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Social media and food: Dietary trends across languages and countries

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ABSTRACT

The rise of social media platforms has remarkably influenced everyday life, including how food is represented, shared, and perceived online. Yet, limited attention has been given to how the nutritional content shared on these platforms reflects and shapes users' dietary preferences over time. This study investigates the relationship between social media recipe-sharing and nutritional patterns by analyzing approximately 8 million Instagram posts from around 200,000 users across five languages (English, French, German, Italian, and Spanish) from 2016 to 2023. Leveraging a novel analytical framework powered by Large Language Models, we extracted ingredients from textual recipe posts and examined temporal trends in calories and macronutrients. Additionally, we evaluated recipes' nutritional quality using the Nutri-Score classification system and assessed how user engagement varies by nutritional category. Our findings indicate stable nutritional patterns overall, with minimal shifts towards either calorie-dense or healthier options. However, significant continental variations emerged, suggesting that regional cultural factors strongly shape the circulation of dietary content online. Moreover, engagement analysis highlights geographic segmentation in food preferences by Nutri-Score categories, pointing to how cultural differences influence the popularity of foods with varying nutritional profiles. These insights underscore the value of understanding digital food discourse and engagement patterns when considering the social dynamics of dietary trends.

1. Introduction

Social media platforms have revolutionized human communications and interactions, becoming integral to our daily lives. These digital ecosystems facilitate the rapid spread of information [1,2], transforming how people access content, participate in discussions, and form opinions [3–6]. While this connectivity fosters knowledge sharing, it also raises concerns [7,8] especially when applied to sensitive domains such as health [9], politics [10,11], and freedom of speech [12]. In the domain of food and nutrition, social media provides unprecedented access to dietary trends and nutritional information, but also presents significant challenges for food policy — particularly regarding food marketing and misinformation [13]. Social media influence may extend beyond individual dietary choices, shaping public perceptions of food safety, nutrition, and health risks. Research highlights its role in both facilitating rapid communication during food crises and amplifying unverified claims [14]. While these platforms can enhance food literacy, they may also distort it through biases and uncontrolled information sharing [15]. Beyond merely disseminating food-related content, social media actively shape public discourse, influencing attitudes and behaviors. Platforms like Instagram have evolved into virtual food ecosystems where recipes, food photography, and diet discussions thrive. This wealth of content creates opportunities for promoting healthier eating habits but also raises concerns about the reliability of shared information. Moreover, social media trends — often fueled by activism, media coverage, and political conflicts — can selectively amplify narratives around food and nutrition, shaping public perception and policymaking in significant ways [16]. These concerns have become more pressing as the global food landscape faces increasing strain from climate change and geopolitical instability. Rising food insecurity and disruptions to supply chains further complicate public health challenges such as obesity [17] and malnutrition [18], reinforcing the urgency of addressing how nutrition is communicated in the digital sphere [19].

Despite increasing attention to these issues, the intersection between digital ecosystems and nutrition remains underexplored. Existing studies have examined dietary discussions on platforms such as Twitter [20,

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21], particularly in crisis contexts such as pandemics [22] or natural disasters [21]. While these studies have demonstrated the potential of digital traces as proxies for analyzing food environments [23], less is known about the long-term evolution of nutritional content in social media and its potential influence on user preferences [24]. Addressing this gap aligns with the UN 2030 Agenda for Sustainable Development Goals, particularly the goal to “end hunger, achieve food security and improved nutrition, and promote sustainable agriculture” [25]. A deeper understanding of how food-related content evolves on social media and how users engage with it is essential for informing effective food policies.

To fill this gap, our study investigates the following research questions:

RQ1 To what extent do continental differences in calorie distribution reflect underlying cultural, political, and socioeconomic factors?

RQ2 How do the nutritional profiles of online recipes evolve over time in terms of macronutrient composition and Nutri-Score classification?

RQ3 How is audience engagement related to healthy and unhealthy Nutri-Score categories, and how do these engagement patterns vary across regions with differing social valuations of healthy diets?

To answer these questions, we examine the relationship between online recipe sharing and nutritional characteristics. First, we analyze the distribution of calories and macronutrients across posts from different countries to identify patterns in shared content. We also examine the Nutri-Score categories of these recipes and their divergence across regions. Next, we explore temporal trends in the nutritional composition of recipes shared online. Finally, we assess the relationship between user engagement and nutritional quality, investigating whether global cultural, economic, and social factors influence the dissemination of food content on Instagram.

The paper is structured as follows: Section 2 reviews the relevant literature. Section 3 details the methodology, including data collection, recipe extraction, nutritional quantification, and the Nutri-Score estimation, concluding with an overview of Principal Component Analysis. Section 4 presents the analysis and findings, which are discussed in Section 5.

2. Related work

2.1. Nutritional analysis through social media data

The increasing use of social media platforms over time [26] has contributed for research in the emerging field of food computing [27]. Early efforts in this area primarily focused on estimating the nutritional values of food by analyzing images of meals [28]. With the advent of social media, this research rapidly expanded by leveraging the vast amounts of food-related content shared on these platforms. Initially, researchers explored the lexical landscape of food-related content on Twitter [29], later extending their analysis to include food-related conversations on Reddit [30]. Moreover, significant efforts were directed towards estimating nutritional intake from social media content, beginning with Twitter [20,21,23] and subsequently expanding to YouTube [31]. These studies have demonstrated the potential of digital food traces not only as indicators of the health of the food environment [23] but also as proxies for assessing the impact of rare events such as pandemics [22,31] and natural disasters [21].

2.2. Extracting food entities from textual data

The proliferation of food content on social media made possible the creation of several annotated food databases [27], which are primarily compiled by paid users and domain experts. These databases have been instrumental in advancing Named Entity Recognition (NER) tasks within food-related content [32]. In information extraction techniques, Named Entity Recognition (NER) refers to a subtask that seeks to identify named entities from unstructured text and classify them into pre-defined categories such as names, codes, quantities. In this specialized subdomain, NER focuses on identifying recipe components such as ingredient names, quantities, and measurement units [32]. However, this task is particularly challenging due to the heterogeneous nature of food language and the scarcity of structured and annotated data, which complicates the application of supervised learning approaches [33]. To overcome these challenges, earlier research introduced rule-based methods for entity extraction [34], which have since been significantly enhanced by transformer-based models [35–38]. These deep learning models have substantially improved NER capabilities in food-related content. However, previous architectures typically relied on multi-step pipelines. Entity recognition and relation extraction were treated as separate, sequential tasks, a design that often led to error propagation. By contrast, large language models (LLMs) represent a paradigm shift towards joint, sequence-to-sequence information extraction. Rather than classifying individual tokens, LLMs exploit their generative capabilities to process unstructured text and directly output complex, structured records [39]. Additionally, the development of LLMs [40–42], with their vastly increased parameter counts, has further extended the performance of previous architectures across numerous NLP tasks [43]. LLMs have achieved promising results even in zero-shot scenarios [44], including those involving food recipes, thereby reducing the reliance on food-specific datasets for NER tasks [45]. NLP techniques and LLMs are increasingly applied to NER on social media data across multiple research domains. In biomedicine, NER is used to extract health-related entities, enabling large-scale analyses of public health discourse [46,47]. In geospatial research, NER supports the extraction and disambiguation of locations from social media texts, facilitating spatial inference and mobility analysis [48,49] for disaster monitoring [50], particularly through the integration of geoparsing and geotagging workflows that resolve linguistic ambiguities to map informal text into precise geographic coordinates [51]. In computational linguistics, social media NER is used both as a benchmark for model robustness and as a means to analyze linguistic variation in noisy, informal settings [52], while also motivating the development of methods explicitly designed to handle the syntactic and structural irregularities of user-generated text [53]. More recently, LLMs have enabled structured information extraction directly from raw text, extending NER beyond token-level classification and improving cross-domain adaptability [39].

3. Methods

The following section outlines the analytical workflow adopted in this study, illustrated in Fig. 1.

3.1. Data collection

The data collection process is achieved through CrowdTangle [54], a Meta-owned tool that tracks interactions on public content from Instagram accounts and Facebook pages, groups, and verified profiles. CrowdTangle does not include paid ads unless those ads began as organic, non-paid posts that were subsequently “boosted” using Meta’s advertising tools. CrowdTangle also does not include the activity of private accounts or posts made visible only to specific groups of followers.

The collection of posts is performed on Instagram, covering a period ranging from 1/1/2016 to 31/12/2023. We employed a keyword search approach based on a list of terms identified as descriptive for recipe-like posts (see Supplementary Table S1 for a complete list of terms). To provide a geographical dimension of content consumption about food, we manually retrieve, from Instagram, the registration country of all those accounts that posted at least 100 times during the analysis

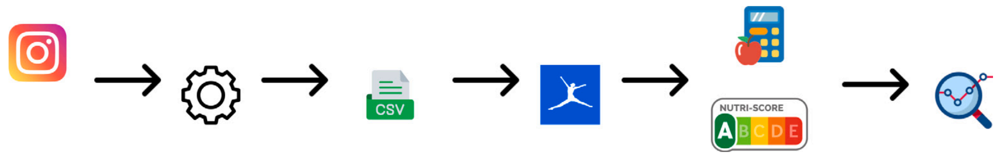

Fig. 1. Analytical workflow. We begin by collecting data from Instagram, which is then processed using a Large Language Model (LLM) to generate CSV files containing recipe information. We then employ MyFitnessPal to retrieve nutritional details and assign a Nutri-Score to each recipe.

Table 1
Data breakdown of posts collected on Instagram and Facebook.

Language	Posts	Users	Users with at least 100 posts	Posts with recipes	% of ingredients from MFP
EN	3,805,090	241,904	6966	305,885 (12.43%)	61.30
IT	276,798	9,202	501	43,549 (16%)	55.74
DE	224,501	11,348	420	39,255 (5.71%)	62.28
FR	106,313	7,116	189	34,120 (32%)	57.91
ES	629,320	27,072	1241	248,720 (41.11%)	59.12

period. Then, we kept only those countries with at least 50 labeled accounts and at least 1000 posts. The results obtained from the data collection procedure are reported in Table 1. It is important to note that advertising campaigns run on the platform are not included in the analysis. Our dataset comprises only organic (non-sponsored) posts. While it is not possible to determine whether some posts contain promotional elements, we can affirm that none of them were published through Meta's advertising system. Consequently, neither microtargeting nor algorithmic advertising mechanisms has any influence on the sample under examination.

3.2. Extract recipes from posts

To perform the extraction of food entities from Instagram posts, we employ the Mistral 7B [55] LLM from Hugging Face [56] as a zero-shot model for our NER task. Mistral 7B is a Large Language Model designed to be highly efficient and powerful despite its relatively small size, making it useful for tasks like answering questions, writing content, and coding, allowing its customization for various applications. The decision to use Mistral 7B was driven by the need for control and computational capability, along with the possibility of running the tasks locally. To maximize the model performance for this task, we make use of prompt engineering techniques [57], i.e., the process of structuring an instruction that can be interpreted and understood by a generative AI model [58]. Specifically, we use a few-shot prompting [59] technique, instructing the model to generate a CSV file from the input text containing the *food name*, *quantity*, and *measurement unit* columns, including an example to aid the model's comprehension.

To evaluate the model's NER performance in the food domain, we test it against the evaluation set provided in the TASTEset [35], a dataset of food recipes specifically designed for the NER task. It includes a total of 700 recipes whose elements were manually annotated using the BRAT algorithm [60]. In this work, we focus exclusively on entities identified with the *Food*, *Quantity*, and *Unit* types. We compare our zero-shot approach with Mistral 7B, with the corresponding prompt described in the Supplementary Section 2.1 "TASTEset Evaluation", and FoodNER [61], a BERT model which provided the best F1 scores for the identification of the entities of interest for this study [35]. The results of this comparison are detailed in Table 2, from which we can observe how our zero-shot approach, based on Mistral 7B and prompt engineering, achieves results comparable to the FoodNER model. In summary, we opted for Mistral 7b due to its superior generalization capabilities in comparison to FoodNER. FoodNER was trained only on 700 recipes that were already in a parsed format, significantly limiting its effectiveness when applied to the informal and diverse language commonly found in social media texts. Additional robustness checks regarding the employed model are described in the Supplementary Section 3 "Robustness Check".

Table 2
Benchmark results between FoodNER and Mistral 7B of TASTEset evaluation set.

Method	F1 Food	F1 Quantity	F1 Unit
FoodNER	0.89 ± 0.01	0.99 ± 0.004	0.98 ± 0.005
Mistral 7B	0.82 ± 0.02	0.80 ± 0.02	0.88 ± 0.03

3.3. Assess nutritional content and Nutri-Score estimation

To estimate the nutritional values of the ingredients extracted from posts, we employ MyFitnessPal (MFP) [62], an online service that acts as a nutritional diary where users can track their nutritional intake by searching an extensive database for their chosen food or drink [63]. Several studies found that MFP confirms its accuracy in real-world settings [64], suggesting its suitability for reliable nutrient analysis in research contexts [65]. Moreover, a randomized crossover trial found that MyFitnessPal outperformed the PortionSize app, showing lower error and higher user preference in estimating energy intake under free-living conditions [66].

We perform a lookup in the MFP database for each ingredient in a recipe using a keyword search, considering only entries matching exactly with the search terms and the specified unit. We select the first 5 items marked as *verified* by the platform to reduce the potential noise due to entries with improperly estimated nutritional values. Then, we compute the average values of the nutritional information from the previous items, namely: *calories*, *protein*, *calcium*, *carbohydrates*, *fats*, *fiber*, *iron*, *monounsaturated fats*, *polyunsaturated fats*, *saturated fats*, *cholesterol*, *potassium*, *sodium*, *vitamin A*, *vitamin C*, *sugar*, and *net carbs*.

Based on this information, we calculated the calorie composition of recipes in terms of macronutrients. To achieve this goal, we calculate the calorie proportion of each macronutrient referring to the Atwater system [67]. The Atwater system is a well-established method used to estimate the caloric content of food by calculating the metabolizable energy derived from carbohydrates, fats, and proteins. In this system, carbohydrates and proteins are assigned a caloric value of 4 kilocalories per gram, while fats are given a value of 9 kilocalories per gram. These values reflect the average energy absorbed by the human body after accounting for losses in digestion and metabolism. Accordingly, the total number of calories in a recipe is computed using the following formula:

$$\text{calories} = C \cdot 4 + F \cdot 9 + P \cdot 4,$$

where C, F, and P represent the amounts in grams of carbohydrates, fats, and proteins, respectively.

On the other hand, we define the salubrity of the recipes by employing the Nutri-Score system.

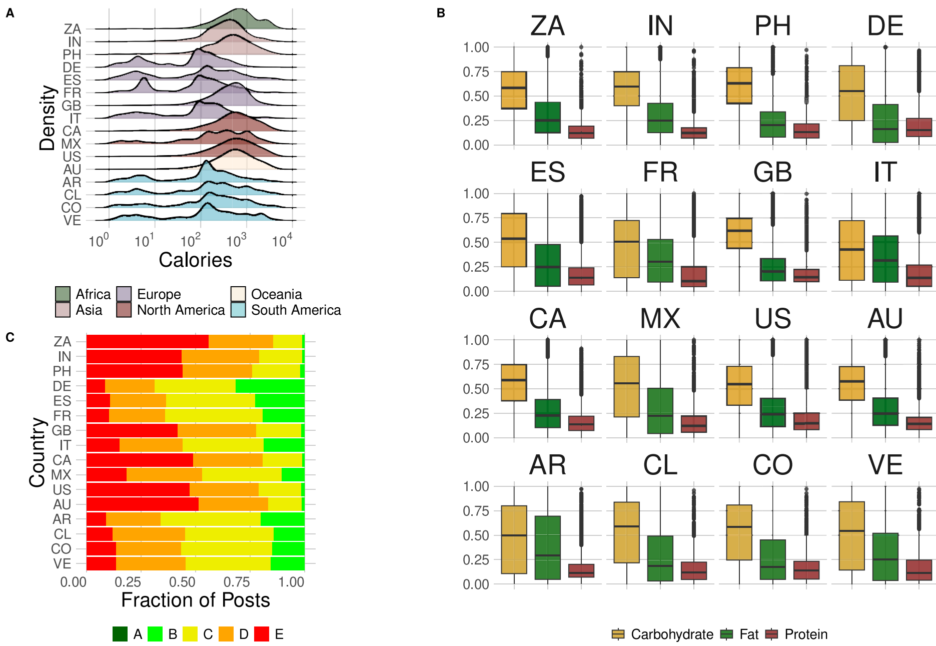

Fig. 2. (A) Distribution of Calories in Instagram recipes divided by country and continent. (B) Distribution of Percentage of Macronutrients for each country. (C) Fraction of Instagram recipes for each Nutri-Score Category divided by country. The Nutri-Score classifies foods into five categories based on their nutritional composition, ranging from A (indicating the highest salubrity) to E (the lowest salubrity), to assess overall nutritional quality. Further details on the Nutri-Score and how it is computed are provided in Section 3.3.

The Nutri-Score is a five-color nutrition label and rating system designed to simplify the understanding of the overall nutritional quality of food products [68]. The rating ranges from A (most nutritious) to E (least nutritious), with corresponding colors from green to red. The score is calculated based on the United Kingdom Food Standards Agency's (FSA) nutrient profiling system [69,70], which the Nutri-Score extends with a detailed algorithm that evaluates the nutritional quality of food products by considering both unfavorable and favorable nutrient content.

The Nutri-Score is composed of Positive (P) and Negative (N) scores for each food product. The Positive score reflects the adverse impact a food can have on health by measuring the amount of energy (kJ), total sugars (g), saturated fatty acids (g), and sodium (mg) per 100 g or milliliters of the product. Conversely, the Negative score quantifies the beneficial effects of the food by assessing the percentage of fruits, vegetables, legumes, and nuts it contains, as well as its fiber (g) and protein (g) content. The final Nutri-Score is obtained by subtracting the Negative score from the Positive score, yielding a range from −15 (healthiest) to 40 (least healthy) [71]. Foods with a Nutri-Score of −1 or lower are graded A, those scoring between 0 and 2 are graded B, scores between 3 and 10 correspond to a C grade, scores from 11 to 18 receive a D grade, and those scoring above 19 are graded E.

In this paper, we compute the Nutri-Score for each recipe as follows.

We first categorize every ingredient from the collected recipes by following the Nutri-Score 2023 Update [72] categories, namely 'General foods', 'Red meat', 'Cheese', 'Fats/oils/nuts/seeds' or 'Drinks', by means of a Mistral 7B LLM, whose prompt, along with an example, is reported in the Supplementary Section 2.2 "Nutri-Score category labeling prompt".

Once each ingredient was labeled, we assigned it a corresponding value according to the Nutri-Score algorithm and its conversion tables [72]. These values were calculated based on the nutritional information obtained from MFP and adjusted for the specific quantity of each ingredient used in the recipe. Finally, we determined the overall Nutri-Score category for each recipe by summing the positive and negative points, in line with the official Nutri-Score algorithm.

3.4. Principal component analysis

Principal component analysis (PCA) [73] is a technique for reducing the dimensionality of some vectors in a high-dimensional space, increasing interpretability while minimizing information loss. It does so by creating new uncorrelated variables that successively maximize variance [74]. Let $\mathbf{M} \in \mathbb{R}^{n \times p}$, where the n rows represent individuals and the p columns are observations of variables measured on each individual. The element $M_{i,j}$ therefore indicates the value of the jth variable for the ith individual.

The results of PCA are often displayed as a biplot [75], that is, a two-dimensional representation whose goal is to maximize the variance for both variables and observations. These plots represent points whose position on the two axes indicates the values they have on the two principal components selected, and a vector for each variable where the PCA was applied, whose distance from the origin indicates how well that variable is represented in the two-dimensional plot. The angle between any two variable vectors indicates their correlation, with the cosine of the angle corresponding to the correlation coefficient. Variables with a positive correlation tend to cluster together, while those with a negative correlation tend to appear in opposite directions.

Beyond its theoretical relevance, we emphasize that in this study we employ PCA to explore the relationship between the nutritional quality of posted recipes within a given country and the level of engagement these posts receive. Specifically, we treat countries as individuals and Nutri-Score categories as variables, constructing the matrix using the fraction of engagement generated by recipes with a given Nutri-Score in each country.

4. Results

4.1. Eating habits around the world

We begin the results by assessing the nutritional quality of recipes posted online across all selected countries (see Section "Data collection" for further details).

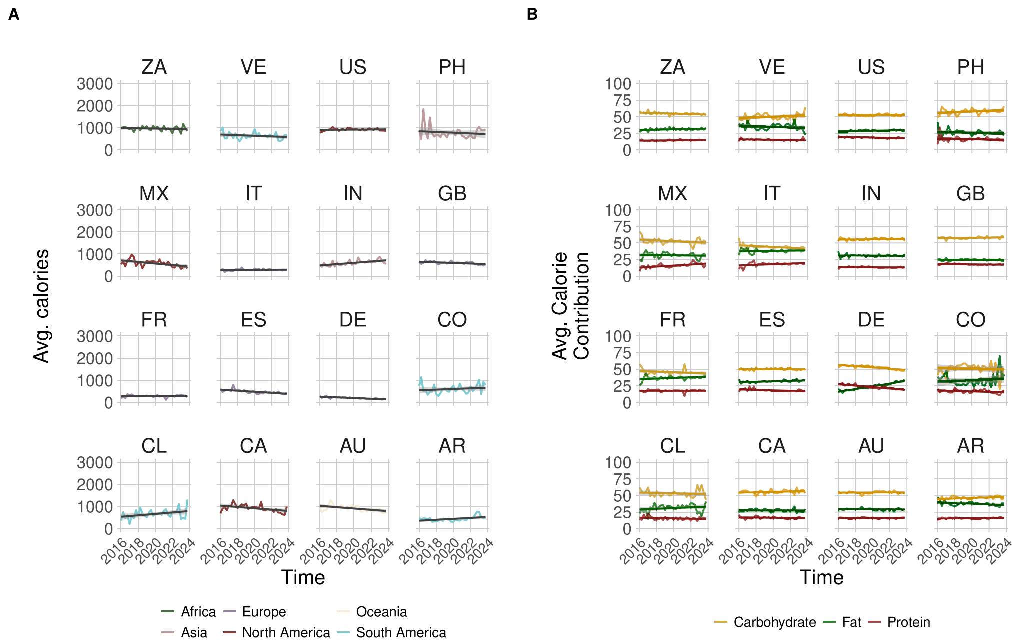

Fig. 3. (A) Average Quarterly calorie evolution by country. (B) Quarterly average calorie composition evolution, in terms of their macronutrients, for each country. In both figures the straight line represents the linear regression equation estimated from the trend, and the gray area the 95% confidence interval obtained from the estimation.

With this objective in mind, we proceed by evaluating the calorie composition of recipes. Details on the calorie composition computation are described in Section 3.3.

First, we begin by examining the calorie intake of recipes for each country. Fig. 2A illustrates the calorie distribution over the entire analysis period.

Our observations reveal that most recipes have a calorie intake of around 100 calories, while only a small number have significantly higher calorie values. Furthermore, it is remarkable how recipes from countries on the same continent tend to exhibit similar caloric distributions. This pattern is especially pronounced in South American and Asian countries.

Next, we examine recipes based on their macronutrient composition. Fig. 2B displays the distribution of macronutrient proportion in online recipes, highlighting that carbohydrates are the primary macronutrient across all analyzed countries. Furthermore, fat content is consistently higher than protein in online recipes from each country. However, the distributions, especially for protein and fat, contain several outliers, which may be attributed to recipes that emphasize only one specific macronutrient.

The calorie and macronutrient distributions of recipes provide a general understanding of their impact if included in our daily diets. However, these elements lack several factors known to affect human health, such as the amount of sugar, saturated fats, and the presence of fibers and vegetal elements. Therefore, we continue the analysis by quantifying the evolution of the average quarterly Nutri-Score obtained from post recipes in different creator countries.

From this perspective, Fig. 2C shows the fraction of recipes for Nutri-Score category, divided by country. The Nutri-Score classifies foods into five categories based on their nutritional composition, ranging from A (indicating the highest salubrity) to E (the lowest salubrity), to assess overall nutritional quality. Further details on the Nutri-Score and how it is computed are provided in Section 3.3.

First of all, we noticed that our dataset contains only one recipe in the A category. This likely occurs because many ingredients with negative values, such as oil and butter, are commonly used in the cooking process. As a result, finding recipes that qualify for the A category proves challenging. Nevertheless, it is interesting to observe that certain countries have a significant proportion of their recipes falling into the worst Nutri-Score categories. These countries include South Africa, India, the Philippines, Great Britain, Canada, the United States, and Australia. Conversely, other countries exhibit a much higher percentage of recipes falling into the B-category. Notably, Germany and Argentina stand out as the leaders in this aspect. Notably, even in the most favorable cases, around 50% of the posts are classified within the B and C nutri-score categories.

Overall, this initial analysis suggests that the production of food content on social media has very common aspects across countries in terms of meal composition. On the other hand, the distribution of calories differs from one country to another, showing continental patterns. Ultimately, the percentage of posts belonging to the top Nutri-Score categories is quite low, except in a few specific countries.

4.2. *Evolution of dietary patterns*

We continue the study by examining the evolution of the nutritional intake of the recipes posted online during the analysis period. Fig. 3A shows the average quarterly evolution of calories posted by accounts from different countries. Ordinary Least Squares (OLS) linear regressions were applied to these time series, with trends statistically assessed using the Mann–Kendall test. Note that the p-values associated with all regressions and statistical tests employed in this section have been adjusted for multiple comparisons by applying the Holm-Bonferroni method [76].

The results, summarized in Supplementary Table S2, reveal heterogeneous trends across countries, with 31.25% of the trends classified as downward, 6.25% as upward, and the remaining 62.5% without a defined direction. However, we note that most of the slopes are not significantly different from 0 and, in general, coefficients have very low magnitudes, thus almost flat behaviors. Interestingly, this indicates that recipes posted online have maintained the same average calorie intake over time.

Thereafter, we go into detail by assessing the evolution of the calorie composition of recipes in terms of macronutrients. Fig. 3B illustrates the average quarterly calorie percentage of the different macronutrients across the analyzed countries. Overall, carbohydrates

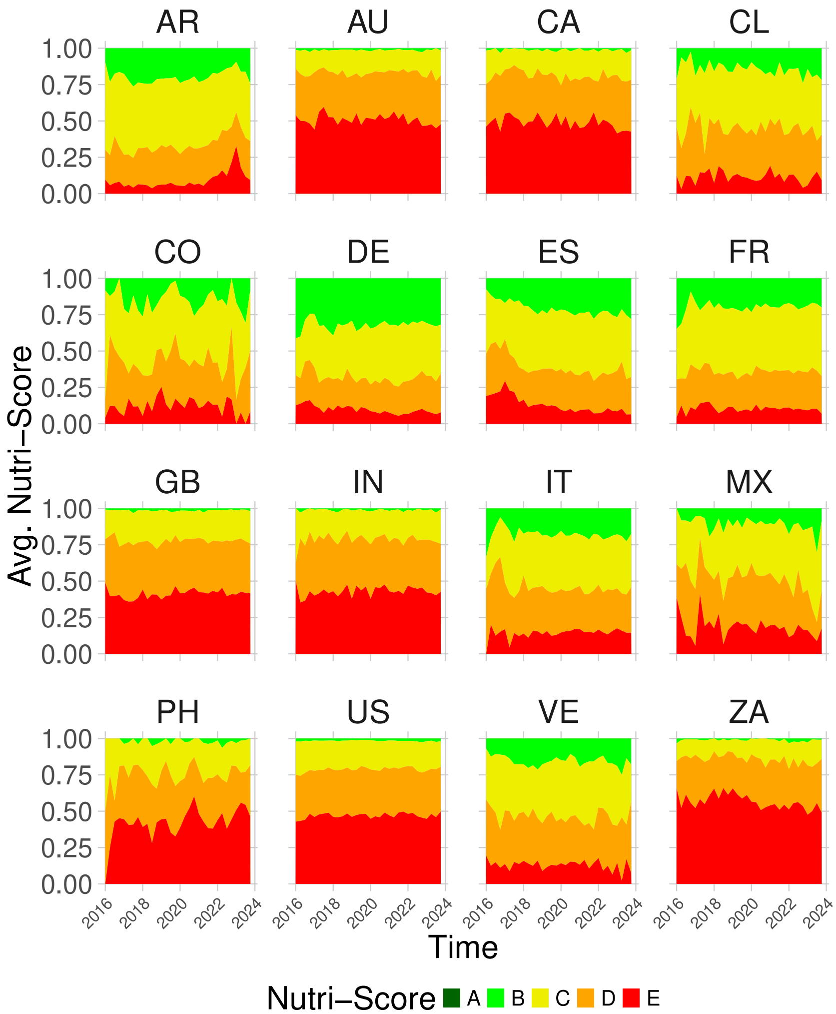

Fig. 4. Average Quarterly Nutri-Score evolution by country during the analysis period.

emerge as the predominant macronutrient in the recipes, followed by fats and proteins, regardless of the country or the period under examination. We employed again OLS and Mann–Kendall test to assess each macronutrient trend, as described in Supplementary Table S3. The results indicate a general steadiness in the trends across countries, with 77.08% of the time series showing no significant upward or downward monotonic trend.

Given that, in this instance as well, most slopes are not significantly different from 0 and the coefficients are generally quite small, our findings indicate that there are no significant changes in the nutritional values of the posted recipes during the analyzed period, both in terms of calories and macronutrients. This suggests that the posting behavior of food creators did not shift towards recipes with a particular composition of macronutrients or calories.

Finally, we analyze the trend in the nutrional quality of recipes shared on Instagram. Fig. 4 illustrates the mean fraction of recipes belonging to a certain Nutri-Score category, for each quarterly. In this Figure, we can observe a heterogeneous distribution of Nutri-Score values, where the presence of recipes falling in the B category can be found in European countries like Italy (IT), nutri (FR), Germany (DE), and Spain (ES). On the contrary, recipes with lower nutritional profiles, tend to be linked with Canada (CA), South Africa (ZA), Australia (AU), United States (US), India (IN), Philippines (PH) and Great Britain (GB).

After conducting the OLS and Mann–Kendall tests again, the analysis indicates a stedy trend in the evolution of Nutri-Score over time, supporting the findings from previous results. Specifically, Supplementary Table S4 shows how in 76.56% of cases, we did not observe a significant upward or downward monotonic trend.

4.3. Investigating the interplay between recipe engagement and nutri-score

We conclude our analysis by examining the relationship between the nutritional quality of the posted recipes and the level of engagement these posts receive. For this purpose, we define engagement as the total number of interactions a post generates. We do so to obtain a comprehensive view of how users interact with individual posts. Mathematically, we sum all available forms of user interactions on Instagram (i.e., likes and comments), as the reposting option had not yet been introduced on the platform during the period under analysis. To do this, we construct a matrix $\mathbb{M}^{c\times n}$, where c represents the number of countries analyzed in this study, and n denotes the Nutri-Score categories (*B, C, D, E*). We excluded category A due to an insufficient number of recipes for meaningful analysis. Each entry M_{ij} captures the fraction of total interactions collected by recipes posted by creators in country i that fall into Nutri-Score category j. We then apply Principal Component Analysis (PCA) and show a lower dimensional representation of the data in the biplot depicted in Fig. 5. Our PCA accounts for a substantial proportion of the total variance, specifically 97.29%; with 81.18% explained by the first principal component and 16.11% by the second one. Moreover, to show the exact values from which our relationship is based, Supplementary Section 6 “Cross-Country Correlation

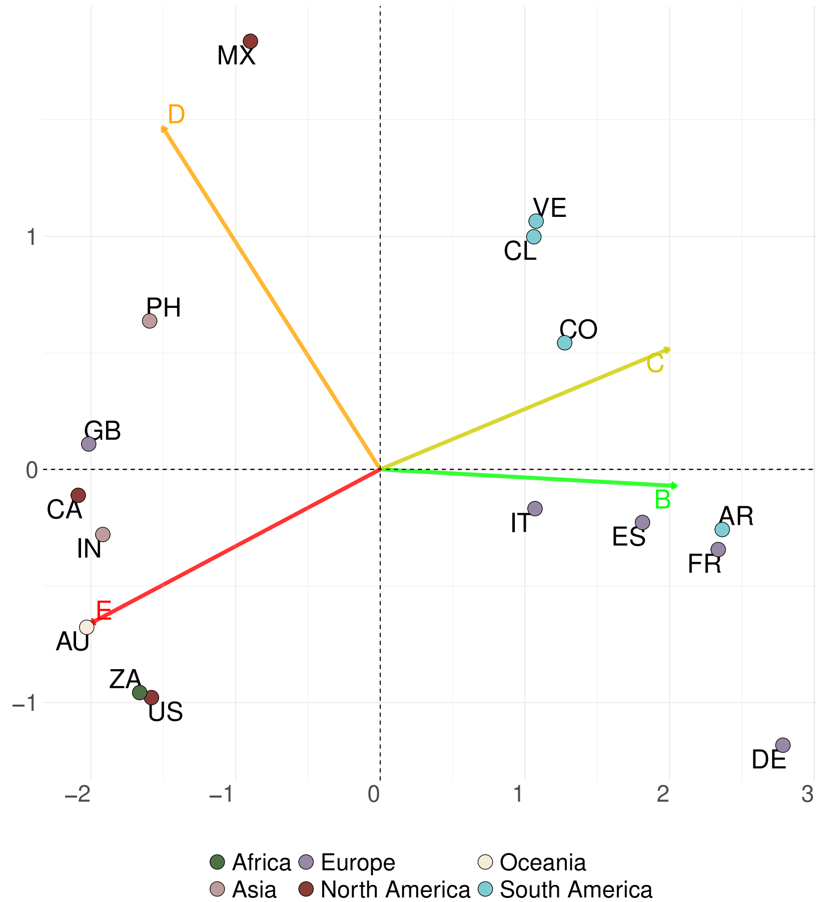

Fig. 5. Results of a Principal Component Analysis (PCA) on the engagement patterns of various countries with different Nutri-Score categories (A, B, C, D, E). Countries are represented by their ISO codes, with their positions reflecting the relationship between user engagement and the nutritional quality of the recipes. Vectors correspond to Nutri-Score categories, and the plot highlights potential regional influences on dietary preferences.

Matrices" reports the country-by-country correlation matrices based on NutriScore profiles.

First, we observe negative correlations between the unhealthy Nutri-Score categories (D and E) and their healthier counterparts (B and C). This suggests that in countries where recipes with higher health ratings receive substantial engagement, recipes with lower health ratings tend to perform less successfully, and viceversa.

Moreover, the results reveal distinct regional patterns in how engagement with Nutri-Score categories varies across countries, reflecting differences in food cultures and health policies. Indeed, the United States (US) and other North American countries, such as Canada (CA) and Mexico (MX), are positioned away from the origin, particularly in the direction associated with Nutri-Score categories D and E—those with the lowest nutritional quality. This suggests a higher level of engagement with less healthy recipes.

In contrast, European countries like Germany (DE), Italy (IT), Spain (ES), and France (FR) are located on the opposite side of the plot, showing higher engagement with healthier recipes, particularly those in the Nutri-Score category B. This pattern aligns with the European health policies aimed at promoting healthier eating habits may contribute to these engagement trends. To examine the phenomenon from a broader perspective, we display the distribution of engagement across different Nutri-Score categories. Supplementary Figure S1 illustrates that there are no significant differences between the distributions across categories, suggesting that the observed patterns likely reflect underlying geographical, social, and cultural factors.

Several countries, including Australia (AU), New Zealand (NZ), Great Britain (GB), South Africa (ZA), India (IN), and the Philippines (PH), fall within the third and fourth quadrants, suggesting a greater level of engagement with less healthy recipes. Notably, Argentina (AR) presents an intriguing case, as recipes classified in the B or C Nutri-Score categories, garnered more interactions than those from other categories.

In summary, the geographical clustering identified through the PCA highlights potential cultural and regional influences on dietary preferences and health communication strategies, particularly concerning engagement with specific Nutri-Score categories. This alignment suggests a correlation between geographical regions and engagement with healthier or less healthy food content. Cultural factors and dietary habits likely drive audience interactions with posts featuring foods of varying Nutri-Scores, further underscoring the role of regional context in shaping public food choices and engagement trends.

5. Discussion

In this paper, we explored how social media reflects and potentially influences nutritional aspects of dietary habits. We began by analyzing the distribution of calories and macronutrients in recipes shared on Instagram, identifying variations across countries and over time. Additionally, we examined the evolution of the nutritional quality of food content, using the Nutri-Score classification, and investigated the relationship between user engagement and recipe healthfulness. Our findings reveal a general stability over time in the nutritional composition of recipes (calories, macronutrients, and Nutri-Score) across the analyzed countries. This stability suggests that social media platforms do not substantially drive shifts towards either calorie-dense or low-calorie foods, nor towards foods particularly high in proteins or fats. Such consistency indicates that despite the dynamic nature of social media, nutritional profiles of shared recipes remain remarkably steady. However, significant continental variations emerged, highlighting the role of cultural, socioeconomic, and political factors influencing online food content. These findings are supported by our analysis of user engagement patterns relative to the Nutri-Score. Indeed, the varying engagement levels observed across Nutri-Score categories geographically may indicate the presence of cultural differences in food preferences, where certain regions may favor recipes that align with their traditional diets, regardless of their nutritional value. Such patterns align with recent work that showed that favorable Nutri-Scores do not necessarily encourage larger portion selections or increased food intake, suggesting that consumer interaction with health labels is complex and culturally nuanced [77]. Furthermore, the disconnect between the healthiness of content and user engagement may also indicate the presence of echo chambers or polarization within online food communities, where users are more likely to interact with content that reinforces their existing beliefs or preferences rather than being swayed by healthier options. Finally, we emphasize the negative relationship between the Nutri-Score's healthy and unhealthy categories in terms of engagement. This dynamic suggests that in countries where healthy food posts generate more interactions, unhealthy food posts are generally unappreciated, and vice versa. As a result, social media may not be as effective in promoting healthier eating habits as one might hope, given the persistent appeal of less healthy but culturally resonant or visually attractive recipes.

The implications of these findings are significant for both research and policymaking. Methodologically, this study introduces a robust framework for analyzing nutritional characteristics of online food content, providing a foundation for future work in this area. Using social media data allows for real-time tracking of dietary trends, offering critical insights into emerging nutritional risks or opportunities for targeted interventions.

For policymakers, the observed stability in nutritional content underscores the nuanced role of social media in reinforcing dietary norms rather than significantly reshaping them. Consequently, nutrition policies can benefit from incorporating social media insights, particularly to counteract misinformation or harmful dietary narratives.

5.1. Limitations and future work

Nonetheless, this study faces limitations. The accuracy of ingredient extraction using Large Language Models (LLMs) is contingent on the quality and diversity of the training data, which may introduce biases. Additionally, the nutritional assessments rely on MyFitnessPal, a third-party app with user-generated data that could contain inaccuracies, although we focused on verified entries. Furthermore, applying the Nutri-Score –a system originally designed for packaged foods–to social media recipes required certain adaptations, potentially affecting the precision of health evaluation.

Future research can expand the analytical framework developed here to include additional social media platforms and a broader set of geographic contexts, providing deeper insight into global dietary trends. Additionally, future studies could investigate the biological properties of ingredients used in social media recipes, exploring how these factors relate to users' nutritional habits and the emergence of new dietary trends. From a platform perspective, further research is needed to understand how polarization influences user interactions with food content on social media. Clarifying the dynamics behind user engagement, especially in relation to nutritional quality and dietary choices, can help inform targeted strategies for effectively promoting healthier eating behaviors online. Moreover, incorporating environmental sustainability alongside nutritional quality could address emerging public concerns related to climate impacts of dietary choices.

In conclusion, by clarifying how social media interactions shape dietary decisions and nutritional perceptions, this research contributes valuable insights for enhancing nutritional communication and informing effective policymaking in a digitally connected world.

CRediT authorship contribution statement

Gabriele Etta: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Emanuele Sangiorgio:** Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Simon Zollo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Niccolò Di Marco:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis. **Fabiana Zollo:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology. **Matteo Cinelli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Walter Quattrociocchi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization.

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.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.osnem.2026.100349.

Data availability

Data will be made available on request.

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