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Emotional Insights for Food Recommendations

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Abstract. Food recommendation systems have become pivotal in offering personalized suggestions, enabling users to discover recipes in line with their tastes. However, despite the existence of numerous such systems, there are still unresolved challenges. Much of the previous research predominantly lies on users' past preferences, neglecting the significant aspect of discerning users' emotional insights. Our framework aims to bridge this gap by pioneering emotion-aware food recommendation. The study strives for enhanced accuracy by delivering recommendations tailored to a broad spectrum of emotional and dietary behaviors. Uniquely, we introduce five novel scores for *Influencer-Followers*, *Visual Motivation*, *Adventurous*, *Health* and *Niche* to gauge a user's inclination toward specific emotional insights. Subsequently, these indices are used to re-rank the preliminary recommendation, placing a heightened focus on the user's emotional disposition. Experimental results on a real-world food social network dataset reveal that our system outperforms alternative emotion-unaware recommender systems, yielding an average performance boost of roughly 6%. Furthermore, the results reveal a rise of over 30% in accuracy metrics for some users exhibiting particular emotional insights.

Keywords: Recommender system · Food recommendation · Cognitive science · Emotional insights

1 Introduction

In today's digital world, an immense amount of information is continuously uploaded to the Internet by various online services and applications. This led to an information overload challenge where users struggled to sort through massive data to find relevant content [29]. To address this challenge, researchers have turned to machine learning and deep learning to develop Recommender Systems (RSs) as key tools. These RSs not only filter out information overload efficiently but also use principles from information retrieval theory to ensure content is accurate and relevant, helping users easily find items that match their preferences [19]. Food recommender systems aim to offer food suggestions to users by assisting them in discovering their preferred food choices. They became

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a vital component in a variety of lifestyle applications and significantly influenced various dietary practices [23,34]. In today's fast-paced world, where food choices abound, food RSs emerge as valuable tools in shaping our dietary habits. While numerous food RSs exist in the literature [10,34], many challenges remain unaddressed. Notably, most prior research has focused mainly on users' historical preferences [25], often overlooking the crucial aspect of identifying emotional users' insights. The impact of informational stimuli on consumer decision-making is moderated by emotional responses [3]. Yang et al. [37] suggest that when users browse fashion brand websites, feelings of dominance and arousal are triggered. These emotions enhance pleasure and subsequently lead to a positive attitude toward the brands. In the realm of dietary choices, the behavioral, emotional, and cognitive profiles of users provide valuable insights into the underlying motivations and triggers that dictate their food preferences and diet style [20]. Based on a survey by the National Restaurant Association regarding ethnic food consumption, 20% of participants were identified as adventurous eaters, expressing a keen interest in trying dishes they have never tasted before [30]. Therefore, classic recommendation systems that emphasize only on the past user's interactions, and neglect their behavioral and emotional insights may struggle to provide efficient recommendations in this regard. Moreover, previous studies examining behavioral patterns of users on food reveal that some users place a higher emphasis on the visual attraction of foods compared to other attributes when making their food choices [4,9]. As a result, traditional food recommender systems, which predominantly rely on user ratings and comments as their primary data resource, fall short of offering appropriate recommendations for users with specific emotional insight. This underscores the need for a more nuanced approach to designing systems that take into account user emotions.

Drawing from prior literature in food science, we can identify diverse emotional insights in interactions with online food and recipes. Each pattern represents a distinct combination of dietary styles and emotions. First, *Social Influencer-followers* (in short, *followers*) align with digital trends, gravitating towards popular items and culinary movements. These trends are often dictated by the narratives promoted by social influencers [24,28]. *Visual Motivated* users in food social media are driven by the aesthetic appeal of dishes, prioritizing the photogenic quality of food presentations in their choices and interactions [33]. In contrast, *Adventurous Eaters* in food-focused social media are the culinary explorers, continuously delving into varied foods and always on the hunt for a diverse array of recipes. *Health Motivated* group prioritizes nutritional value and wellness, often seeking recipes and foods that align with a holistic and health-conscious lifestyle. Lastly, the *Niche Users* group is passionate about discovering lesser-known foods and exotic flavors, often engaging with less-explored gastronomic delights. Together, these user emotional insights underscore the diverse motivations and inclinations driving user engagement with food on social media.

In this study, our primary objective is to address the oversight of emotional patterns in food recommendations on social media. To capture the diversity in users' emotional patterns and attitudes, we innovate by introducing a re-ranking method that integrates the identified emotional attitudes of users. Using these

five scores, we adjust the initial recommendation list. Experiments conducted on a renowned food recommendation dataset showed that our model significantly improves the accuracy for both users with specific emotional patterns and the average community group. Importantly, our emotional-aware food recommendation approach enhances the performance of food recommendation systems by approximately 6%. Our contributions can be summarized as follows:

- To the best of our knowledge, this study is the first emotional user pattern-aware food recommendation system tackled in the information retrieval community. Although the features used to identify these patterns are straightforward and simple, this research lays the groundwork for future advancements in incorporating emotional patterns into a wide variety of RSs.
- We get inspirations from cognitive science and bring them into RS, contributing to a growing body of research aimed at improving personalization.
- We investigate the impact of our model on users with varied patterns. Results showed that users with pronounced health and visual motivation patterns experienced improvements of 30% and 18% in NDCG@10, respectively.
- We examine the significance of the emotion-aware model and its influence on aspects beyond accuracy, such as diversity and health.

2 Related Work

In contrast to conventional recommendation systems that only make use of content or collaborative filtering signals to model user preferences, context-aware recommendation systems take different contextual attributes into consideration and try to capture user preferences more correctly [16]. One of the approaches in context-aware recommendation is contextual post-filtering which involves two steps: generation of predicted ratings similar to conventional RSs, and then, use of contextual information to adjust those ratings for every user [22]. A special case of context-aware RSs that has gained attention in recent years is using personality [1,6–8,31], and other cognitive aspects such as behavior, and attitude [2,5,18,35] to enhance recommendation accuracy. Personality-aware RSs are based on measurable scales of personality traits, defined by personality theories. The Five Factors Model (FFM) [11] is one of the most popular in RS literature. The human personality is defined by five factors in FFM, namely Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. For instance, the impact of personality modeling using FFM was analyzed in [14] on music recommendation error. In [36], the impact of popularity bias on different personality traits was investigated. In [6], both users and items were grouped according to the influence of the recommendation on users' behavior, and the extreme scenarios of recommending influential items to sensitive users were studied. In [8] four different personality models were combined to represent the user's personality in a more precise way that fits various recommendation scenarios.

Many previous traditional behavior and personality-aware methods that categorize users based solely on behavioral or personality traits often oversimplify the vast emotional spectrum by categorizing them into *positive* or *negative* groups.

This reductionist approach misses the depth and intricacies of human emotions, limiting the potential for truly personalized recommendations. Embracing a multidimensional emotional representation and creating an emotional user-item profile, as we propose in this study, recognizes the intricate nature of emotions. This approach sets the stage for a more efficient emotion-aware model.

3 Proposed Method

The diversity of emotional insights reflects the vast array of individual experiences, backgrounds, and perspectives in human interactions and decision-making [12,26]. Diversity in emotional insights greatly influences decision-making, both on social media platforms and in the real world. Diversity plays a pivotal role when considering the emotional insights of individuals in the context of food choices. These patterns can vary significantly among individuals and can be even more pronounced due to the unique criteria and decision-making patterns each user employs when deciding what to eat. For instance, while one person might prioritize the visual appeal, shape, and imagery of a recipe, another might be more inclined to consider the healthiness of the food. This vast array of preferences suggests that a one-size-fits-all system may not cater adequately to the diverse needs of users. Therefore, it becomes imperative to first identify and analyze these emotional insights to subsequently personalize the system to better cater to individual preferences.

In this section, we introduce a framework that incorporates identified emotional user insights in food recommendations. The primary objective of this framework is to establish an emotion-aware model to improve overall performance by providing more tailored recommendations based on diverse emotional dietary preferences. It is important to note that behavioral patterns, such as Adventurous and Healthy motivation, do not inherently conflict with one another, and it is an oversimplification to categorize users solely based on a behavioral aspect. For instance, a user can prioritize Adventurous while also being Health-motivated. This nuanced understanding sets our RS apart from previous community detection-based models that pigeonhole users based on specific measures.

3.1 Problem Formulating

Consider a food recommendation system with n users and m foods. Assume $U = \{u_1, u_2, u_3, ..., u_n\}$ and $F = \{f_1, f_2, f_3, ..., f_m\}$ represent the sets of users and foods, respectively. Let R denote the user–food matrix containing the user ratings assigned to individual food items. In the scenario of not considering emotional insights, a list of top-N items, $L(u) = \{f_1, f_2, f_3, ..., f_N\}$, is suggested to the user $u \in U$ employing a base recommendation model. Given that basic food recommendations often overlook the intricacies of emotional insights, they tend to suggest items that might not align with individuals whose behaviors diverge from societal norms. To address this, we employ a re-ranking binary matrix,$A = [A_{ij}]_{n \times m}$, to determine if a food f_j should be included in the emotion-aware list for the user u_i or not.

3.2 Emotional Insights Identification

This method aims to provide more personalized emotion-aware food recommendations by adjusting the initial lists produced by traditional models. As previously pointed out, users interacting with online food and recipes typically exhibit five predominant emotional insights: Followers, Visual Motivated, Adventurous, Health Motivated, and Niche. In the subsequent phase, using these identified attitudes, we ascertain an individual's inclination weight towards each of them. To achieve this, we introduce for the first time, five novel criteria to score user's tendency towards these emotional attitudes and re-rank the initial recommendation list accordingly. In this step, as opposed to other behavioral-based food recommendation models that categorize users into predefined categories, we assign weight values to different emotional aspects. In fact, we aim to personalize the recommendation list by placing a greater emphasis on the emotional attitude of users. We describe these emotion scores in detail in the following subsections.

Followers: In the expansive realm of food-centric digital networks, the phenomenon of Social Influencer-followers stands out distinctly. These individuals not only demonstrate a keen sensitivity to the rapidly changing digital landscape but also exhibit a marked preference for following and engaging with popular foods and the latest culinary trends. Their behaviors and choices consistently align with these prevailing trends, which are predominantly influenced and shaped by the compelling narratives crafted and propagated by leading social influencers. In this study, we quantify the Followers' score by calculating the Social Influence value of the recipe items rated by them. As mentioned in [21], this value can be determined by considering three factors of average rating, the number of recorded ratings, and the number of comments as below:

$$Influence(f_i) = 2 \times \frac{AveRating(f_i) + Rating(f_i) + Comment(f_i)}{3} - 1 \quad (1)$$

where, $AveRating(f_i)$, $Rating(f_i)$ and $Comment(f_i)$ represent the normalized values of the average rating, the number of recorded ratings, and the number of comments, respectively, each ranging from 0 to 1. Given this normalization, the final computed $Influence(f_i)$ value will fall within the range $[-1, 1]$, where -1 and 1 respectively indicate low and high tendencies to follow influencers and trends. Next, the Social Influencer-followers value of user u_i calculated as:

$$InfluencerValue\,(u_i) = \sum_{f_j \in F_{u_i}} Rate\,(u_i, f_j) \times (Influence(f_j)) \quad (2)$$

where F_{u_i} is set of rated recipes by user u_i, $Rate(u_i, f_j)$ is our new defined rating scale denoting the rating of user u_i to recipe f_j. The new scale transforms the original ratings, ranging from [1, 5], into a new range of -1 to $+1$, indicating levels of strong disagreement to strong agreement. When a user consistently rates food items with high Influence Values highly or gives lower ratings to food items with low Influence Values, their Social Influencer-followers value is increased. As a result, Social Influencer-followers values will also range from -1 to $+1$.

Visual Attraction: Users influenced by the Visual Attraction emotional attitude are profoundly driven by the aesthetic allure of recipes, prioritizing the photogenic quality of food presentations in their interactions. These users, captivated by visual appeal, often base their choices and dining decisions on the visual spectacle of the food. This underscores the significant power of a food's visual presentation in the digital age. In this study, we determine the Visual Attraction value for users by computing the Visual Attraction value of a recipe item they rated. Drawing inspiration from [33], this value is determined by evaluating four factors: Sharpness, Contrast, Saturation, and Brightness:

$$Attraction(f_i) = \frac{Sharpness(f_i)+Contrast(f_i)+Saturation(f_i)+Brightness(f_i)}{2} - 1 \quad (3)$$

where, $Sharpness(f_i)$, $Contrast(f_i)$, $Saturation(f_i)$, and $Brightness(f_i)$ represent the normalized values of the Sharpness, Contrast, Saturation, and Brightness of the food f_i, respectively, each ranging from 0 to 1. Given this normalization, the final computed $Attraction(f_i)$ value will fall within the range $[-1, 1]$, where -1 and 1 respectively indicate low and high tendencies to follow Visual Attraction of the recipes. Next, the Visual Attraction value of user u_i can be calculated as below:

$$VisualValue\,(u_i) = \sum_{f_j \in F_{u_i}} Rate\,(u_i, f_j) \times (Attraction(f_j)) \quad (4)$$

Adventurous: Adventurous explorers are characterized not just by their curiosity, but by their continuous pursuit of diverse recipes, their openness to unfamiliar flavors, and their relentless quest for a broad spectrum of foods and recipes. The Adventurous value for a given user u_i can be defined as:

$$AdventurousValue\,(u_i) = \sum_{f_j, f_k \in F_{u_i}} Rate\,(u_i, f_j) \times Rate\,(u_i, f_k) \times (1 - Sim(f_j, f_k))$$

where $sim(f_i, f_j)$ is the similarity of f_i and f_j which as calculated as below:

$$Sim(f_i, f_j) = 2 \times \frac{\widetilde{G}_i . \widetilde{G}_j}{\left\|\widetilde{G}_i\right\|_2 \times \left\|\widetilde{G}_j\right\|_2} - 1 \quad (5)$$

where $\widetilde{G}_i$ is deep embedding vector of food f_i based on its ingredients.

Health Motivation: This emotional insight places paramount importance on nutritional value and overall wellness. These users are consistently on the lookout for recipes and foods that resonate with a holistic and health-conscious approach. To determine the Health Motivation value of a user, we must first compute the health factor of recipe items as follows:

$$Health(f_i) = \frac{12 - FSA(f_i)}{4} - 1 \quad (6)$$

where, $FSA(f_i)$ is the health level for food f_i. In this study, to calculate the healthiness of a specific recipe, we utilize the "traffic light" system [32]. This method, a universally acknowledged standard set by the UK Food Standard Agency (FSA) for food labeling and health assessment as referenced by Starke et al. [27], evaluates the health score of a food item based on four macronutrients: fats, saturated fats, salt, and sugar content. The FSA score assigned to each recipe falls between 4 and 12. Consequently, the ultimate $Health(f_i)$ value will span the range $[0, 1]$. Following the determination of a recipe item's health level, the Health Motivation for user u_i can be computed as follows:

$$HealthValue\,(u_i) = \sum_{f_j \in F_{u_i}} Rate\,(u_i, f_j) \times (Health(f_j)) \tag{7}$$

Niche Motivation: This emotional insight is mainly devoted to unearthing lesser-known recipes, and users who are mainly into exotic flavors. The Niche Motivation of user u_i can be defined as:

$$NicheValue\,(u_i) = \sum_{f_j \in F_{u_i}} Rate\,(u_i, f_j) \times (Novelty(f_j)) \tag{8}$$

where $Novelty(f_j)$ is the level of novelty of f_j can be calculated as:

$$Novelty(f_j) = 2 \times \frac{\sum_{f_k \in F, f_k \neq f_j} (1 - Sim(f_k, f_j))}{m - 1} - 1 \tag{9}$$

where m is the number of all foods in the dataset.

3.3 Re-ranking Recommendation

In this phase, we present a framework for harnessing the determined emotional tendencies of users. The objective is to generate a recommendation list that prioritizes user-specific emotional states and preferences. By doing so, this framework aims to produce a balanced and highly personalized food recommendation system that respects the unique emotional attributes of each user.

$$\begin{aligned} Maximize \quad & \sum_{i=1}^{n} \left[\sum_{j=1}^{m} A_{ij} \times S_{ij} \right. \\ & + \sum_{j=1}^{m} A_{ij} \times Influence(f_j) \times InfluencerValue(u_i) \\ & + \sum_{j=1}^{m} A_{ij} \times Attraction(f_j) \times VisualValue(u_i) \\ & \left. + \sum_{j=1}^{m} A_{ij} \times \sum_{f_k \in F_{u_i}}^{m} (1 - Sim(f_k, f_j)) \times AdventurousValue(u_i) \right. \end{aligned} \tag{10}$$

$$+\sum_{j=1}^{m} A_{ij} \times Health(f_j) \times HealthValue(u_i)$$
$$+\sum_{j=1}^{m} A_{ij} \times Novelty(f_j) \times NicheValue(u_i)\Bigg],$$
$$subject\ to \quad \sum_{j=1}^{m} A_{ij} = K$$

4 Experimental Results and Discussion

In this section, we assess the performance of the developed method through a set of comprehensive experiments using a real-world dataset.

Baselines: We discuss the effectiveness of our model in comparison to other emotion-unaware models. Below, we provide a brief overview of the baseline recommendation methods in the experiments.

- **Collaborative Filtering (CF)** predicts user favorite items by examining both user interactions and similarities among users.
- **Matrix Factorization (MF)** [15] takes into account users, items, and global bias terms for generating recommendations.
- **Neural Collaborative Filtering model (NeuMF)** [13] leverages a deep neural network to learn a function that effectively pairs users with items.
- **Variational Autoencoder Collaborative Filtering (VAECF)** [17] employs variational autoencoders to implement a generative approach, supported by a multinomial likelihood function.

Dataset: To assess the efficacy of our developed approach, we use a large-scale dataset featuring millions of ratings sourced from AllRecipes.com [10]. In this dataset, a total of 52,821 recipes were collected. The dataset includes user ratings, user comments, ingredients, and nutritional information about the recipes. After a pre-processing stage, the dataset contains 68,768 users, 45,630 food items with 33,147 ingredients, and 1,093,845 user interactions.

Evaluation metrics: In this study, we employ four accuracy evaluation metrics, including Precision@K (P@K), Recall@K (R@K), F1@K, and NDCG@K (N@K), to assess the performance of the models being compared. In addition to accuracy metrics, we introduce four alternative metrics to evaluate models from different perspectives: the Health, Popularity, Novelty, and Diversity Indexes. The first three metrics are defined as follows:

$$\text{Metric}Index\,(A) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} A_{ij} \times \text{Metric}\,(f_j)}{n \times K}$$

where Metric $\in \{Health, Popularity, Novelty\}$, while the Diversity Index is defined as follows:

$$DiversityIndex\,(A) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=j+1}^{m} A_{ij} \times A_{ik} \times (1 - Sim\,(f_j, f_k))}{\left(\frac{K(K-1)}{2}\right)}$$

Table 1. Recommendation accuracy performance of different models. * indicates statistically significant improvements of each Emotion-Aware model, compared to their Emotion-Unaware model (Friedman test, p-value < 0.05).

Method	Emotion-Unaware				Emotion-Aware (ours)			
	P@10	R@10	F1@10	N@10	P@10	R@10	F1@10	N@10
CF	0.0601	0.0604	0.0645	0.0385	0.0643*	0.0652*	0.0647*	0.0411*
MF	0.0684	0.0681	0.0682	0.0465	0.0728*	0.0723*	0.0725*	0.0484*
NeuMF	0.0707	0.0685	0.0696	0.0467	0.0751*	0.0724*	0.0737*	0.0492*
VAECF	0.0712	0.0691	0.0701	0.0490	0.0761*	0.0741*	0.0751*	0.0518*

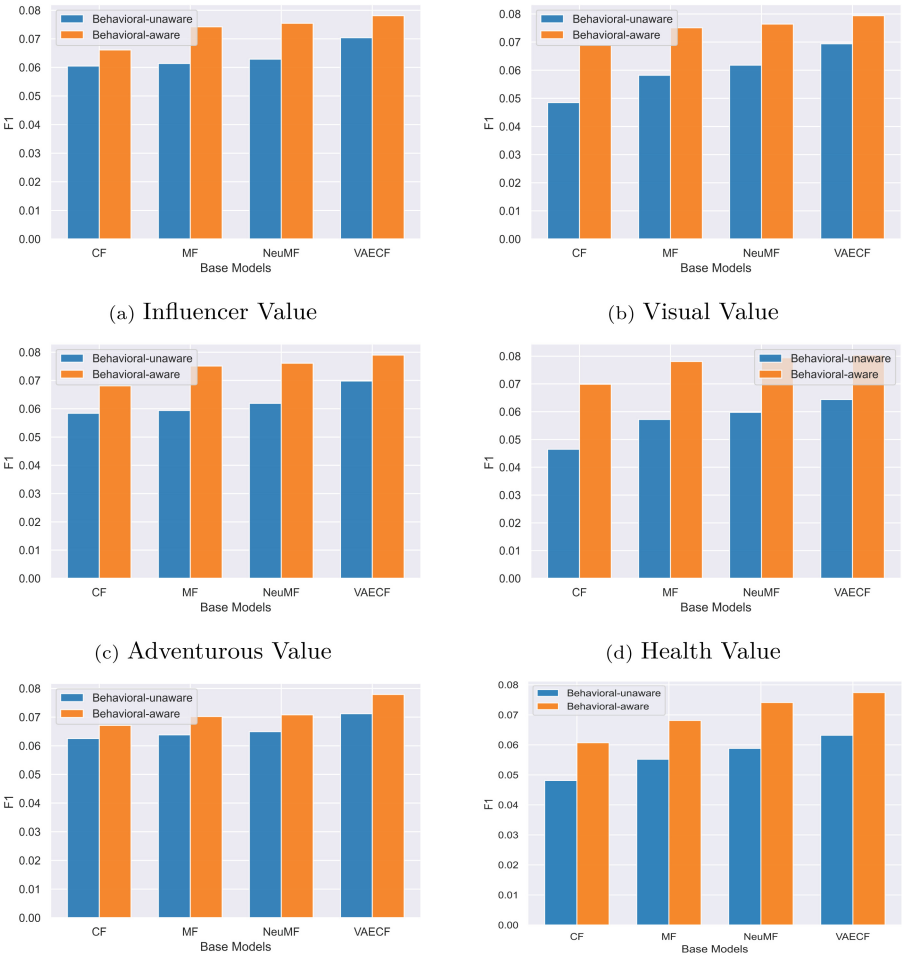
Table 2. Recommendation beyond-accuracy performance of different models

Method	Emotion-Unaware				Emotion-Aware (ours)			
	Health	Popularity	Novelty	Diversity	Health	Popularity	Novelty	Diversity
CF	-0.03	0.24	0.12	0.16	-0.04	0.28	0.14	0.17
MF	0.04	0.20	0.17	0.24	0.03	0.23	0.18	0.21
NeuMF	-0.05	0.23	0.14	0.21	-0.07	0.27	0.12	0.22
VAECF	0.06	0.21	0.15	0.22	0.04	0.26	0.14	0.20

It is important to note that all of these metrics range from -1 to 1. For the Health, Novelty, and Diversity Indexes, higher values denote better recommendation lists. However, for the Popularity index, a higher value could be interpreted as an indication of system bias.

Results: In Table. 1, we report the accuracy performance metrics including P@10, R@10, F1@10, and N@10. These are compared between two recommendation scenarios: Emotion-Unaware and Emotion-Aware. Our analysis suggests a consistent trend: using emotional insights to inform food recommendations enhances performance across all metrics. For example, in the case of VAECF, improvements of 6.88%, 7.24%, 7.13%, and 5.71% are observed for P@10, R@10, F1@10, and N10, respectively, indicating the advantage of understanding user's emotional tendencies. This enables more tailored personalized recommendations. Furthermore, we note that all the improvements between the emotion-aware models are statistically significant, when compared to their emotion-aware models, indicating the significance of incorporating emotion-inspired scores in the recommendation algorithm.

Additionally, in Table. 2, we detail the metrics focused on beyond-accuracy metrics, specifically the Health, Popularity, Novelty, and Diversity Indexes. An intriguing observation is that when emotional insights are incorporated into the recommendation system, there is a potential decline in the Health Index. A plausible explanation for this trend lies in individual preferences; many people are naturally drawn to unhealthy food options. Consequently, these identified emotional insights might inadvertently amplify the recommendation of less healthy food options. In other words, the preference of many users towards



(a) Influencer Value

(b) Visual Value

(c) Adventurous Value

(d) Health Value

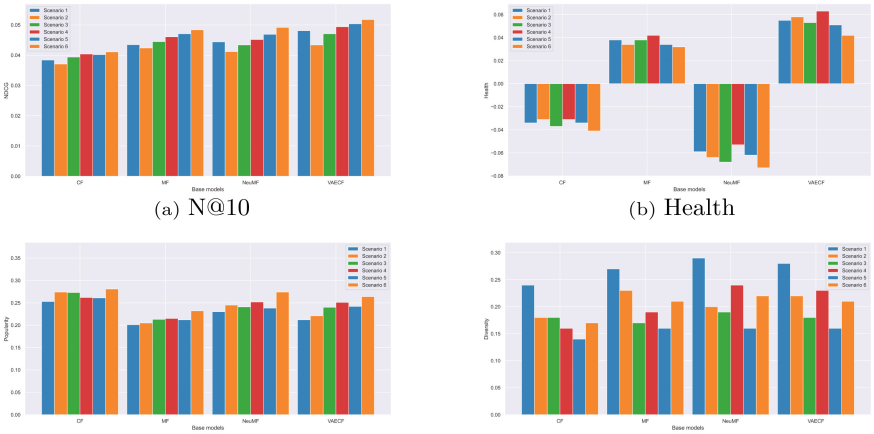
(e) Niche Value

(f) Cold start

Fig. 1. Performance improvement across various user emotion insights

unhealthy food choices prompts the RS to echo this behavior, recommending more unhealthy foods. A similar trend is observed in the Popularity index. This indicates that the system identifies a predominant emotional insight aligning with popular preferences, leading to recommendations of more popular food items. It is worth noting that a rise in the Popularity Index for recommended foods could also point to an inherent bias in the system recommending items with higher Influence value (i.e., average rating, number of ratings, and comments).

However, the situation differs for Novelty and Diversity. In certain cases, our model performs better on these criteria. This inconsistency might arise because the system contains an equal number of users who are hesitant to try novel food recipes as there are users who display a penchant for trying unknown foods.



(a) N@10 (b) Health

(c) Popularity (d) Diversity

Fig. 2. Ablation study on different accuracy and non-accuracy measures

One of the primary benefits of our model is that it accounts for the diversity in user emotions, thereby enhancing re-ranking based on their identified emotional insights. In our subsequent experiments, we have crafted diverse scenarios to illustrate the effectiveness of our model in enhancing recommendation metrics. These scenarios specifically focus on situations where the presence of users with distinct emotional inclinations might negatively impact the performance of recommendation systems. This approach allows us to showcase how our model adeptly addresses and mitigates these challenges, thereby improving the overall quality of RSs.

To demonstrate this, we outline five scenarios in Fig. 1. In the first scenario, we focus solely on 10% of users with a high InfluencerValue for evaluation. This is to specifically gauge the impact of our model on this user segment. For the second to fifth scenarios, we consider 10% of users with high levels of VisualValue, AdventurousValue, HealthValue, and NicheValue, respectively. The reported results indicate significant performance improvement for these user groups. For instance, for the top 10% of users with a high InfluencerValue, our model exhibits an average improvement of 13% in terms of F1@10. Furthermore, we see that users with a high HealthValue experience a maximum improvement of 36% in terms of F1@10. Conversely, we observe the minimum improvement for users with a high NicheValue, i.e., 8% in terms of F1@10. In addition to analyzing five user segments, we also assess the performance of various RSs for cold start users. The results demonstrate that our emotional-aware model significantly improves recommendation performance for these users.

Our model's primary contribution lies in its ability to identify user inclinations toward the aforementioned five distinct emotional insights. This part of our analysis assesses the significance of each user insight in improving the quality of food recommendations generated by our model. To illustrate this, we con-

duct an ablation study, examining how the performance of our model is affected when each of these user insights is excluded from the optimization equation (i.e., Eq (10)). Specifically, we outline five scenarios labeled as Scenario 1 through 5. In each, we exclude the Influence, Visual Motivation, Adventurous, Health Motivation, and Niche emotional insights, respectively. Moreover in Scenario 6, we consider all of these emotional user insights. Based on the described scenarios, we conduct experiments using various evaluation metrics. Figure 2 shows the results of the ablation study concerning accuracy and beyond-accuracy measures. Examining the accuracy performance (i.e., N@10) reveals maximum drops in Scenarios 2 and 3, indicating the importance of Visual Motivation and Adventurous. Upon examining various beyond-accuracy measures, it becomes evident that each term uniquely influences these measures. In terms of the Health measures, the findings are more interesting. The figure shows that omitting the Health term from the optimization equation enhances the final Health measure. This result arises because including this term often results in recommending unhealthier food options to those who already have unhealthy eating emotional insights, thereby directing them towards even more unhealthy recipes. As for the Popularity measure, the results are anticipated. The Influence and Niche terms emerge as the most pivotal. Additionally, our analysis shows that excluding the Influence term positively impacts the Diversity measure.

5 Discussion and Conclusion

Food RSs help users find their preferred food choices and play a pivotal role in many lifestyle apps. While many of these systems exist, they often focus on users' past preferences including user ratings and comments, neglecting their emotional insights. This makes recommendations less effective for users with specific emotional insights. In our study, we specifically addressed this gap and tested our approach on the social media food dataset. Specifically, our approach introduces a re-ranking mechanism that integrates users' behavioral and emotional insights. We assessed each user's emotional inclination toward each of the five factors: Social Influence Follower, Visual Motivation, Adventure, Health Motivation, and Niche. These factors are then used to refine the recommendation list. Testing on a well-known food recommendation dataset revealed that our approach enhances the accuracy of recommendations by boosting the match with users' preferred recipes by around 6%. The results also indicated that incorporating emotional insights into a recommendation system can lead to a decrease in the Health Index due to users' emotional inclination towards unhealthy food options, resulting in the system recommending such foods more frequently. A similar trend is observed in the Popularity Index, recommending more popular food items. Additionally, the results showed that specific users with high HealthValue and VisualValue yield improvements of 36% in F1@10, 30% in N@10, 27% in F1@10, and 18% in N@10. This underscores the adaptability of our model to cater to a broad spectrum of users with varying emotional aspects, rather than merely focusing on the community's average.

Our initial findings are promising, hinting at potential applications of emotional analysis and cognitive science in enhancing personalized recommendations. Our approach to Emotional Insights for Food Recommendations can be extended to other areas of recommender systems. By identifying specific emotional insights for users and items in various domains, such as E-Commerce, Fashion and Lifestyle, Travel and Tourism, our method can be adapted for emotional-aware recommendations in these fields. This generalization allows for a more nuanced understanding of user preferences across different sectors, leveraging the emotional aspect to enhance the recommendation experience. However, several areas require further investigation to enhance the performance of our model:

- ***Concept Drift:*** The current model of the RS relies on static data and does not account for potential shifts in user's emotional attitudes towards food, diet, or lifestyle. For a more accurate recommendation, it is essential to detect concept drift, which refers to changes in the relationship between users and their emotional responses.

- ***Controllable Recommendation:*** Controllable RSs allow users to influence recommendations, enhancing transparency and trust. Our emotion-aware model does not consider controllability. This omission could lead users to perceive the system as overly deterministic, possibly causing dissatisfaction if they feel their emotions are misinterpreted. Providing user control, especially regarding emotional states, is vital for user acceptance.

- ***Intensification of Negative Attitude***: The emotion-aware system could inadvertently intensify negative emotional attitudes. If users display emotions related to an unhealthy diet, the system might predominantly recommend unhealthy foods. This could unintentionally promote detrimental dietary habits, with the system potentially acting as an enabler of such behaviors. Therefore, in future work, we should emphasize the role of AI in promoting a healthy lifestyle, rather than solely focusing on increasing user satisfaction.

- ***Not Considering Seasonality and Social Media Trends***: Key elements such as seasonality, which plays a crucial role in the availability and popularity of certain foods and recipes, are not integrated into our system. This omission means that the recommendations may not always align with seasonal products or dishes, potentially leading to less relevant or appealing suggestions for users. Additionally, our system does not factor in the dynamic and influential social media trends. Given that social media significantly shapes culinary trends and public interest in specific types of cuisine or dishes, this exclusion could result in the system being out of sync with current food fads or popular eating habits.

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