Exploring the Sentiment of Latvian Twitter Food Posts in Various Weather Conditions

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Abstract
Food choice is a complex phenomenon influenced by factors such as taste, environment, culture, weather and many others. Although people spend most of their lives indoors, weather conditions remain influential, both in shaping seasonal food cultures in particular geographical areas and in influencing individual choices. With the recent increase in the availability of datasets on food and its perception as reflected in Twitter and historical weather data, we seek to explore food-related tweets in different weather conditions. In this paper, we examine a Latvian food tweet dataset covering the last decade in conjunction with a weather observation dataset consisting of average temperature, precipitation and other phenomena. We find out which weather conditions lead to specific food information sharing; we automatically classify tweet sentiment and discuss how it changes depending on the weather. We also explore the dynamics of sentiment related to meat and meat consumption on Twitter over a ten-year period. The rationale for focusing on tweeters’ sentiments about different meat-containing foods is due to the emergence of new discourses related to food consumption - the meat industry’s impact on planetary health, the levels of biodiversity, pollution and CO2 that influence and shape climate change, as well as the planet’s ecosystems as a whole.

Keywords
Linguistics, Social Network, Analysis, Food

1. Introduction

Food choice and consumption play an important role in public health. Obesity, type 2 diabetes and cardiovascular diseases are just some of the health problems associated with poor diet. According to the WHO Global Health Observatory (2016), one in four adults is overweight and one in ten is obese. The global prevalence of obesity has reached pandemic level. Therefore, it is of utmost importance to understand the underlying factors of food choice, which is a complex process influenced by various endogenous factors such as taste, quality, texture, colour and others, as well as exogenous or external factors ranging from demography, education level, time of day, weather, the environment in which food is consumed and others [1, 2, 3, 4].

Although most of our modern lives are spent indoors, weather and climate conditions still influence our food preferences and consumption [5]. Sunny weather and moderate temperatures
lead to better moods among food consumers, while more extreme weather (hot, cold, any precipitation) means less pleasant weather conditions that affect mood and thus food consumption experiences. This is important in understanding that mood is the determining factor in food choices, with good mood associated with healthier food choices and bad mood associated with less healthy food choices [3].

While the impact of food on personal health is an area discussed by food policy makers and nutritionists globally, another new discourse has emerged in relation to food consumption, namely, the impact on planetary health or levels of biodiversity, pollution and CO2 that influence and shape climate change, as well as the planet’s ecosystems overall [6]. One third of global carbon dioxide emissions are assigned to food systems, where the largest contribution comes from agriculture and land-use activities (estimated 71% of the total emissions), while the food supply chain - transport, consumption, retail and other related processes account for 29% respectively [7]. Meat production makes the largest impact when it comes to producing greenhouse gases, as it accounts for nearly 60% of all greenhouse gases from food production [8]. Beef accounts for one quarter of the total emissions, and in general, the use of animals for meat causes twice the pollution of producing plant-based foods [8].

The high emissions caused by meat production in the context of climate change have meant that the current food start-up and innovation scene is dominated by ideas focused on developing alternative plant-based proteins. The discourse on the future of food is therefore largely about the future of meat. Alternative proteins, lab-grown meat, vegan diets and flexitarian lifestyles - all of these concepts contribute to the discussion of how or whether we will consume meat in the future. Despite a fairly unified political push towards reduced meat consumption [9], the issue is becoming increasingly polarised at the level of social sentiment [6]. While there is increasing investment in meat replacement innovation, there is currently no evidence of a mass shift away from meat consumption globally.

Given the complexity of food consumption and our willingness to illustrate this complexity, we choose to focus our analysis on weather data and meat consumption. We justify this choice by illustrating that both areas are under-researched and should be considered holistically, taking into account the complex nature of food choices as such. We also use an under-utilised resource in food analysis - big data from social media, particularly Twitter. Social media in general is one of the best places to track sentiment around specific food consumption, where food is widely documented and discussed in multiple formats [10]. The analysis of social network data has become popular in consumer studies where language data is analysed. Food emerges as one of the key topics discussed on Twitter, the social network we focus on in our work. As a platform primarily for text rather than images, and because of its accessibility for research purposes, Twitter is the digital space where it has become possible to track the most random details of tweeters’ everyday lives - including information about what, how and where they eat [11].

The driving motivation for this research is to build a better understanding of the world, in particular by looking at food consumption and the exchange of food-related information on social media. Food choices made by consumers have a major impact on public health and the sustainability of the planet, but due to the interdisciplinary nature of food, many important issues have been under-researched in narrowly focused research disciplines. This research aims to fill this gap and provide a methodology focused on sentiment analysis to understand food consumers, given the role that social media plays in modern lifestyles. With our approach, we aim
to contribute to a growing area of research that focuses on interdisciplinary research questions and insights into the future of food [12]. The collection of food-related data is an unmet challenge, so innovative ways of using social media and other large-scale data are the key innovative approach that this research offers.

2. Research Focus

We chose the social network Twitter for the analysis due to the availability of a large food-related data corpus in Latvian language that has been recently published - the Latvian Twitter Eater Corpus (LTEC [13]). We focused on a specific social media - Twitter, where food is one of the main topics discussed, providing us with spontaneous reactions of food consumers, which is a unique feature compared to other data collection methods such as reviews or food diaries [14]. Our analysis of the LTEC provided a series of food-related discussions that we could correlate with the weather data, leading to the following research questions 1) Is there a correlation between food tweet sentiment and the weather the tweet authors are experiencing at the time of tweeting? 2) Are there differences in the frequency of food mentioned in tweets depending on the weather, and if so, what are the differences? As Twitter is a digital space where food experiences are shared instantly, we can better explain the context in which tweet authors share their thoughts with our analysis of weather data. Given previous studies that have demonstrated the link between weather, mood and food perception, our work aims to illustrate this link through tweet sentiment analysis. We refine our study by looking at frequencies - which food authors tweet more in pleasant weather and unpleasant weather conditions, mapping the weather-related food scene in Latvian language Twitter. With this analysis of weather-related dynamics in LTEC, we contribute to the field of research on the impact of weather on food consumption for the geographical region of Latvia and contribute to a broader understanding of the impact of weather on food consumers globally.

We focused our analysis on all entries related to meat and meat products found in food-related tweets. The sentiment of the tweets was then analysed in terms of their positive, neutral or negative valence. Bearing in mind that social media is generally considered to present mostly positive experiences [15], we carried out a general sentiment analysis of the food tweets. We looked at the representation of meat and meat products in time dynamics, trying to capture both the historical and contemporary ‘zeitgeist’ in relation to meat consumption as it is represented in the Latvian-speaking community. In addition to an analysis of meat, we also looked at the representation of vegan and vegetarian food on Twitter, as well as debates about alternative proteins.

When analysing the discourse on meat in social media, it is important to be aware of the context of the society in question. When it comes to Latvian food culture and national cuisine, there is general agreement that the basis of Latvian cuisine is potatoes, dairy products, fish and meat, especially pork. It has developed as a heritage of peasant food in a mixture with aristocratic influence, similar to other European countries. ¹ A slightly better understanding of food consumption can be based on the different seasons that Latvian society goes through during

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the year. Latvia also has its seasonal food preferences, as depicted on social media: grey peas, tangerines and gingerbread during the Christmas season, and cold soup, strawberries and ice cream during the hot spring and summer [11].

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As a northern European country, Latvia has four distinct seasons where autumn and winter are relatively cold, dark and rainy, while summers are short and warm. What regards food choices, any society is sensitive to temperature and weather fluctuations, which is particularly evident in countries with greater seasonal variations in temperature [3]. Thus, Latvia is an example with various weather conditions that can be analysed from the perspective of tweeting about food: winter lasts from December until February, spring from March until May, summer is from June until August and finally, autumn from September until November. The average annual air temperature in Latvia is only +5.9°C. The year’s warmest month is July, and the coldest months are January and February. February is also the snowiest month of the year there. The months with the most precipitation are July and August, while the least is in February and March. The highest wind speeds are in November, December and January, and the lowest wind speeds are in July and August. The months from May to August have the most days of sunshine, while in November, December and January, the Sun shines on average only 2-3 hours a day [16].

3. Related Work

In this section, we will review research that links weather and food data, as well as research related to meat consumption and perception. We will first look at studies of weather-related data, which are few and far between, indicating the difficulty of using big data in food-related research [17].

Weather people is a term used by Bakhshi [18] to explain our dependence on the weather for food choice and satisfaction. While the weather is known to significantly alter consumers’ moods and consequently their behaviour [4], there have been surprisingly few studies illustrating the weather’s impact on food perception and choice, except for some that have used online and offline restaurant reviews as a proxy to measure it [1, 4]. It has been concluded that weather affects both the frequency and the content of feedback provided by food consumers. Typically, sunny and pleasant weather leads to more frequent and more positive feedback, as low humidity and high sunlight are associated with high mood. At the same time, reviews written on rainy or snowy days, i.e. days with precipitation, tend to have lower ratings. While seasonal food consumption

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2News portal of Latvian Radio and Latvian Television
patterns are culturally specific and vary across geographic regions, weather-related preferences appear to be universal.

A large-scale study of demographics, weather and online reviews of restaurant recommendations shows that pleasant weather not only affects the content of the review, but also the frequency, which is higher than in less pleasant weather conditions [1]. This is an important indicator that a review can serve as a proxy for measuring the impact of the weather on mood, and thus on the food consumption experience. Consumer comments and word-of-mouth have also been studied in relation to the weather, suggesting that consumers’ pre-consumption mood directly influences their post-consumption mood and, accordingly, their satisfaction with the service. Pre-consumption mood, in turn, is considered via weather conditions, with eight weather-related variables considered, including visibility, rain, storm, humidity, wind speed, barometric pressure and other variables. By including temperature, air pressure and rain as covariates, the researchers were able to reduce unexplained variance and improve the results of the experiment. This study successfully links weather to mood and its transfer to affective experience and consumer behaviour [4].

Reviews, word of mouth or tweets are language based proxies to determine attitude and related emotions towards the given topic, therefore, a deeper understanding of language and how we describe foods is a prerequisite to understanding the dynamics between the individual and the group when it comes to food choice. The language of how the dish is described matters, and the taste of the dish can change just because the wording of how food is described, has been changed [19]. Instead of language analysis of how particular foods are described, we focus on sentiment analysis which can be of great use for food language analysts to gain a more holistic view of how particular foods are discussed in different societies. With this research we aim to illustrate the utility of data coming from languages less resourced and less spoken. Thus, the LTEC, a unique resource devised for the analysis of Latvian food-related tweets, has been used in this research. It might serve as a pilot corpus for other less-resourced languages and contribute to a better understanding of the differences in food narratives depending on the language we use [20].

The interdisciplinary nature of food-related data poses challenges for the use of social network data. There are limitations to the fragmented nature of social media data: for example, Twitter users are digitally active and a relatively affluent part of the population, so results cannot be generalised to the whole of society. Nevertheless, even acknowledging the fragmentation, new research exploring the use of social media data can be of value to policy makers and those encouraging particular behaviours among food consumers. Another line of research that demonstrates the usefulness of social media analysis is looking at how digital food affects our analogue lives and eating behaviour in particular [21]. Correlating social media results about food in a particular region with sales data could be the next step in our analytical approach, as there is general agreement that digital content influences purchasing behaviour in our analogue lives, but this lacks granularity when it comes to exact correlations and proof of statements.

4. Data Collection and Processing

Our analysis examines the LTEC, which contains 2.4M tweets generated by 169k users. It has been collected for over 10 years by following 363 eating-related keywords in Latvian. The dataset
provides some additional metadata about each tweet, such as location (when available), a list of food items mentioned in the tweet text, and a separate subset of tweets with manually annotated sentiment classes - positive, neutral and negative.

Since the corpus contains normalised versions of all food items in singular nominative form for each tweet, we used these to further select only the specific tweets for our analysis. This was done by firstly compiling a list of most used meat-related nouns (see Table 1), and then selecting only the very narrow subset which mentions either beef, chicken or pork.

<table>
<thead>
<tr>
<th>liver</th>
<th>sausage</th>
<th>chop</th>
<th>bacon</th>
<th>roast</th>
<th>chicken</th>
<th>deer</th>
<th>bratwurst</th>
</tr>
</thead>
<tbody>
<tr>
<td>beef</td>
<td>schnitzel</td>
<td>fillet</td>
<td>goose</td>
<td>gyros</td>
<td>ribs</td>
<td>ham</td>
<td>salami</td>
</tr>
<tr>
<td>steak</td>
<td>pork</td>
<td>cutlet</td>
<td>steak</td>
<td>lamb</td>
<td>meat</td>
<td>meatball</td>
<td>turkey</td>
</tr>
</tbody>
</table>

Table 1
The list of meat products included in our experiment.

4.1. Tweet Sentiment Analysis

We used the 5420 annotated tweets to fine-tune a pre-trained multilingual BERT [22] model for the sentiment analysis task along with ~20,000 sentiment-annotated Latvian tweets from other sources\(^3\) so that the model would generalise better. We evaluated the sentiment model on the 743 tweet test set provided in LTEC and reached an accuracy of 74.06%. Our result outperforms the best accuracy reported by the authors of LTEC, who used a Naive Bayes model on stemmed data and reached 61.23%. However, this was expected since they used ~20% less training data, and BERT or other transformer-based models have outperformed previous state-of-the-art methods in many language processing tasks, including classification. We then used the model to automatically classify all tweets in LTEC as positive, neutral or negative for further analysis.

To verify the quality of the sentiment analysis model, we selected 50 random automatically classified tweets from each year between 2011 and 2020 and performed a manual evaluation. Twelve human evaluators were asked to individually judge each of the 500 predictions by the model and provide a suggested alternative sentiment class for cases where they deemed the model to be incorrect. We used the majority vote of the human evaluators as the correct answer in cases where they disagreed on a particular evaluation and considered two classifications as correct in the 21 cases where the majority opinion was split in half (for example, 6 positive and 6 neutral). The overall agreement of the evaluators was 70.48% with a free marginal kappa [23] of 0.56 (values from 0.40 to 0.75 are considered intermediate to good agreement). The accuracy of the model according to the majority of human evaluators on this set was even higher, reaching 86.40%, while the accuracy of the average human evaluator compared to the majority was only 80.25%. This shows that 1) the tweet texts are not always trivial enough to be unequivocally classified into just one of the three sentiment classes, and 2) the model is good enough to be used on the scale of the whole dataset.

\(^3\)https://github.com/Usprogis/Latvian-Twitter-Eater-Corpus/tree/master/sub-corpora/sentiment-analysis#other-latvian-twitter-sentiment-corpora
4.2. Tweet Alignment with Weather Data

To conduct our analysis in relation to weather data, we used a combination of two data sources - the LTEC for tweets and weather data exported from Meteostat\(^4\). We mainly focused on tweets and weather relating to Riga, the capital of Latvia, since most tweets with location data originated there, and it was difficult to obtain detailed historical weather data for the smaller regions.

Among the tweets, 167k have location metadata specified, of which 68k were from Riga and 9k more from areas around Riga. To further increase the number of location-related tweets, we selected all remaining tweets which mention Riga or any of its surrounding areas (like Marupe, Kekava, Salaspils, Adazi, etc.) in any valid inflected form. This added 54k tweets, giving a total of 131,595.

From the Meteostat website, we could reliably obtain only data for temperature and precipitation, while data for snowfall was only available up to the end of 2017, and data for wind speed and air pressure was only available from July 2018 and onward. Figure 1 shows a visual depiction of the data gathered. There was no available data to trace daily sunshine directly, but it can be inferred from looking at precipitation, snowfall and air pressure.

![Figure 1: Visualisation of available weather data from Meteostat.](https://meteostat.net/en/place/lv/riga)

4.3. Limitations and Assumptions

Our work has several important limitations that can be grouped into the categories of 1) data availability, 2) demographic profile of the tweet author, and 3) generalisation of results. First, we were only able to obtain fairly superficial weather data, while subtleties such as weather changes during the same day were not taken into account due to the lack of such details. Second, we cannot provide a demographic perspective of the usual tweet author in LTEC, and our analysis includes

\(^4\)https://meteostat.net/en/place/lv/riga
tweets from generally digitally literate people active on Twitter. Third, given the limitations discussed, our results are not an exact extrapolation of weather-related food perceptions in Latvian society. Nevertheless, our approach makes use of the growing LTEC and contributes to the understanding of the impact of weather on the part of Latvian society that tweets about food.

5. Analysis and Results

5.1. Food Tweet Relation to Type of Weather

While the results of tweet sentiment in terms of the percentage of negative, neutral and positive tweets are largely the same for all weather conditions, we can still observe significantly fewer positive tweets during windy and high pressure weather conditions, as can be seen in Table 2. We were surprised to see that even during low pressure weather conditions, tweets are not necessarily dominated by negative sentiment - on the contrary, food tweets were mostly associated with positive sentiment. This could be explained by the fact that people tweet about comfort food (e.g. coffee, chocolate, other) or that any food could be comforting during days of low pressure. This remains to be answered in a more fine-grained manual analysis.

<table>
<thead>
<tr>
<th></th>
<th>Cold</th>
<th>Warm</th>
<th>Windy</th>
<th>Snowy</th>
<th>Rainy</th>
<th>High Pres</th>
<th>Low Pres</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td>12.59%</td>
<td>13.20%</td>
<td>23.15%</td>
<td>11.88%</td>
<td>13.63%</td>
<td>23.10%</td>
<td>12.63%</td>
<td>13.07%</td>
</tr>
<tr>
<td>0</td>
<td>37.25%</td>
<td>38.68%</td>
<td>23.15%</td>
<td>36.06%</td>
<td>38.64%</td>
<td>23.10%</td>
<td>38.72%</td>
<td>38.38%</td>
</tr>
<tr>
<td>+</td>
<td>50.17%</td>
<td>48.12%</td>
<td>28.45%</td>
<td>52.06%</td>
<td>47.73%</td>
<td>28.63%</td>
<td>48.65%</td>
<td>48.55%</td>
</tr>
</tbody>
</table>

Table 2
Weather relation to tweet sentiment. Rows -, 0, + specify negative, neutral and positive sentiment respectively.

The Table 3 shows that tea surpasses coffee in cold weather, and there is also a slight increase in tweets about chocolate in cold weather, while the frequency of ice-cream tweets doubles in warm weather. Interestingly, the number of tweets about meat, cake or soup in hot or cold weather remains broadly similar. While warm weather tweets include strawberries, cold weather tweets include gingerbread, which coincides with seasonal Christmas food. There are no other notable differences between warm and cold weather tweets, suggesting that spending most of our lives indoors has harmonised the foods we tweet about in different seasons and weather conditions.

<table>
<thead>
<tr>
<th>Product</th>
<th>Tea</th>
<th>Coffee</th>
<th>Meat</th>
<th>Chocolate</th>
<th>Cake</th>
<th>Ice cream</th>
<th>Salad</th>
<th>Dumplings</th>
<th>Pancake</th>
<th>Sauce</th>
<th>Gingerbread</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainy</td>
<td>6.78%</td>
<td>6.59%</td>
<td>4.20%</td>
<td>4.83%</td>
<td>2.77%</td>
<td>3.05%</td>
<td>2.19%</td>
<td>2.35%</td>
<td>2.16%</td>
<td>2.01%</td>
<td>1.49%</td>
</tr>
<tr>
<td>Windy</td>
<td>6.64%</td>
<td>5.94%</td>
<td>9.44%</td>
<td>3.50%</td>
<td>4.20%</td>
<td>1.75%</td>
<td>3.15%</td>
<td>1.05%</td>
<td>0.70%</td>
<td>0.70%</td>
<td>2.10%</td>
</tr>
<tr>
<td>Warm</td>
<td>7.70%</td>
<td>6.77%</td>
<td>4.38%</td>
<td>4.96%</td>
<td>2.88%</td>
<td>4.04%</td>
<td>2.14%</td>
<td>2.28%</td>
<td>2.91%</td>
<td>2.07%</td>
<td>0.74%</td>
</tr>
<tr>
<td>Cold</td>
<td>10.08%</td>
<td>6.73%</td>
<td>3.95%</td>
<td>5.14%</td>
<td>2.33%</td>
<td>2.35%</td>
<td>1.81%</td>
<td>2.12%</td>
<td>2.20%</td>
<td>1.65%</td>
<td>2.10%</td>
</tr>
</tbody>
</table>

Table 3
Comparison of top products during windy (wind speed ≥ 20km/h), rainy (precipitation > 0), cold (≤ 0 °C), and warm weather (≥ 0 °C).

A slightly different result can be seen in the Table 3 in relation to meat. It shows that in windy weather meat becomes the most popular food, while in rainy weather the results are similar to cold weather - where tea dominates. Although it is difficult to explain this result, it could be that wind
is less visible than the temperature often reported in the media or precipitation, which can be seen before leaving the house, and therefore people may feel uncomfortably cold in windy weather without appropriate clothing, which could lead to a greater willingness to eat meat. Chocolate is twice as popular in rainy weather as in windy weather, and this could be related to the lack of sunshine in rainy weather, which needs to be compensated by chocolate, whereas a windy day can still be sunny.

5.2. Meat-related Tweet Analysis

Before turning to the results of the sentiment analysis of meat-related tweets, we first look at the distribution of sentiment across all food tweets in the dataset. In the tweets from 2011-2020, we can observe an overall decrease in positive sentiment and an increase in negative sentiment, as well as a comparatively large proportion of neutral tweets. Figure 2 shows the overall sentiment distribution over this period. It also shows that the number of positive tweets decreased until 2015, that the number of neutral tweets increased from 2015, and that the number of negative tweets increased from around 2018.

Figure 2: Distribution of overall tweet sentiment in LTEC over time from 2011 to 2020.

Figure 3 shows the sentiment over time of all meat-related tweets. In addition to selecting all inflections of the word "meat", we also include the specific meat products listed in Table 1 in this overview. Here we can see that until 2016, Twitter users were not overly active in discussions about meat overall. The proportion of tweets with neutral sentiments increased significantly between 2016 and 2018 and has remained largely stable since then, while the proportion of more polarised opinions - positive and negative meat-related tweets - still seems to be increasing slightly. Although the level of negative tweets is largely flat between 2011 and 2017, the one spike in March 2013 can be attributed to a scandal over the alleged use of horse meat in a popular butchery chain from Latvia\(^5\). Since 2016, tweets with negative sentiment have outnumbered those with positive sentiment, although the majority of meat-related food tweets can still be classified as neutral.

\(^5\)https://www.theguardian.com/uk-news/2013/jul/19/horsemeat-scandal-meat-pies-latvia
To take a closer look at specific meat products, Figure 4 shows the differences in sentiment towards chicken, beef and pork. Again, we can see a sharp increase in neutral tweets from 2016, which could be explained by the rise in popularity of public lunch offers at local restaurants and other types of food-specific advertising. A neutral tweet in this case is a tweet that simply informs about the daily specials at a café or restaurant, without any emotional connotation to the food listed in those specials. However, with the onset of the Covid-19 pandemic, neutrality has given way to either positive or negative valence. One possible reason for this could be the closure of restaurants and other public spaces for food consumption, and correspondingly fewer such neutral lunch-offer-type tweets from the corporate sector.

Figure 3: Temporal sentiment dynamics of meat-related tweets LTEC in 2011-2020.

Figure 4: Temporal sentiment dynamics in 2011-2020: tweets mentioning beef, chicken or pork.
5.3. Vegans, Vegetarians and Alternative Proteins

In addition to posts directly mentioning meat-related products, we were also interested in whether meat alternatives are mentioned and how they are perceived on Twitter. Figures 5 and 6 give an overview of tweets mentioning either ‘vegan’ or ‘vegetarian’ in any inflection of the Latvian language or any inflection of the word ‘protein’ in Latvian. Overall, we can observe a lower amount of tweets compared to those mentioning ‘meat’, as well as a higher tendency of positive sentiment tweets. The dominance of positive sentiment tweets over neutral tweets, which dominate meat-related discourses, may mean that there are few tweets from, for example, the corporate sector in the form of lunch offers or sales of vegan/vegetarian food, or other marketing-related neutral tweets. Instead, as veganism and vegetarianism are not yet mainstream discourses, they are mostly discussed by people with strictly positive or negative attitudes towards them.

Regarding negative sentiments, it should be noted that ‘vegan’ is sometimes used as an insult in the Latvian Twitter space, referring to a person who is weak, incapable of doing activities that require physical strength, and does not have the work experience of younger generations. A new term, ‘soy latte drinkers’, emerged in the debate when conscription was extended following Russia’s invasion of Ukraine. Young people protesting against conscription were ironically called ‘soy latte drinkers’, implying their weakness due to their vegetarian or vegan lifestyle.

With regard to (alternative) proteins, we see a similar dynamic to that of vegan and vegetarian discourse, but with even lower frequencies, which means that the discussion about proteins in the Latvian Twitter space is very low, and when it takes place, it is mostly positive or neutral, with little informative content generated. These results of low frequencies mean that vegan and vegetarian diets and the search for alternative proteins remain marginal in the everyday discussions of Twitter users in Latvia.

![Figure 5: Distribution of tweet sentiment in LTEC over time from 2011 to 2020 of tweets mentioning vegan or vegetarian.](image-url)
6. Conclusion

Our analysis contributes to the understanding of how weather affects the mood of food consumers by showing that certain weather conditions, such as windy weather, affect the content of food tweets. This knowledge of tweet frequency and sentiment can be useful to public health policy makers and applied when nudging consumers to choose healthier food alternatives in different weather conditions and seasons. Recognising and understanding the impact of weather on food consumers and their affective responses helps to explain the complexities associated with food consumption - food waste, healthy vs unhealthy food choices and other issues.

We started with the statement that the future of food will be largely determined/dependent on the future of meat, as policy recommendations push for reduced meat consumption. This has paved the way for e.g. the development of alternative proteins, as more and more investment flows into this area, as well as the appreciation of vegetarian/vegan diets, which has come to shape the discourse in stark contrast to the discourse of meat lovers. In this case, social media can serve as a litmus test for public sentiment and attitudes towards meat consumption. Our research shows that negative sentiment towards meat is steadily increasing on Latvian Twitter, although neutral sentiment still dominates. The spread of the Covid-19 pandemic seems to have significantly reduced neutrality towards certain types of meat - chicken, beef and pork. All these data help us to track public attitudes towards meat consumption and to assess their willingness to change in the direction of the lower meat consumption future envisaged by policymakers. Looking at the sentiments and frequencies related to vegan/vegetarian food and protein, we conclude that there are not many discussions on Twitter related to these topics compared to meat.

These data can be useful for policymakers working with the public diets’ shift towards more environmentally conscious choices. Knowing the dominating discourse in the society related to meat and being able to trace the sentiment changes over time, can potentially best signify the society’s maturity for change as suggested by public health policymakers. These data can be useful
also for industry players, such as retailers and meat producers who shape their own discourse on meat consumption in particular markets. For marketers, temporal sentiment dynamics related to meat are valuable sales and marketing data and can be utilised in their promotional activities.

Taking into account the seldom use of social media data in academic research due to the fragmented nature - user demographics unknown, data only from the relatively wealthy and digitally active part of society, particular preferences of the social network in focus - Twitter, while other different social networks also of use, we consider that our research provides important encouragement to utilise social network data. The utility of our research results can be seen via creating valuable insights into group dynamics of the particular society, and while fragmented and in many ways incomplete, social media data of a particular social network Twitter, can to a large extent impact individual food choices. Group dynamics of social media can signify and determine the trends that impact individual preferences and ultimately food choices. Therefore, when developing individual food and health applications, it is of utmost importance to include the context data of the individual, society, national cuisine, weather and seasonality in their analysis. Social media data serve to signify those various influential context factors as can be seen also from our analysis of a particular focus on meat consumption sentiments in the Latvian Twitter community.

To conclude, through our interdisciplinary research, we unravel the complex interplay between economics, digital platforms and practical knowledge within the Latvian food market and Twitter food posts. By understanding the impact of weather on consumer sentiment and tweet content, we provide valuable insights for policymakers to nudge consumers towards healthier choices. This highlights the potential of social media data to shape individual food preferences and drive societal trends, fostering a more sustainable and conscious food market in Latvia.

We plan to release the additional data and models generated in this research publicly. The automatically assigned sentiment classes will be added to the main corpus data repository on GitHub\(^6\), and publish the sentiment analysis model to Hugging Face’s model hub\(^7\).

**Acknowledgement**

This research is supported by the project "Strengthening of the capacity of doctoral studies at the University of Latvia within the framework of the new doctoral model", identification No. 8.2.2.0/20/I/006

**References**


\(^6\)https://github.com/Usprogis/Latvian-Twitter-Eater-Corpus/

\(^7\)https://huggingface.co/models


*August 22, 2022*