional neural network* (CNN) for food ingredient recognition and recipe recommendation based on ingredients. Padhiar et al. [54] introduce the Food Explanation Ontology (FEO), which offers a formal framework for representing explanations provided to users regarding food-related recommendations. FEO employs concepts from the field of explanations to generate responses to user inquiries about the food recommendations they receive from AI systems. Shi et al. [55] proposed a method for identifying food safety risks using a heterogeneous graph and attention network. Song et al. [10] proposed a *self-supervised calorie-aware heterogeneous graph network* (SCHGN) for food recommendations. Meng et al. [56] presented a visually aware meal recommender system using a heterogeneous multi-task learning architecture called PiNet. Tian et al. [57] developed *RecipeRec*, i.e. a recipe recommendation system utilizing a heterogeneous graph learning model.

2.2. Recommender systems using graph neural networks

Graph neural networks (GNN) have proven to be effective in capturing the structural information of graphs and deriving meaningful representations of nodes [30,58]. The capacity of GNNs to represent information has sparked interest among researchers in developing GNN-based recommendation models. Although simple neural networks such as *multilayer perceptron* (MLP) models employ nonlinear transformations to extend existing recommendation approaches, CNNs are suitable for Euclidean data such as text and images [30,59]. *Attention mechanism* via GAT has been incorporated into recommender systems to select the most relevant items or components, enhancing the quality of recommendations [31]. Co-attention mechanisms have also been employed to improve recommendation models by integrating visual and textual information and learning more informative user and item embeddings [60,61].

Next, we review several studies that utilized the attention mechanism in recommender systems, which is the basis of the proposed method in our study. Recently, an increasing number of researchers have adopted the attention mechanism to model user preferences, yielding state-of-the-art results. For instance, Chen et al. [62] introduced the attention network into classic collaborative filtering models, making it the first multimedia collaborative filtering recommendation model. Wang et al. [63] utilized high-order connectivity and semantic relations in knowledge-aware recommendation systems using the attention mechanism with a Knowledge Graph. In a related study, Wang et al. [31] presented a method that performs unsupervised representation learning on heterogeneous graph-structured data. Zhang et al. [64] developed an approach for embedding and interaction learning specifically for ID features, which served as inspiration for our methodology that uses the *identity feature learning model* (IFLM). In a similar vein, Chen et al. [65] addressed the issue of sparse data in travel recommendations by utilizing the multi-view graph attention network framework, which incorporates a GNN.

Wu et al. [66] proposed a personalized attention network that leveraged user ID embeddings to generate query vectors for word- and news-level attention. Wang et al. [67] presented a time-aware deep collaborative filtering framework consisting of two stages: dynamic user preference modelling based on the attention mechanism and matching score prediction based on deep learning. Zhang et al. [68] integrated the attention mechanism with network embedding, focusing on task-relevant components while disregarding noisy parts of the network. Liu et al. [69] proposed a model for the cold-start recommendation, combining the attention mechanism with meta-learning. This approach improves the ability to model personalized user interests by learning attention-based weights between users and items, ultimately enhancing the performance of cold-start recommendation systems.

3. Methodology

3.1. Preliminaries

We first provide an introduction to the fundamental concepts of heterogeneous graphs and the symbols utilized in this paper through the following definitions.

Definition 1. Heterogeneous Information networks (HIN): A HIN is a graph composed of two sets, namely nodes represented by V and links represented by E. Each node and link has its own mapping function, denoted by $\phi(v) : V \rightarrow A$ and $\psi(e) : E \rightarrow R$, respectively. Here, A and R indicate the node and link types, respectively. If $|A| > 1$ and $|R| > 1$, it is referred to as a heterogeneous information network [55,70,71]. On the other hand, if $|A| = 1$ and $|R| = 1$, it is considered a homogeneous information network. The objective of heterogeneous graph embedding is to learn a function $\Phi : V \rightarrow R^d$ that maps the nodes in HIN into a low-dimensional Euclidean space with $d \ll |V|$ [72,73]. It is worth noting that each entity in a heterogeneous graph has distinct relationships, where each association carries a specific meaning and interpretation.

Definition 2. Network schema: The network schema $S = (A, R)$ serves as a meta template for a Heterogeneous Information Network (HIN) denoted by $G = (V, E)$, incorporating object and link mapping functions, namely ϕ and ψ. In a HIN, there can be numerous entities linked through diverse semantic paths which are identified as meta-paths [55,71].

Definition 3. Meta-path: A meta-path is a path that is defined on the graph of a network schema, denoted by $G_T = (A, R)$. It is composed of a sequence of relationships, denoted by $R_1, R_2, \ldots, R_k$, that connect different types of nodes in the network, denoted by $A_0, A_1, \ldots, A_k$. The meta-path defines a new composite relation between the initial and final node types, which is given by $R_1 R_2 \ldots R_k$. These meta-paths can be used to extract connectivity features in a heterogeneous information network [72,73].

Definition 4. Meta-path-based neighbours: In a heterogeneous graph, the neighbours of a given node i based on a meta-path ψ are denoted as $\mathcal{N}_i^{\psi}$. These neighbours consist of nodes that are connected to node i through the meta-path ψ. It is important to note that a node is also considered a neighbour of itself [72].

Definition 5. HIN-based recommendation: A HIN can be utilized to represent various types of information in a recommender system. In a recommendation-based HIN, there are two primary entities: users and items, with connections between them. To denote sets of users and items, we use $U \subset V$ and $I \subset V$ respectively. The rating of an item by users is represented by the triplet $\langle u, i, r \rangle$, which we denote as $r_{u,i}$. It should be noted that $U \subset V$, $I \subset V$, and $R \subset E$. Given the HIN $G = (V, E)$, the objective is to predict the rating score $r_{u,i'}$ assigned by user $u \in U$ to a non-rated item $i' \in I$.

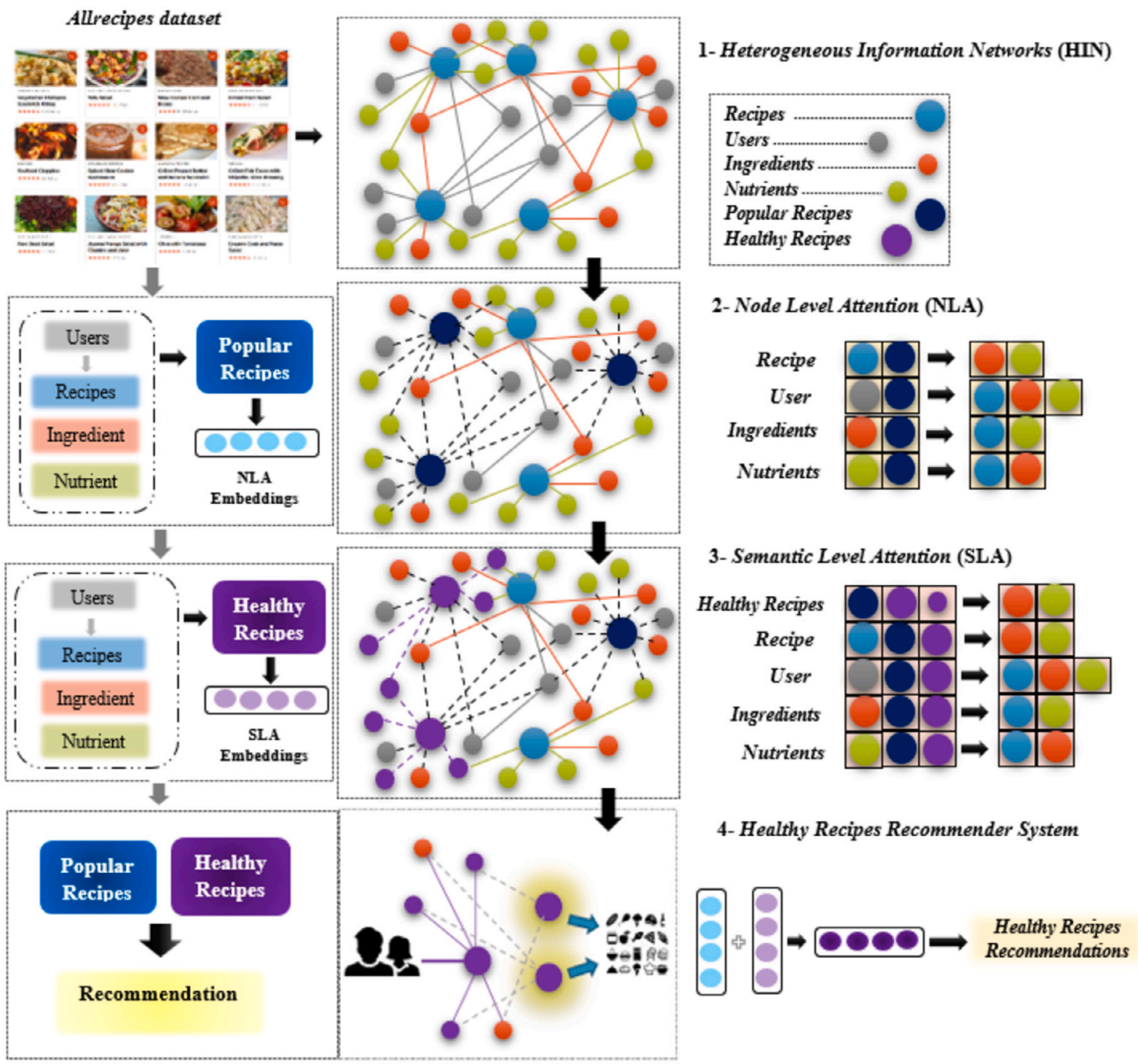


Fig. 1. HFRS-DA has three main components. The first column displays the input dataset from Allrecipes with a visual flowchart showing the sequence of operations. The second column illustrates the creation of a heterogeneous graph from the dataset, depicting relationships among user nodes, recipes, and recipe components. The method employs dual attention, which consists of node-level attention (NLA) and semantic-level attention (SLA). It involves training meta-paths to assess the significance of nodes based on factors such as recipe popularity and health. This process results in the generation of embedding vectors in two steps. The output of the method provides users with recommendations for popular and healthy recipes, as defined by the WHO.

3.2. Framework

The objective of this study is to develop the HFRS-DA framework, a healthy recipe recommendation system that utilizes an attention mechanism to suggest suitable recipes to users. The HIN is comprised of users who have selected and rated different recipes. It features links connecting users to the recipes they have rated. Furthermore, each recipe is linked to its corresponding ingredients and nutrients. Consequently, the HIN indirectly establishes connections between recipes, based on shared ingredients and nutritional content. It also links users to the ingredients and nutrients of the recipes they have rated. As a result, this network forms a comprehensive heterogeneous graph with four distinct entities. We employ a meta-path approach to assess the significance of different paths in the HIN. The recommendation process comprises two stages. Initially, we identify a set of popular recipes based on user and recipe ratings and define a meta-path that encompasses multiple paths involving these popular recipes. Subsequently, we define node-level attention (NLA) [31,32] based on these popular nodes, as per the definition, and generate embedding vectors. Following that, our focus shifts to finding paths that include healthy recipes, as defined by the World Health Organization (WHO) guidelines [4,74]. We assign weights to the edges corresponding to popular and healthy recipes using the attention mechanism, highlighting their importance within the HIN. Then, we generate embedding vectors using semantic-level attention (SLA). Consequently, within the HIN, we have two types of embedding vectors. By combining and converting them into a single enriched embedding vector, we incorporate information about the relationships between users and recipes in the HIN. Finally, based on users' similarity in embedding vectors, we can provide recipe recommendations to users, considering both popular and healthy recipes. Fig. 1 provides a visual representation of our approach and how the attention mechanism is employed to identify important pathways at each stage of the recommendation process.

HFRS-DA consists of four main components (Fig. 1) that are defined as follows.

1. The heterogeneous graph/HIN includes the four entities Recipe, Users, Ingredients, and Nutrients. Each user may have rated several recipes, and recipe nodes are connected to their ingredients and nutrient entities. Other connections between the nodes are extracted via the recipe node, which is indirect. If the user has

Table 1
Notations and descriptions.

Row	Notations	Descriptions
1	ϑ	Meta-path
2	R_{pop}	Popular recipes
3	$H(r_i)$	The health factors of recipes
4	R_H	Healthy recipes
5	$\alpha_{i,j}^{\vartheta}$	The Node Level Attention between two nodes i and j in the meta-path ϑ
6	E_{NLA}^{ϑ}	The learning embedding of the meta-path ϑ - NLA
7	Softmax^{S}	Normalizing the weight ratio to discover meaningful edges - SLA
8	$S_{(i,j)}^{\vartheta}$	Meta-path learning to move from node i to node j - SLA
9	E_{SLA}^{ϑ}	The learning embedding of the meta-path ϑ - SLA
10	$\mathcal{W}^{S_i,S_j}$	Weighting the meta-path based on node pair (i,j) - SLA
11	E	The final embedding vector

rated the recipe, the user can connect through the recipe node with the ingredients and nutrients nodes.

2. NLA on popular recipes to generate embedding vectors in the graph based on the nodes that possess popular properties. In Fig. 1, the left side displays five nodes, consisting of two types: Recipes and Popular Recipes. In the HFRS-DA (Health Food Recommendation System with Deep Aggregation), a recipe item is considered popular users if its rating is above average. On the right-hand side, we demonstrate how the meta-path is trained based on embedding vectors. Initially, the popular recipe node connects with four other nodes, and subsequent vectors illustrate that additional nodes can be accessed through the corresponding vector. In this step, we first define a condition for the meta-path to consider only paths containing popular recipes. Then, based on the obtained routes, node levels attention are performed. The output provides embedding vectors obtained specifically from popular recipes. For example, the first vector indicates that the meta-path is trained to access the ingredient and nutrient nodes of a recipe when it is popular.
3. SLA, training the meta-path to identify semantically significant edges. Healthy recipes are defined based on nutrient nodes, and the connected nutrient nodes of healthy recipes are highlighted in purple in Fig. 1 on the left side. This indicates that healthy recipe nodes include nutrient nodes connected to healthy recipes and popular recipe nodes, per the WHO definition. This process involves finding popular recipes with healthy nutrient nodes and weighting these paths as more meaningful in the heterogeneous graph. Similarly, similar to the previous step, all nodes connected to healthy recipe nodes are considered. On the right-hand side, the meta-path training process, based on the aggregation of neighbours and generation of embedding vectors for recognizing healthy recipes, is shown. Each node needs to be a popular recipe and its healthiness is assessed. For example, the first vector shows that a popular recipe becomes a healthy recipe when it contains a healthy nutrient amount, and if the recipe is healthy, the meta-path to its ingredient and nutrient nodes is accessible.
4. The fourth component of HFRS-DA is the healthy recipe recommendation system. It relies on the vectors obtained during the NLA and SLA stages, where the final embedding vectors are generated by summing these embeddings. Subsequently, we employ cosine similarity to identify users whose embedding vectors exhibit higher similarity. This approach allows us to provide recipe recommendations to users, focusing on dishes that are both popular and healthy.

Following this, Table 1 shows the notations used in this study.

3.3. Node-level attention

In the realm of heterogeneous graphs, the relevance of node relationships and pathways can vary depending on the defined meta-path. To address this, we employ an attention mechanism that assigns weights to different paths to reflect their significance. Central to this mechanism is Node-Level Attention (NLA), which enhances the meta-path by comprehending the interconnections between nodes and their immediate surroundings in the heterogeneous graph [31,32]. NLA is used to create embedding vectors influenced by the popularity of recipe items for each user. This process involves establishing a filter that targets recipes popular among users, based on their rating scores for each recipe. Consequently, for each user, pathways are activated, connecting these recipes to their corresponding nutrients and ingredients. The popularity of a recipe item extends to its associated nutrients and ingredients. The Graph Neural Network (GNN) operates within the NLA framework, detecting the most pertinent neighbours and routes linking popular recipes and their constituent elements. Leveraging the GNN, NLA facilitates a nuanced assessment of path importance, considering node attributes and connections. The essence of NLA lies in its capacity to adeptly capture the significance of diverse pathways and prioritize those most relevant to the recommendation process. When forming a meta-path in a heterogeneous graph, nodes hold varying degrees of significance. The establishment of pathways between nodes relies on evaluating these nodes according to specific criteria. The utilization of the attention mechanism within the NLA model enriches our understanding of user preferences and enables the generation of highly relevant and personalized embedding vectors.

3.3.1. Popular recipes

In HFRS-DA, we establish two levels of attention: NLA and SLA. Within NLA, the weighting of the meta-path hinges on popular nodes for users, specifically recipes that boast a rating score equal to or greater than the average score derived from ratings provided by all users for that particular recipe item. It is essential to note that when a recipe item attains popularity status, its corresponding ingredients and nutrients also earn the same distinction, and the user's rankings or preferences for these popular nodes are duly considered. Our objective is to gauge the significance of various paths within the heterogeneous graph. To achieve this, we take into account the popularity of nodes in the NLA in conjunction with the utilization of the GNN (Graph Neural Network). Our emphasis is on paths that lead to popular recipes and their associated ingredients. This approach empowers us to furnish users with meaningful and personalized recommendations. At this level, both the recipes and ingredients of the nodes are considered popular, shaping the definition of the NLA process accordingly. It is worth noting that while users may have rated numerous recipes, we specifically focus on the selection of popular recipes. As a result, in HFRS-DA, we define popular recipes as follows:

$$\bar{r}_i = \frac{\sum_{u=1}^{n} r_{u,i}}{\sum_{i=1}^{n} \mathbb{I}(r_{u,i} \neq 0)}, \tag{1}$$

where n is the number of users and $\mathbb{I}(\cdot)$ is the indicator function, so that $\bar{r}_i$ is the average rating recipe r has received. Therefore, we obtain the set of popular recipes R_{pop} based on Equation (1), using set-builder notation as follows:

$$R_{\text{pop}} = \{1 \leq r \leq m | \bar{r}_i \geq \frac{1}{m} \sum_{r'=1}^{m} \bar{r}_i\}, \tag{2}$$

where m is the number of recipes. Every recipe is composed of ingredients and possesses a nutritional makeup. The popularity of an ingredient can be inferred from the popularity of the recipes that contain it, and similarly for nutrients. Therefore, the meta-path based on a popular recipe includes its ingredients and its nutritional makeup.

Given the diversity of node types in heterogeneous graphs, each node holds a distinct level of significance. We hold the belief that nodes representing recipes, ingredients, and their associated nutrients carry differing degrees of importance for users. The importance attributed to each node varies and is contingent upon the user's scoring of recipes. Consequently, to account for the significance of nodes in embedding vectors for users, we employ an attention mechanism. The utilization of this attention mechanism is essential because it allows us to discern the relative importance of different nodes within the heterogeneous graph. It should be noted that constructing the meta-path in the NLA stage is based on nodes. We leverage the generated meta-path as input for the NLA model. By considering the unique contributions of each node type, especially recipes, and their associated ingredients and nutrients, we gain a nuanced understanding of their significance to users. The NLA evaluates the importance of the nodes within the specific meta-path ϑ by applying attention-based computations on these feature vectors. We execute the NLA for all pairs of nodes in the meta-path that exhibit popular properties. Subsequently, these coefficients are normalized using the Softmax function, ensuring comparability across different neighbourhoods. Furthermore, the weight coefficient $\alpha_{i,j}^{\vartheta}$ is obtained by normalizing the values further using the Softmax function, as follows:

$$\alpha_{i,j}^{\vartheta} = \frac{\exp(\sigma(N_{\vartheta} \cdot [x_i, x_j, a_i]))}{\sum_{j' \in N_i^{\vartheta}} \exp(\sigma(N_{\vartheta} \cdot [x_i, x_{j'}, a_{i'}]))}, \tag{3}$$

where, $\alpha_{i,j}^{\vartheta}$ represents the attention weight between node i and node j within the graph, specifically concerning the meta-path ϑ. σ denotes the activation function, typically leaky ReLU, and is applied element-wise. The matrix N_{ϑ} is a weight matrix that can be learned and is associated with the meta-path ϑ. The variable a_i signifies the aggregated attention scores for node i which are based on previous iterations and initialized to zeros. Additionally, N_{ϑ} represents the set of neighbouring nodes connected to node i according to the meta-path ϑ. In essence, the equation described in (3) calculates the attention weight between node i and each of its neighbouring nodes within the context of the meta-path ϑ. The Softmax function is employed to ensure that the attention weights collectively sum to 1 across all neighbouring nodes.

It is important to note that the weight coefficient of (i, j) depends on the attributes of the nodes. Furthermore, the weight coefficient $\alpha_{i,j}^{\vartheta}$ is also asymmetric, capturing distinct contributions between the nodes. This distinction is maintained due to the order in which the numerator is concatenated and the fact that it operates on different neighbours within the meta-path. The heterogeneous graphs are scale-free, which means that the variance of the graph data is relatively high and this helps to stabilize the process of self-attention learning. We developed the NLA to multi-head attention to solve the above challenge and stabilize the training process. We developed the NLA with multi-head attention to address the above challenge and stabilize the training process. We utilized node-level attention for k iterations and combined the resulting embeddings to create a semantically specific embedding. Next, we aggregate the meta-path-based embedding of node i by using its neighbouring nodes and the corresponding coefficients as follows:

$$E_i^{\vartheta} = \sigma(\sum_{j \in N_i^{\vartheta}} \alpha_{i,j}^{\vartheta} \cdot x_{j,k}), \tag{4}$$

where E_i^{ϑ} signifies the acquired embedding of node i concerning the meta-path ϑ. The value $\alpha_{i,j}^{\vartheta}$ is employed to determine the influence or weight of each neighbouring node j on the embedding of node i. Subsequently, the NLA stage utilizes the embedding vector in the following manner

Table 2
Ideal ranges of macronutrients based on WHO suggestion.

Row	Dietary factor	Ideal range
1	Proteins	10%–15%
2	Carbohydrates	55%–75%
3	Sugars	<10%
4	Sodium	<5 g
5	Fat	15%–30%
6	Saturated fats	<10%
7	fibres	>10 g

$$E_{\text{NLA}}^{\vartheta} = E_i^{\vartheta}(\theta_{\vartheta_0}, \theta_{\vartheta_1}, \theta_{\vartheta_2}, \dots, \theta_{\vartheta_n}), \tag{5}$$

where $E_{\text{NLA}}^{\vartheta}$ discovers and calculates the E_i^{ϑ} for node i to node j in the meta-path θ_{ϑ_n}. Furthermore, (ϑ_0) is the starter node for the meta-path, and (ϑ_n) is the last node with the popular recipe property in HIN.

3.4. Semantic-level attention

We observe that handling HIN can be time-consuming and costly due to the presence of various entities and links between nodes, each carrying distinct levels of significance. To address this, we utilize GNNs and attention mechanisms to assess the importance of paths within HIN, which involves two stages. In the second stage, known as SLA, we select paths with higher semantic value. While SLA's meta-path navigation relies on edges, NLA operates based on nodes. Despite the potential existence of multiple links between two entities in HIN, our focus is on identifying the path that holds more meaningful value [31,32,75]. Hence, we emphasize a more significant property of paths at this stage, training the meta-path to recognize edges with more valuable meanings. Consequently, we must semantically define the value of each path, usually achieved by assigning weights to edges between nodes and constructing a meta-path [76]. In the context of SLA, the criterion for determining edge meaningfulness is based on properties related to healthy recipes. This implies that any edges leading to healthy recipes are deemed significantly valuable. A detailed definition of a healthy recipe is provided in the following section.

3.4.1. Recipe health factor

The WHO encourages the use of nutrient profiling tools for promoting healthy eating and reducing non-communicable disease burdens [4]. Moreover, such tools should be capable of adapting to various conditions and circumstances. Therefore, consideration of recipe preferences and individualized nutrient recommendations has resulted in the development of healthy recipe recommendation systems. According to our measure, the amount of macronutrients is used to determine the health factor of a given recipe. In this factor, seven recipe nutrient facts are taken into consideration: proteins, carbohydrates, sugar, sodium, fat, saturated fat, and fibre. The WHO has provided an appropriate range for each of these nutrient facts, which indicates how much each should contain to be healthy [4]. Table 2 provides the WHO's healthy ranges for each nutrient fact. According to WHO dietary recommendations, the health factor of a recipe r (such as fried rice) for a nutrient i (such as egg and rice) can be calculated as follows

$$H(r_i) = \text{Pro}(r_i) + \text{Carb}(r_i) + \text{Sug}(r_i) + \text{Sod}(r_i) + \text{Fat}(r_i) + \text{Sat}(r_i) + \text{Fib}(r_i), \tag{6}$$

where the values of specific nutritional components of a recipe item are considered, including proteins, carbohydrates, sugars, sodium, fats, saturated fats, and fibres. These values determine whether the corresponding component of the recipe item falls within an ideal range or not, as specified in Table 2. For instance, $\text{Pro}(r_i)$ takes the value of 1 if the protein content falls within the ideal range, and 0 otherwise.

Accordingly, according to Table 2, any recipe that contains seven nutrients and has the desired ideal range is known as a healthy recipe. As you know, finding a particular recipe with all features simultaneously is complex, and usually, recipes have some of the components Table 2. Therefore, based on the definition of this research hypothesis, a recipe containing at least three nutrients is considered healthy. Thus, for each nutrient in Table 2, one score is assumed; for example, if a special recipe has four nutrients, the weight of the edge corresponding to the recipe will equal four. Thus, if each recipe has a criterion for being healthy, it has a score ranging from one to seven. The critical point is that the healthy recipe neighbours have been labelled. Consequently, healthy recipe ingredients are also healthy, and the same work was done for popular recipes at the NLA. As a result, finding healthy recipes is a three-step process that includes searching for them based on recipes, ingredients, and users, as shown below

$$R_H = \{1 \leq i \leq n | N_{H_i} \geq 3\}, \tag{7}$$

where R_H represents the set of healthy recipes, n denotes the total number of health nutrients, and N_{H_i} signifies the presence of nutrients with healthy attributes, as specified in Table 2. A recipe is considered healthy if it includes at least three of these healthy nutrients ($N_{H_i} \geq 3$). At this level, SLA generates meta-paths to find healthy recipes, which include both the health-related nutritional aspects and the ingredients of each healthy recipe. Once a recipe is identified as meeting the healthy criteria, it is applied to the relevant edge between the source and destination nodes. This method helps us recognize these edges as more important and meaningful in the HIN, as demonstrated in the following equation

$$S^{\vartheta}_{(i,j)} = \mu(F_{H_i}^{\ \vartheta} \rightarrow F_{H_j}^{\ \vartheta}), \tag{8}$$

where $S^{\vartheta}_{(i,j)}$ indicates the impression coefficient between two nodes and from node i ($F_{H_i}^{\ \vartheta}$) to node j ($F_{H_j}^{\ \vartheta}$) based on the meta-path ϑ on the HIN. Therefore, in the next phase and after learning the meta-path to discover the next node in HIN, the embedding vector is applied in the SLA stage as follows

$$E^{\vartheta}_{\text{SLA}} = S^{\vartheta}_{(i,j)}(\phi_{\vartheta_0}, \phi_{\vartheta_1}, \phi_{\vartheta_2}, \dots, \phi_{\vartheta_m}) \tag{9}$$

where $E^{\vartheta}_{\text{SLA}}$, the meta-path ϑ was developed based on the impression coefficient (μ) and $S^{\vartheta}_{(i,j)}$. Accordingly, the SLA meta-path ($\phi_{\vartheta_0}, \phi_{\vartheta_1}, \phi_{\vartheta_2}, \dots, \phi\vartheta_m$) is created according to the extended $S^{\vartheta}_{(i,j)}$ on the nodes of HIN. ϕ_{ϑ_0} is the starter node for the meta-path based on SLA, and ϕ_{ϑ_n} is the last node with healthy recipe properties in HIN. The volume of each meta-path indicated as $\mathcal{W}^{S_i,S_j}$, is established weighting from node i to node j as follows

$$\mathcal{W}^{S_i,S_j} = \sum_{i=1}^{n} \sigma(\sum E^{\vartheta}_{\text{SLA}}), \tag{10}$$

where SLA shows the number of repetitions of the healthy recipe criterion, and σ denotes the activation function. Note that all the above parameters are transmitted for meta-paths and semantic-specific embedding for meaningful comparison. After getting the significance of each meta path based on the healthy recipe, we normalize them through the Softmax function.

$$\text{Softmax}^{S}(S^{\vartheta}_{(i,j)}) = \frac{\exp(\mathcal{W}^{S_i,S_j})}{\sum_{i=1}^{n} \exp(\mathcal{W}^{S_i,S_j})}, \tag{11}$$

Obviously (11), the higher SLA, the more meaningful meta-path equals $\text{Softmax}^{S}(S^{\vartheta}_{(i,j)})$. Accordingly, the final embedding vector E is similar to the sum of two meta-paths θ_{ϑ_i}, and ϕ_{ϑ_i} based on node and semantic levels attention as follows:

$$E = \sum_{i=1}^{n} E^{\vartheta}_{\text{NLA}} + E^{\vartheta}_{\text{SLA}}, \tag{12}$$

According to (12), it is important to note that before aggregating information from neighbours for each node in the two meta-paths, we should consider that the neighbours based on meta-paths play various roles and have significance in learning the final vector embedding. Therefore, our research introduces two learning groups to create the final vector embedding: NLA and SLA. These groups correspond to the meta-path constructions based on NLA and SLA at each level. NLA and SLA have the capability to understand the importance of meta-path-based peers for individual nodes within a mixed graph. They then gather the representations of these significant peers to generate a node embedding using edge weighting. Finally, the outcomes of these two learning approaches are combined to create the final embedding vector, denoted as E.

3.4.2. Loss function

HFRS-DA reconstructs both the nodes (NLA) and the edges (SLA); hence the define of the loss function must include two parts: the node loss and the edge loss of the meta-path in the heterogeneous graph. The loss of the node feature during reconstruction has been reduced as follows

$$\mathcal{L}_{\text{Node}} = \sum_{i=1}^{n} \sum_{j=1}^{n} \| X_i - \hat{X}_i \|_2, \tag{13}$$

where X_i and $\hat{X}_i$ indicate the loss of the NLA stage calculated with popular ($\hat{X}_i$) and without popular nodes X_i in the HIN. The representations of the neighbouring nodes based on the meta-path should be similar to reduce the reconstruction loss of the edges of the heterogeneous graph

$$\mathcal{L}_{\text{Edge}} = -\log(\frac{1}{1 + \exp(\mathcal{W}^{S_i,S_j})}), \tag{14}$$

where $\mathcal{L}_{\text{Edge}}$ represents the edge loss and ($\mathcal{W}^{S_i,S_j}$) is the weight calculated using leaky ReLU activation from the Softmax of the impression coefficient We compute the overall loss function that consists of merging the loss functions at NLA loss and SLA loss as follows

$$\mathcal{L} = \mathcal{L}_{\text{Node}} + \mathcal{L}_{\text{Edge}}, \tag{15}$$

The essential point regarding the calculation of the loss function is that at the level of NLA, the path of the meta-path is based on the meet nodes, and it is restricted whether the recipe nodes are popular or not. But at the SLA level, the meta-path meets various edges and nodes, which causes us to examine the types of conditions that may end up with healthy recipe nodes via different edges. The number of recipes and users and the size of the meta-path are also affected.

3.5. A health-aware recipe recommendation system

The healthy recipe recommendation system relies on the user's behaviour in rating healthy recipes, which is evaluated through attention mechanisms employed in the two preceding stages. In this section, we arrive at a final embedding vector for both users and items. This vector is the sum of two other embedding vectors obtained from the NLA and SLA stages. To offer recommendations to users, we utilize the cosine similarity function as follows

$$C_S(a, b) = \frac{(a \cdot b)}{(\|a\| \cdot \|b\|)}, \tag{16}$$

Where $(a \cdot b)$ represents the dot product of vectors a and b, $\|a\|$ and $\|b\|$ represent the Euclidean norms of vectors A and B.

Additionally, based on the dataset structure and the number of user-rated recipes as detailed in Table 3, our recommendation system employs a combination of similarity-based and popularity-based approaches. For each user, we identify a group of similar users using cosine similarity scores above a specified threshold. From this pool of similar users, we compile a set of recipes that they have rated. The popularity of each recipe in this compiled set is determined by the frequency of ratings it has received. The popularity score (P_i) for a recipe (i) is calculated as the count of ratings given to that specific recipe.

$$P_i = \sum_{r \in C_S} |R_{i,r}|, \tag{17}$$

Where P_i is the popularity score for recipe i, C_S is the set of similar users based on cosine similarity scores above a given threshold, r_i is a recipe in the set C_S and $R_{i,r}$ is the count of ratings given to recipe r by users in the set C_S. $|R_{i,r}|$ represents the count of ratings in the set $R_{i,r}$.

This equation calculates the popularity score P_i for a recipe by summing the counts of ratings given to that recipe by users in the set of similar users C_S. The more ratings a recipe has received from these similar users, the higher its popularity score. This equation expresses the popularity score P_i as the sum of the counts of ratings given to recipe i by users in the set C_S, using the cardinality operator $|\cdot|$ to denote the count of ratings.

The general function of HFRS-DA is represented in Algorithm 1.

Algorithm 1 HFRS-DA: Health-aware Recipe Recommendation System with Dual Attention in Heterogeneous Graphs

Input:
The heterogeneous graph comprises nodes for users, recipes, ingredients, and nutrients.
The meta-path set $\vartheta_{\vartheta_0}, \vartheta_{\vartheta_1}, \ldots, \vartheta_{\vartheta_n}$, including popular recipes.
The meta-path set $\phi_{\vartheta_0}, \phi_{\vartheta_1}, \ldots, \phi_{\vartheta_m}$, including healthy recipes.
Output:
Node-level attention embedding vectors based on the popular recipes ($E^{\vartheta}_{\mathrm{NLA}}$).
Semantic-level attention embedding vectors based on the healthy recipes ($E^{\vartheta}_{\mathrm{SLA}}$).
Final embedding: E.
for $\vartheta_i \in \vartheta_0, \vartheta_1, \ldots, \vartheta_n$ **do**
  for $n = 1$ to N **do**
    Find the popular recipes and generate the meta-path based on the popular recipes and subsets ($f(x)$) according to Eq. (2).
    Calculate the node-level attention using the Softmax function ($\alpha^{\vartheta}_{i,j}$), as per Eq. (3).
    Aggregate the meta-path based on the node-level attention (E^{ϑ}_{i}) using Eq. (4).
    Generate an embedding based on the node-level attention $E^{\vartheta}_{\mathrm{NLA}}$ using Eq. (5).
  end for
  for $m = 1$ to M **do**
    Define and find the healthy recipes and subsets based on Eq. (7).
    Define and calculate the impression coefficient (μ) for learning the meta-path based on the SLA stage ($S^{\vartheta}_{(i,j)}$), according to Eq. (8).
    Generate the embedding based on the semantic-level attention ($E^{\vartheta}_{\mathrm{SLA}}$) using Eq. (9).
    Weight the edges between nodes ($\mathcal{W}^{S_i,S_j}$) in the meta-path based on SLA, according to Eq.(10).
    Calculate Softmax in the SLA meta-path as per Eq. (11).
  end for
  Generate the final embedding vector (E) and popularity score for recipe according to Eq. (12).
end for
Calculate the final loss function based on the two loss functions in the NLA and SLA stages (E) according to Eq. (15).
Calculate the cosine similarity between embedding vectors according to Eqs. (16) and (17).
Generate healthy recipe recommendations.

4. Experiments and results

Several studies have been done to review and evaluate the efficiency of recipe recommendation systems [11,22,23]. Accordingly, we compare our methodology with studies that have also used the Allrecipes dataset [5,6,10,77].

4.1. The allrecipes dataset

Since Allrecipes is the only publicly available dataset for recipe recommendation, we conduct our experiments as previously done in related research [5,6,10,77]. The dataset consisted of 70,390 users, 46,702 recipes with 230,475 ingredients, and 231,637 interactions. The users in the training and testing sets are kept consistent. The process of creating the initial heterogeneous graph is illustrated in Fig. 1, where direct links are established between the user and the recipes they have rated. Furthermore, each recipe is connected to its corresponding ingredients and nutrients through neighbourhood links. The graph includes 132,041 nodes and 1,987,779 edges. In each stage of model training, we determine the number of links between nodes by ignoring less important links. We convert the dataset into a heterogeneous graph that includes nodes for users, recipes, ingredients, and nutrients, sourced from *Allrecipes.com*. We construct our test set using the most recent 30% of historical interactions, while the remaining data 70% is used to evaluate the effectiveness of HFRS-DA. This validation set is used to optimize the performance of the model during the training process.

Table 3
User ratings distribution in the Allrecipes dataset.

Rating count	Percentage of users
One recipe	74%
Two recipes	10%
Three recipes	4.5%
Four recipes	2.5%
Five or more recipes	9%

Next, we present the distribution of data in the Allrecipes dataset, focusing on two key aspects: the distribution of users' ratings and the distribution of health factors among all the recipes. These distributions can be seen in Fig. 2.

In Fig. 2, both sections present histograms that depict the frequency of different rating values and health factors as percentages. Panel (a) focuses on the distribution of users' ratings within the dataset, ranging from 1 to 5. The histogram illustrates the percentage frequency of each rating value. Similarly, Panel (b) displays the distribution of health factors among all the recipes, ranging from 0 to 7. The histogram visually represents the percentage frequency of each health factor across the dataset. It is worth mentioning that a health factor value of 0 indicates that the recipes do not contain any health-related components.

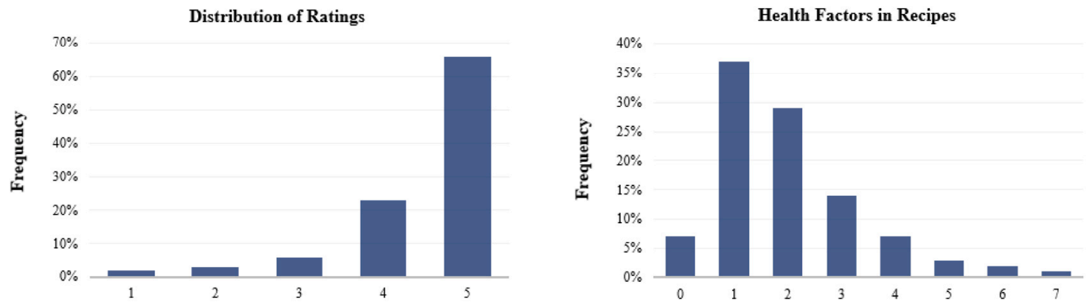
Moreover, a significant challenge associated with the Allrecipes dataset is its extensive dispersion, equating to 99.99%. This dispersion has a notable impact on the outcomes. Table 3 illustrates the distribution of user ratings based on the number of items they have rated.

The table in Fig. 3 highlights the sparsity inherent in the Allrecipes dataset by revealing the distribution of users based on the number of recipes they have rated. In this context, sparsity denotes the phenomenon where a significant portion of users has rated only a limited number of recipes, resulting in numerous missing ratings.

4.2. Evaluation parameters

AUC, NDCG, Precision,recall, and F1-scores are five commonly employed metrics for assessing the performance of recommendation systems. These metrics help us evaluate the effectiveness of the ranking lists in recommendations.

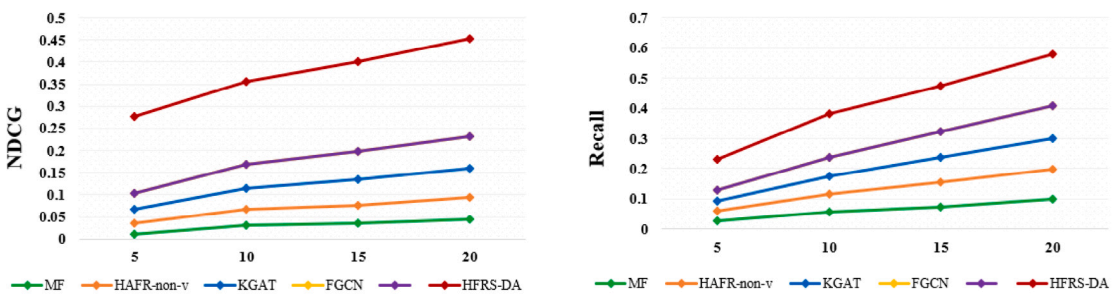
1. The Area Under the Curve(**AUC**) measures the probability that a classifier will correctly rank a randomly selected positive instance higher than a randomly selected negative instance.
2. The Normalized Discounted Cumulative Gain (**NDCG**) gives higher scores to hits that appear higher on the ranking list. NDCG assesses the quality of ranked recommendations by assigning higher scores to hits that appear higher on the ranking list. It takes into account both the relevance of recommended items and their positions in the list. To calculate NDCG, relevance scores for each item in the list are assigned (based on user ratings). The discounted cumulative gain (DCG) is then computed by summing the relevance scores, with the relevance of each item discounted by its position in the list. Finally, the DCG is normalized by dividing it by the ideal DCG (IDCG), which represents the maximum achievable DCG for the given list.
   Precision, Recall, and F1-scores are well-known metrics within the information retrieval community. These metrics are computed by categorizing recipe items into four groups using a



(a) The distribution of users' ratings

(b) The distribution of health factors for all recipes

Fig. 2. Distribution of users' ratings and health factors in recipes from the Allrecipes Dataset.



(a) Compared HFRS-DA based on NDCG

(b) Compared HFRS-DA based on Recall

Fig. 3. Compared HFRS-DA with other models based on NDCG and Recall.

confusion matrix. In this matrix, recipes that are deemed relevant are assigned to either the true positive (TP) or false negative (FN) categories, depending on whether the system correctly identifies them as relevant or not. False positives (FP) are recipes that the system incorrectly recommends as relevant, while true negatives (TN) are recipes that the system correctly identifies as irrelevant based on user preferences.

3. **Precision** which is defined as the proportion of relevant recommendations among the total number of recommended recipes, can be expressed as follows:

$$Precision = \frac{TP}{Tp + FP}, \tag{18}$$

4. **Recall** Likewise, this metric ratio is determined by dividing the number of relevant recommended recipes by the total count of relevant recipes that are available:

$$Recall = \frac{TP}{Tp + FN}, \tag{19}$$

   The Precision and Recall criteria inherently exhibit a straightforward conflict. When there are more top recommendations, the count of relevant recipes also increases, leading to an increase in the Recall measure, but this, in turn, causes a decrease in the Precision measure.

5. **F1-scores** offers a weighted combination measure by blending Precision and Recall in the following manner:

$$Precision = \frac{2 \times Precision \times Recall}{Precision + Recall}, \tag{20}$$

In certain situations, it is not possible to directly evaluate Precision or Recall when there is no available ground truth regarding the relevance of a given recipe, such as when users have not provided ratings. To tackle this challenge, our experiments employed Precision@k, Recall@k, and F1@k, where k represents the size of the recommendation list.

4.3. Baseline algorithms

We selected several baseline algorithms to evaluate the effectiveness of HFRS-DA using the same dataset. It is evident that the presented method outperforms other techniques in three key metrics. HFRS-DA demonstrates significantly higher efficiency compared to previous studies, as illustrated below:

1. **HAFR**: This study combined user–recipe relationships, recipe images, and ingredients to generate meal recommendations as a multimedia activity. To infer consumers' preferences over recipes for meal suggestions, a Hierarchical Attention-based Recipe Recommendation (HAFR) system was introduced in this work [5,10].
2. **FM-VBPR**: Authors incorporate visual features into the FM architecture, which is projected into an embedding as the user ID, recipe ID, and ingredients, to test the utility of visual and ingredient features simultaneously [5].
3. **HAFR-non-v and HAFR-non-i**: Two HAFR variations, HAFR-non-v and HAFR-non-i, do not require the input of a recipe image or ingredients [5].
4. **FGCN**: This study proposes a recipe recommendation approach that considers the complex relationships between ingredients, recipes, and users. The method uses Graph Convolutional Network (GCN) to improve the learning algorithm and capture high-order connectivity. Information propagation technique and multiple embedding propagation layers are used to achieve this [6].
5. **Collaborative Filtering Recipe Recommendations (CFRR)**: The objective of this research is to create a food recommendation system that utilizes user preferences conveyed through feedback, ratings, and various interactions. This system employs Collaborative Filtering techniques to achieve its goal [77].

6. **LDA**: This paper is related to the dietary recommendations approach. Users are treated as documents by the LDA recommender, while recipes are treated as words. After that, they adjust the topic number and utilize the Librec3 implementation [10,74].
7. **FM**: By simulating all interactions between each pair of attributes using factorized interaction parameters, the Factorization Machine (FM) calculates the target. User ID, recipe ID, and ingredients were chosen as the input features for this study [10, 78].
8. **VBPR**: The technique uses visual components, predicting user preferences for recipes by including the visual components as elements of recipe descriptions [10,79].
9. **NGCF**: Neural Graph Collaborative Filtering (NGCF) is a cutting-edge neural network-based recommendation method. Users and recipes are shown as nodes in a network, with the edges connecting them representing interactions. Learning user and recipe representation through graph convolution methods is the following phase for NGCF [80].
10. **MF**: MF uses the famous BPR as a loss function to improve the model. Keep in mind that this model only considers ID embeddings when describing users and recipes [81].
11. **KGAT**: The technique models high-order relations using a graph neural network architecture. To distinguish the relevance of the neighbours, it specifically builds a collaborative knowledge graph and uses an attention method [5].
12. **HAFR-non-v**: This method of meal recommendation uses a deep neural network to combine user–recipe interactions and recipe ingredients. It does this by taking advantage of a hierarchical attention mechanism [42].
13. **MF-BPR**: This study uses a typical Bayesian Personalized Ranking (BPR) by loss-optimized matrix factorization technique. This method is used without considering content information and utilizes recipe ID embeddings [10,23].
14. **PUP**: This approach is a graph-based general recommendation that captures the user's price preference while incorporating the item's price and category into the user–item graph [6,10].
15. **Cal-HAFR**: This method applies the calorie factor to HAFR, which is used to learn the recipe representation through hierarchical Attention as a recipe component [10].
16. **SCHGN-FR**: The authors propose a novel approach called SCHGN (Self-supervised Calorie-aware Heterogeneous Graph Network) to consider ingredient connections and track meal calories concurrently. They used an attention-based method to determine recipe recommendations based on the similarity between the user's calorie-aware model and a recipe aligned with their preferences [10].
17. **HTFRS**: This research presents the food recommendation model that considers user preferences and food nutrition data. The Health-Aware and Time-Efficient Food Recommender System operates in two stages. In the initial phase, the system forecasts user ratings by leveraging historical data. In the subsequent phase, it categorizes initial food items into clusters using a unique attribute-based community detection algorithm [77].

4.4. Compared baseline algorithms with HFRS-DA

In this section, we conduct a comparative analysis of the proposed method against several baseline algorithms, employing the introduced metrics for evaluation. The proposed method, denoted as **HFRS-DA**, aims to identify popular recipes by considering the number of ratings provided by users similar to the target user. This similarity is determined using cosine similarity, as outlined in Eqs. (16) and (17) . It is noteworthy that the NDCG and Recall metrics may exhibit discrepancies with the AUC statistic. This divergence could be attributed to the fact that while NDCG and Recall focus more on recipe placements, AUC aligns with the BPR loss. The methods discussed in Table 4 are enumerated below: It should be noted that the NDCG and Recall measurements do not agree with the AUC statistic. The explanation could be that whereas NDCG and Recall are more concerned about recipe locations, AUC is consistent with BPR loss. The methods discussed in Table 4 are listed below:

Table 4
Compared HFRS-DA with other algorithms based on AUC, NDCG@10, and Recall@10.

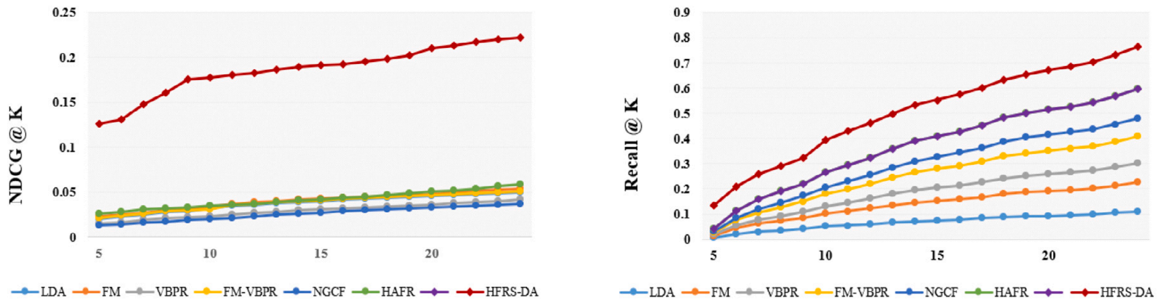
Row	Methods	AUC	NDCG@10	Recall@10
1	LDA	0.5154	0.0376	0.0601
2	FM	0.5710	0.0396	0.0607
3	VBPR	0.5808	0.0296	0.0431
4	FM-VBPR	0.5840	0.0372	0.0580
5	NGCF	0.5828	0.0269	0.0386
6	HAFR-non-v	0.6004	0.0332	0.0517
7	HAFR-non-i	0.6133	0.0418	0.0608
8	HAFR	0.6435	0.0455	0.0674
9	MF-BPR	0.5622	0.0376	0.0567
10	PUP	0.6526	0.0441	0.0676
11	Cal-HAFR	0.6562	0.0482	0.0708
12	HTFRS	0.6878	0.0509	0.0692
13	SCHGN-FR	0.7212	0.0569	0.0883
14	**HFRS-DA**	**0.7589**	**0.1890**	**0.1437**

HFRS-DA attains an AUC of **0.7589**, surpassing all other methods. A higher AUC signifies superior discriminatory power in ranking recommended items. This outcome implies that HFRS-DA adeptly discriminates between positive and negative instances, thereby enhancing overall ranking performance. In terms of NDCG@10, HFRS-DA stands out with a value of **0.1890**, the highest in the comparison. NDCG considers both the relevance and ranking of recommended items. The elevated NDCG@10 for HFRS-DA suggests that the proposed method excels in presenting relevant items at the top positions, taking into account the graded relevance of items. This underscores the method's success not only in recommending relevant items but also in prioritizing them effectively within the top positions. Additionally, HFRS-DA achieves a Recall@10 of **0.1437**, a notably competitive score. Recall measures the model's ability to retrieve relevant items. The strong performance of HFRS-DA in Recall@10 indicates its effectiveness in capturing a substantial proportion of relevant items within the top recommendations. Collectively, these results suggest that HFRS-DA offers a well-balanced and effective approach to recommendation compared to the other methods evaluated.

In the following and in Fig. 3, the evaluation method is based on the NDCG and Recall metrics. These metrics assess the ranking performance by evaluating one recommendation at a time. The ranking position indicates the position or rank of a recommended recipe item within the recommendation list. In our evaluation, we considered a range of ranking positions from 5 to 20, representing the top 5 to top 20 recommendations generated by the HFRS-DA model. To illustrate further, a ranking position of 15 indicates that we assessed the performance of the HFRS-DA model based on the top 15 recommendations it provided. We repeated this process for each ranking position within the range of 5 to 20, effectively evaluating the effectiveness of the HFRS-DA model across various positions in the recommendation list. The summarized results are as follows:

As you can see in Fig. 3, HFRS-DA had a higher performance in both metrics than other methods, and we followed the evaluation method based on the papers [5,10], and the results are shown in Table 4. In the following, the performance of the Top-K recipe recommendation is shown in Fig. 4, where K represents the ranking position and varies from 1 to 20, as described in [5]

As can be seen in Fig. 4, HFRS-DA consistently performs the best execution on both NDCG and Recall metrics. HFRS-DA has raised the attention mechanism's robustness and significance in exhaustively exploring information. In the next step, we aim to compare our proposed



(a) Comparison of HFRS-DA in the Top-K recipe recommendation based on NDCG@K

(b) Comparison of HFRS-DA in the Top-K recipe recommendation based on Recall@K

Fig. 4. Compared HFRS-DA with other models based on NDCG@K and Recall@K, the ranking position K ranges from 1 to 20.

Table 5
Evaluating HFRS-DA using metrics such as Precision@K, Recall@10, and F1@K.

Rows	Algorithm	Precision@10	Recall@10	F1@10
1	HAFR	0.0698	0.0672	0.0686
2	CFRR	0.0674	0.0648	0.0639
3	FGCN	0.0706	0.0682	0.0694
4	HTFRS	0.0732	0.0692	0.0712
5	**HFRS-DA**	**0.0614**	**0.1437**	**0.086**

method with other algorithms based on Precision@10,Recall@10, and F1@10 metrics, as shown in Table 5.

HFRS-DA demonstrates a lower Precision@10 compared to certain other methods. Precision@10 measures the proportion of relevant recommendations within the top 10. The lower precision values suggest that both methods may include more non-relevant items in their top recommendations. On a positive note, HFRS-DA exhibits an exceptional Recall@10 score of **0.1437**, surpassing other methods significantly. This implies that these methods effectively capture and recommend a larger proportion of relevant items within the top 10, potentially appealing to users who value broader coverage and are tolerant of a few less relevant recommendations. Furthermore, HFRS-DA achieves an F1@10 score of **0.086**, the highest among the compared methods. F1@10 combines Precision and Recall into a balanced measure. HFRS-DA strikes a commendable balance between Precision and Recall within the top 10 recommendations.

As evident, the performance of **HFRS-DA** at different stages of K on various metrics surpasses that of other approaches, highlighting the high quality of the proposed method in this research. The superiority of the proposed method in the evaluation can be attributed to several key factors:

1. **Enhanced Dual Attention Mechanism**: HFRS-DA incorporates an advanced dual attention mechanism that efficiently explores and captures relevant information from the input data. This heightened attention mechanism focuses on important features and patterns related to popular recipes and healthy recipes, resulting in improved recommendation accuracy.
2. **Comprehensive Information Exploration**: HFRS-DA exhibits superior performance by extracting data for popular and healthy recipes in two steps. Its comprehensive information exploration capabilities enable it to provide more personalized and accurate recommendations.
3. **Effective Representation Learning**: HFRS-DA leverages powerful representation learning techniques, creating meaningful and compact representations of users and items. The model captures latent patterns and embeddings in the data through two steps: NLA and SLA embedding, which are then combined together to enhance recommendation quality.
4. **Optimization of Ranking Performance**: The discrepancies observed in the metrics measurements further underscore the strengths of HFRS-DA. While it is true that the Precision@10 metric shows a slightly lower value compared to some other methods, the broader context reveals a more nuanced picture. HFRS-DA excels in the critical aspects of generating accurate and highly relevant top-N recommendations. Its ability to discern and suggest items that strongly align with users' health-conscious preferences is a standout feature. This results in higher scores across metrics, even when the overall pairwise ranking may not exhibit a significant difference from other techniques.
5. **Method of recommendations**: The generation of recommendations in this research involves two stages based on generated embedding vectors by a graph attention network. In the first level, for each user, we find similar users based on cosine similarity in embedding vectors. In the second level, we recommend recipes to users that have the highest ratings from other users who are similar to the target user. This strategy is one of the main reasons for the increased accuracy of recommendations, especially when the dataset has a large sparsity and users have low-rated items (Fig. 4).

In summary, these factors collectively contribute to HFRS-DA's prowess as a powerful and efficient recommendation system. It not only outperforms previous studies but also advances the state-of-the-art in recipe recommendation. HFRS-DA's remarkable performance in metrics demonstrates its ability to identify and recommend relevant health-conscious recipes effectively. This achievement positions HFRS-DA as a compelling choice for practical recipe recommendation applications, especially for users who prioritize health and a comprehensive set of recommendations.

4.5. Ablation study: The impact of SLA on HFRS-DA

Our objective is to assess the accuracy of the proposed HFRS-DA method through an ablation study. We evaluate the impact of removing two sections that generate embeddings based on NLA and SLA. We conduct two experiments, one using NLA embeddings and another using SLA embeddings, to provide recommendations. We then compare the results with HFRS-DA metrics, including AUC, NDCG@10, Precision@10, Recall@10, and F1@10. Table 6 presents the results of this evaluation.

The results of the Ablation Study, as presented in Table 6, offer valuable insights into the performance of HFRS-DA. This table provides a comparative analysis of HFRS-DA's performance in generating embeddings and delivering recommendations when utilizing NLA and SLA levels separately. Upon examining the outcomes, it becomes evident that employing the dual attention mechanism from both NLA and SLA

Table 6
Evaluation of the HFRS-DA system based on ablation study.

Row	Methods	AUC	NDCG@10	Precision@10	Recall@10	F1@10
1	Embedding with NLA	0.4995	0.0727	0.0277	0.0904	0.0424
2	Embedding with SLA	0.5002	0.0836	0.0379	0.1063	0.0558
3	HFRS-DA	**0.7589**	**0.1890**	**0.0614**	**0.1437**	**0.086**

stages for generating embeddings has a profound impact on the quality of the results, as evidenced by the metrics under consideration, such as AUC, NDCG@10, Precision@10, Recall@10, and F1@10. Although the results did not exhibit a stark contrast when NLA and SLA were used together versus separately, there is still a notable advantage to utilizing both components simultaneously. This advantage lies in the improved stability and robustness of the recommendation system. The synergy between NLA and SLA contributes to the system's overall performance by ensuring that it consistently provides high-quality recommendations across various scenarios. Therefore, while the performance gap may not be substantial, the combined utilization of NLA and SLA remains a strategic choice to maintain the system's reliability and effectiveness in diverse contexts.

5. Discussion

HFRS-DA features a dual attention mechanism as a health-aware recommendation system to identify healthy recipes in the Allrecipes dataset. Through extensive experimentation, we have demonstrated the high efficiency and effectiveness of HFRS-DA when compared to other recipe recommendation methods from the literature. Our results demonstrate that the use of the attention mechanism allows for a more comprehensive explanation of the heterogeneous graph, highlighting meaningful nodes and meta-paths relevant to the specific task. This level of interpretability provides valuable insights into the relationships and patterns in the heterogeneous graphs, enabling a deeper understanding and interpretation of the results.

It is important to note the distinctions when comparing our approach with previous studies. HFRS-DA leverages unsupervised graph representation learning, which is unlike supervised learning techniques that require a time-consuming process of creating labelled datasets. HFRS-DA utilizes meta-paths based on weighted importance paths at the nodes and edges levels. Additionally, the incorporation of inductive and transductive learning [31,32] into HFRS-DA enables learning from part to whole with minimal and ideal retention time. This unique approach allows for the integration of rich semantics in the heterogeneous graph, enabling the handling of various node and relation patterns. The parallelized nature of attention computation in HFRS-DA further contributes to its efficiency and effectiveness.

One of the key theoretical implications of our research is the potential for high-quality interpretability of the learned node embeddings for heterogeneous graph analysis. The HFRS-DA model offers a more comprehensive explanation of a heterogeneous graph by focusing on selected meaningful nodes or meta-paths for the specific task, thanks to the importance of nodes and meta-paths as determined by the attention values. This provides valuable insights into the relationships and patterns in the heterogeneous graphs, allowing for a better understanding and interpretation of the results.

Although our study presents promising results and advancements, it is essential to acknowledge its limitations. One potential drawback is the choice of meta-paths, as they heavily influence the final recommendations. Therefore, careful selection and optimization of meta-paths are essential to ensure the model's performance. Additionally, similar to other machine learning approaches, our model's performance heavily depends on the quality and quantity of the input data. The Allrecipes dataset, in particular, may introduce biases and limitations in terms of recipe diversity and cultural variations. As the Allrecipes dataset grows or as new recipe-related data sources emerge, refinements of the model will be possible.

Furthermore, our research has several practical implications. The HFRS-DA model offers advantages over previous models, including unsupervised graph representation learning, adaptability for heterogeneous graphs, and practicality for transductive and inductive learning. The incorporation of inductive and transductive learning into HFRS-DA allows for learning from part to whole, with minimal and ideal retention time. The parallelized nature of the attention computation in HFRS-DA, where each node and meta-path independently performs attention computation, makes the method effective and efficient. Moving forward, several exciting directions emerge from our research. One area of exploration is the incorporation of domain knowledge and expert insights to refine the selection of meta-paths and further improve the model's interpretability. Additionally, investigating advanced attention mechanisms and graph neural networks [31,32] could enhance the model's capability to capture more intricate relationships within the heterogeneous graph. Lastly, integrating user feedback and personalized preferences into the recommendation process could enhance the user experience and satisfaction with the recipe recommendation system.

In summary, our research contributes to the field of recipe recommendation by introducing a novel approach that leverages the dual attention mechanism and heterogeneous graph representations to overcome the limitations of existing methods. The theoretical implications of our research include the potential for high-quality interpretability of the learned node embeddings, while the practical implications encompass the advantages of unsupervised graph representation learning, adaptability for heterogeneous graphs, and the ability to incorporate inductive and transductive learning. Overall, our HFRS-DA model offers a promising solution for improving the effectiveness and efficiency of recipe recommendation systems.

6. Conclusion

In this study, we presented a novel health-aware recipe recommendation system called HFRS-DA, which is based on a heterogeneous attention network. Our model incorporates node-level attention and semantic-level attention to identify popular and healthy recipe nodes and to analyse user behaviour for recommending popular and healthy recipes. By leveraging the neighbours of ingredient and nutrient nodes associated with healthy recipes, HFRS-DA recommends recipes that are both popular and possess healthy characteristics to each user introduced to the recommender system. We conducted comprehensive experiments on the Allrecipes dataset to assess the effectiveness of our method to emphasize the importance of employing recommender systems that prioritize healthy recipes within heterogeneous attention networks. The results of our experiments highlight the high efficiency and accuracy achieved by the HFRS-DA model when compared to related methods. In summary, our HFRS-DA model offers practical implications for recommending popular and healthy recipes, providing comprehensive explanations for heterogeneous graph analysis, and making significant contributions to the advancement of health-aware recipe recommendation systems. Our study demonstrates the significance of leveraging recommender systems based on healthy recipes within heterogeneous attention networks.

CRediT authorship contribution statement

Saman Forouzandeh: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Supervision, Writing – original draft. **Mehrdad Rostami:** Conceptualization, Data curation, Investigation, Validation, Visualization, Writing – review & editing. **Kamal Berahmand:** Data curation, Formal analysis, Investigation, Resources, Validation, Writing – review & editing. **Razieh Sheikhpour:** Formal analysis, Investigation, Resources, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data and code availability

Data and Python code for the HFRS-DA model are given via GitHub repo: https://github.com/S-Forouzandeh/Health-aware-Food-Recommendation-System-with-Dual-Attention-in-Heterogeneous-Graphs.

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